REMOTE SENSING OF THE SPATIO-TEMPORAL DISTRIBUTION OF INVASIVE WATER HYACINTH (*Eichhornia crassipes*) IN THE GREATER LETABA RIVER SYSTEM IN TZANEEN, SOUTH AFRICA

BY

KGABO HUMPHREY THAMAGA

A DISSERTATION SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE MASTER OF SCIENCE IN GEOGRAPHY

DEPARTMENT OF GEOGRAPHY AND ENVIRONMENTAL STUDIES, SCHOOL OF AGRICULTURAL AND ENVIRONMENTAL SCIENCES, FACULTY OF SCIENCE AND AGRICULTURE, UNIVERSITY OF LIMPOPO, SOUTH AFRICA

SUPERVISOR: TIMOTHY DUBE (MSc, Ph.D)

JUNE, 2018

Abstract

Water hyacinth (*Eichhornia crassipes*) is recognised as the most notorious invasive species the world-over. Although its threats and effects are fully documented, its distribution is not yet understood, especially in complex environments, such as river systems. This has been associated with the lack of accurate (high spatial resolution) and robust techniques, together with the reliable data sources necessary for its quantification and monitoring. The advent of new generation sensors i.e. Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multi-Spectral Instrument (MSI) data, with unique sensor design and improved sensing characteristics is therefore perceived to provide new opportunities for mapping the distribution of invasive water hyacinth in small waterbodies. This study aimed at mapping and understanding the spatio-temporal distribution of invasive water hyacinth in the Greater Letaba river system in Tzaneen, Limpopo Province of South Africa using Landsat 8 OLI and Sentinel-2 MSI data. Specifically, the study sought to identify multispectral remote sensing variables that can optimally detect and map invasive water hyacinth. Landsat 8 OLI and Sentinel-2 MSI were tested based on the spectral bands, vegetation indices, as well as the combined spectral bands plus vegetation indices, using discriminant analysis algorithm. From the findings, Sentinel-2 MSI outperformed Landsat 8 OLI in mapping water hyacinth, with an overall classification (OA) accuracy of 77.56% and 68.44%, respectively. This observation was further confirmed by a *t*-test statistical analysis which showed that there were significant differences (t=6.313, p<0.04) between the performance of the two sensors. Secondly, the study sought to map the spatial distribution of invasive water hyacinth in the river system over time (Seasonal). Multi-date 10 m Sentinel-2 MSI images were used to detect and monitor the seasonal distribution and variations of water hyacinth in the Greater Letaba River system. The study demonstrated that, about 63.82% of the river system was infested with water hyacinth during the wet season and 28.34% during the dry season. Sentinel-2 MSI managed to depict species spatio-temporal distribution with an OA of 80.79% during wet season and 79.04% in dry season, using integrated spectral bands and vegetation indices. New generation sensors provide new opportunities and potential for seasonal or long-term monitoring of aquatic invasive species like water hyacinth- a previously challenging task with broadband multispectral sensors.

Keywords: eutrophication; freshwater system; mixed pixels; monitoring; phenological change; remote sensing; seasonal variations.

Preface

This research study was conducted in the Department of Geography and Environmental Studies, University of Limpopo, South Africa, from January 2017 to June 2018, under the supervision of Dr Timothy Dube.

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

Kgabo Humphrey Thamaga signed   Date: 26 July 2018

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

Dr Timothy Dube   signed   Date: 26 July 2018

Declaration

Full names of student: Kgabo Humphrey Thamaga

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

Publication and manuscripts

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

Thamaga, K.H. and Dube, T., 2018. Remote sensing of invasive water hyacinth (*Eichhornia crassipes*): A review on applications and challenges. *Remote Sensing Applications: Society and Environment*, 10:36-46.

Thamaga K.H. and Dube, T., 2018. Testing two methods for mapping water hyacinth (*Eichhornia crassipes*) in the Greater Letaba river system, South Africa: Discrimination and mapping potential of the polar-orbiting Sentinel-2 MSI and Landsat 8 OLI sensors. *International Journal of Remote Sensing*, https://doi.org/10.1080/01431161.2018.1479796.

Thamaga K.H. and Dube, T., 2018. Mapping the seasonal dynamics of invasive water hyacinth (*Eichhornia crassipes*) in the Greater Letaba river system using multi-temporal Sentinel-2 satellite data. *GIScience and Remote Sensing*, TGRS-S-18-00114. (**Manuscript under review**).

Dedication

This dissertation is dedicated to the late Kwena Frans Thamaga, My father.

To my mother Mosima Gladys Thamaga and Rebabaletswe my daughter.

Acknowledgements

I honour You LORD for protecting me since birth until today. I would like to express my sincere gratitude to the Risk and Vulnerability Science Centre (RSVC) for funding this project. I am very grateful to my promoter and supervisor Dr Timothy Dube for supervising this research project. His diligent constructive criticism and guidance encouraged me to put more effort on this research project, and without his dedicated guidance I would not have reached this stage. From him, I learnt remote sensing as a tool to solve problems, and to be critical to my own work, as well as being independent researcher. Dr Dube, thank you again for always opening your door for me. At first, I was not confident enough on how to tackle this study, but along the way you taught me not only to be positive but also problem-solving skills. To Mr Terrence K. Sepuru and Mr Inos Dhau thank you for assisting with data collection. I would also like to also thank Mr Mpho Gegana for his technical support. Your ideas really aided me despite the difficulties during field data collection. It is my pleasure as well to extend word of thanks to Mrs Makgalake P. Randingoana for grammar and spelling checks and for her motivational talks, which inspired me to work even harder. More so, I would like to thank colleagues from the Department of Geography and Environmental Studies, University of Limpopo for their support system. My deepest gratitude goes specifically to my mother and daughter (Rebabaletswe) for their patience, support, courage, as well as understanding during a lengthy period of absence. To my mom and sister Makwena Mildred, you played a very critical role in my life, *may the good LORD protect and bless you*. Vote of thanks to Karabo B. Mboweni, Fulgence Morifi, Kelvin Mabela, Glen J.R. Kgopong, Pearl R. Mailula, Manare M. Thamaga, Enerst N. Thamaga, Ireen N. Thamaga, Eliot Sebuyi and Selina M. Maunatla; thank you for your support and courage until the very end. Finally, I would like to thank my entire family and friends whoever in a wide range of spectrum helped me anyhow and I do not have to mention, thank you all.

"All in the power of God", Amen

Kgabo Humphrey Thamaga

Table of Contents

List of tables

List of figures

1. CHAPTER ONE

GENERAL INTRODUCTION

1.1 Introduction

Water resources provide numerous socio-economic and ecological benefits to the country ranging from domestic, agricultural and industrial use. The sustainable utilization of this resource is however, affected by the effects of invasive species, climate change and pressure from mankind. Previous studies indicate that, inland rivers, wetlands, ponds and dams are heavily polluted (de Troyer *et al*., 2016). Fast urban growth (70%), especially from developing countries together with rural-to-urban migration generates continuous expansion of slums or shanty towns resulting in poor provision of proper sanitation infrastructure (Mabogunje, 2002; Ogwueleka, 2009). This in turn leads to direct discharge of untreated sewage into rivers and streams (Norah *et al*., 2015). This largely contributes to the pollution of rivers traversing urban areas in most developing countries, resulting in the proliferation of aquatic invasive species e.g. water hyacinth (*Eichhornia crassipes*) in polluted water ways. Malik (2017) describes water hyacinth as the most notorious free-floating aquatic alien weed that is often linked with an increase in nutrients in water. Due to its extremely fast growth, it has become the major floating aquatic weed in the tropical and subtropical regions globally (Cilliers *et al*., 2003; Sotolu, 2013). Furthermore, agricultural intensification has resulted in intensified pressure on freshwater systems, due to the amount of fertilizers or nutrients carried into rivers or streams.

Also, favourable climatic conditions have been found to enhance the infestation rates in most vulnerable rivers and other open water bodies (Penfound and Earle, 1948; Giardino *et al*., 2015). This result in a decline in water resources availability for agricultural production, clogging of navigation route, disturbs aquatic life and acts as a breeding ground for mosquitoes, snakes, crocodiles and vectors of *schistosomiasis*, which cause diseases (Villamagna and Murphy, 2010). All these problems in turn affect socio-economies and the environment of the surrounding communities (Shekede *et al*., 2008). Besides, in South Africa the weed has become unmanageable, despite huge resources and efforts allocated towards its control (Byrne *et al*., 2010). Lack of up-to-date and reliable spatial information further complicates the management of this weed. So far, management efforts rely on non-periodic surveys, which are costly, laborious and sometimes inaccurate for integrated water resources management (Shekede *et al*., 2010; Dube *et al*., 2017a). There is therefore, a need to continuously map and monitor waterbodies from invasive species infestation and identify areas already affected, as this can help develop effective management strategies of water hyacinth. This information can also contribute to already on going South African National Programs, such as “Working for Water” and “Finding New Water” through the clearance of invasive species (Binns *et al.*, 2001; Bek *et al.*, 2007; DWAF, 2007; Turpie *et al.*, 2008; van Wilgen and Wannenburgh, 2015).

However, for the above national initiatives to be successful there is a need for accurate and up-to-date information on the spatial distribution of aquatic weeds to understand their evolution, determine affected areas and evaluate the efficiency of control measures and management actions in place (Shekede *et al*., 2008). Geospatial technologies (remote sensing and Geographic Information systems) have since emerged as a tool that offer quick and more efficient methods to identify and map plant species and the associated changes over time. These technologies have so far, proved to be useful in mapping invasive species in large waterbodies such as lakes, but their performance on slightly narrow river systems remains untested, due to the lack of high resolution spatial data. It is therefore hypothesized that, the advent of Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multi-Spectral Instrument (MSI) sensors provides a new opportunity to derive thematic maps that can discern the spatial location and distribution of invasive water hyacinth in smaller waterbodies, over time and space. It is assumed also that these sensors can be used to timely and accurately map, as well as identify emergent and floating-leaved plants in open waterbodies without any pixel-mixing problems. Thematic maps can be incorporated into GIS to model the distribution of water hyacinth over time and help understand their impacts on the already scarce water resources.

The use of newly launched satellite sensors e.g. Landsat 8 OLI and Senetinel-2 MSI is perceived to provide the most needed primary data sources appropriate for repeated monitoring of small or large-scale waterbodies. Shoko and Mutanga, (2017) showed that these two sensors, with improved image acquisition and sensing characteristics provides renewed capability for vegetation mapping and monitoring. Dube *et al*. (2014) and Sheng *et al*. (2016) showed that Landsat data series has a good global footprint and a repeated coverage. Other related studies demonstrated their successful application and performance in land cover mapping (Scharsich *et al*., 2017, Zhang *et al*., 2018), soil erosion mapping (Price, K.P., 1993; Babaeian *et al*., 2016; Sepuru and Dube, 2018) and biomass mapping (Chen *et a*l., 2016; Aslan *et al*., 2016; Matasci *et al*., 2018). The advent of new generation sensors i.e.

Landsat 8 OLI and Sentinel-2 MSI data, with unique sensor design and improved sensing characteristics is therefore, perceived to provide new opportunities for mapping the distribution of invasive water hyacinth in small waterbodies. It is on this premise that this sought to map the spatio-temporal distribution of invasive water hyacinth in the Greater Letaba river system, using the two new generation sensors – a previously challenging task with broadband sensors.

1.1.1 Aims and objectives

The overall aim of the study was to map the spatio-temporal distribution of invasive water hyacinth in the Greater Letaba river system using new generation sensors.

Objectives:

- To identify multispectral remote sensing variables that can optimally detect the spatial distribution of invasive water hyacinth in the Greater Letaba river system.
- To map the spatial distribution of invasive water hyacinth in the river over time.

1.1.2 Key research questions

- Which of the two sensors (Landsat 8 OLI and Sentinel-2 MSI) can optimally detect and map the spatial distribution of water hyacinth?
- Does the occurrence and spatial distribution of water hyacinth in a river system vary across seasons?

1.1.3 Main hypothesis

The newly generation sensors Landsat 8 OLI and Sentinel-2 MSI with unique characteristics (improved spatial, spectral and time revisit) can accurately detect, discriminate and map the spatial distribution of water hyacinth in a river system.

1.2 Description of Study Area

The study was conducted at the Greater Letaba river system in Tzaneen, Limpopo Province of South Africa. The area is located at -23° 39.036'S, 31° 9.006'E geographical co-ordinates (Figure 1.1). The Greater Letaba river system is the main freshwater supply for the neighbouring communities and farmlands in Tzaneen area. The river system serves a variety of services, such as: irrigation, domestic use, as well as the aquatic ecology, especially in the upper stream. The river system has been affected by a widespread invasion by water hyacinth (*Eichhornia crassipes*), and has deteriorated by continuous accretion of fertilizers from the surrounding farmlands carried out through run-off and disposal of raw sewage from the surrounding urban areas. The area has a mean annual precipitation of 612 mm, mean annual temperature of 28 °C in summer and they drop to 18°C in winter (DEAT, 2001), which influences the growth and distribution of water hyacinth in freshwater ecosystem. The main land cover types within the study area include croplands, grasslands, fruit trees, built up areas, roads and plantation (DEAT, 2001). Commercial farming is the dominant human activity in the area.

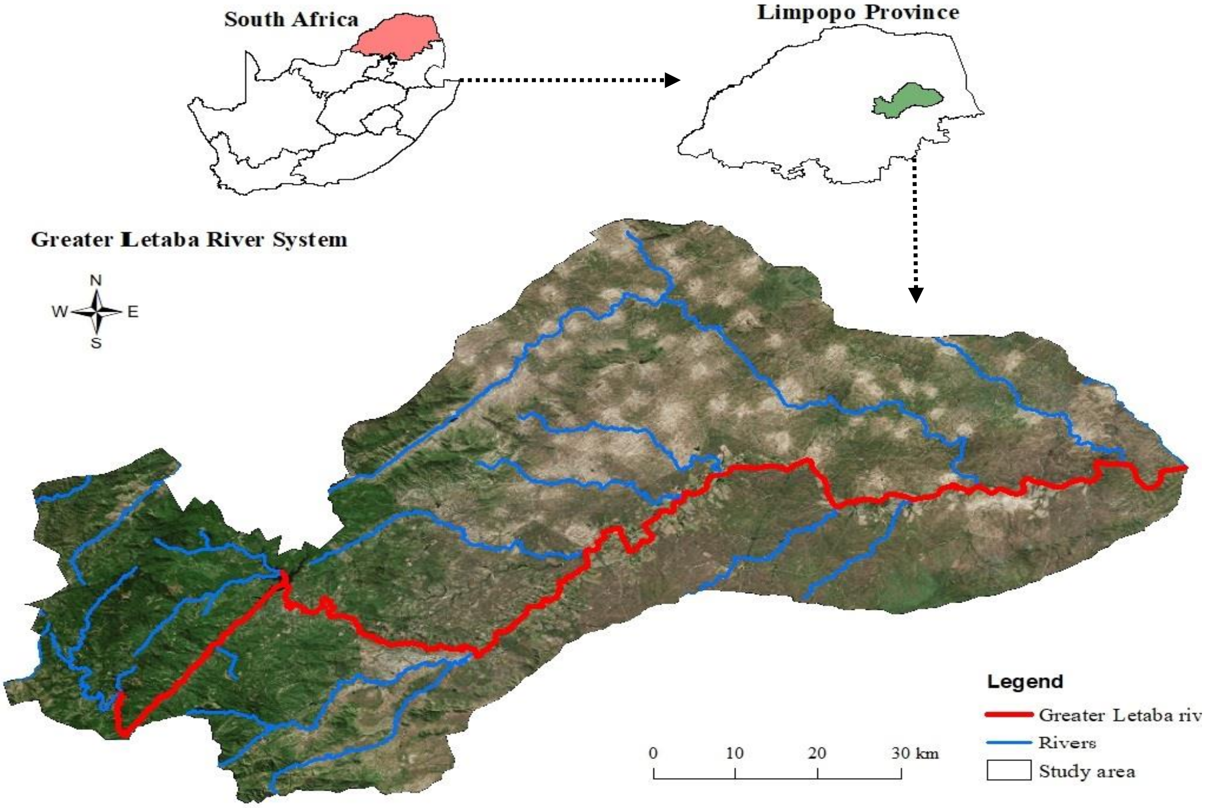

Figure 1.1: Locational map of the study area

1.3 Structure of the research

General outline of the dissertation

This dissertation consists of five chapters. Excluding the first chapter which focused on the general introduction and last chapter containing synthesis of research work, this dissertation has three stand-alone papers (Chapter 2, 3 and 4). The papers are published in different journals and they answer each objective in this study. Consequently, each paper comprises of an individual introduction, material and methods, results and discussion section. The published chapters have their own style, according to the publishing journal. Although attempts were made to conform to a general style in the dissertation, there may be some overlapping and repetition in some of the sections.

Chapter one:

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

Chapter two:

This chapter reviews the applications and challenges in detecting and mapping spatial distribution of water hyacinth using remote sensing. The study highlighted gaps and possible future directions in using freely and readily available sensors to detect and map water hyacinth in complex environments.

Chapter three:

In this chapter, two newly launched remote sensing satellite imagery (Landsat 8 OLI and Sentinel-2 MSI) are tested in optimally detecting, and mapping water hyacinth from other land cover features. Sentinel-2 MSI with improved spectral and spatial resolution showed its capability in mapping water hyacinth as compared to Landsat 8 OLI.

Chapter four:

Since in Chapter three Sentinel 2 data appeared to be the best in mapping water hyacinth, the data set is further used to derive temporal dynamics of water hyacinth over different seasons. This chapter focused on the use of Sentinel-2 MSI data in seasonal mapping and monitoring of water hyacinth variations in the Greater Letaba river system (wet and dry season). The seasonal information is of importance in understanding the configuration and distribution of water hyacinth in a river system and in informing effective management strategies.

Chapter five:

This chapter provides a synthesis that consolidates the findings of the research, discussions and overall conclusions of the three preceding chapters. Based on the limitations pointed out in the study this chapter draw recommendations for future research. Lastly, the reference list is provided at the end to acknowledge author’s work that was used in the dissertation.

2. CHAPTER TWO

Remote Sensing of invasive water hyacinth (*Eichhornia crassipes*): a review on applications and challenges

This chapter is based on a published review paper:

Thamaga, K.H. and Dube, T., 2018. Remote sensing of invasive water hyacinth (*Eichhornia crassipes*): A review on applications and challenges. *Remote Sensing Applications: Society and Environment*, 10:36-46.

Abstract

Aquatic invasive species threaten socio-economic and ecological systems, by invading freshwater ecosystems, and influencing their functionality and productivity, as well as disturbing key hydrological processes. Ecologically, water hyacinth can impact zooplankton and phytoplankton productivity in freshwater ecosystems by modifying surface water clarity and cause hypoxia or a decrease in the concentration of related nutrients and contaminants, such as nitrogen, phosphorous and heavy metals. Field surveys and water-related reports indicate that water hyacinth (*Eichhornia crassipes*), which is one of the most aggressive and lethal floating aquatic weed; has invaded most water bodies in the sub tropics. Its spread is largely linked to eutrophication emanating from poor land use management practices, and other environmental and climatic factors. Besides its threats and effects, its distribution in streams and rivers is not yet fully understood. This gap in knowledge is due to over reliance on traditional surveys and lack of financial resources and most importantly the lack of readily available or affordable satellite platforms, with optimal spatial and spectral settings that can discern water hyacinth from other co-existing plant species. In sub-Saharan Africa for instance, the use of high resolution satellite data is constrained by the acquisition costs and in some cases lack of technical expertise. There is, therefore, a need to develop new and robust methodologies that can map aquatic water weeds, especially in small freshwater bodies. The use of recently launched crop of new generation sensors like Sentinel-2 and Landsat 8 sensors, with improved sensing characteristics, unlike the previous broadband multispectral sensors provides untapped prospective alternatives.

Keywords: aquatic weeds; control mechanisms; eutrophication; monitoring; satellite data.

2.1 Introduction

Water is the most valuable resource on earth providing numerous socio-economic and ecological benefits at household, farm and global scale such as agricultural, industrial and domestic use. The world's freshwater resources are, however, on a steady decline, due to increased pressure resulting from poor domestic waste disposal as well as agricultural and industrial intensification, which causes eutrophication not only in lakes, but also streams, rivers, reservoirs (induces by dams) and consequently massive spread of aquatic weeds (Selman *et al.*, 2008). For example, increasing population pressure and land development pose on-going difficulties towards the administration of the environment and the associated river ecosystems (Hardoy and Mitlin, 2001; Achankeng, 2003). This problem is further exacerbated by anthropogenic activities and extreme weather events, which favours invasive species propagation. Water hyacinth causes significant ecological alterations in the invaded community by modifying the habitat. This subsequently disrupts the food chain, nutrient cycle, invertebrate and fish assemblage, as well as the entire food web structure (Brendonck *et al*., 2003; Toft *et al*., 2003; Coetzee *et al*., 2014). Therefore, International Union for Conservation of Nature (IUCN) rates the water hyacinth as one of the hundred most harmful invasive species (Téllez *et al*., 2008). This assertion is further confirmed by Shanab *et al*. (2010) and Patel (2012) who stated that, water hyacinth is one of the top ten worst weeds globally. However, in its native range, water hyacinth plays a vital role for phytoplankton, zooplankton and fish in freshwater ecosystems, by providing habitat complexity, shelter and feeding grounds (Brendonck *et al*., 2003; Meerhoff *et al*., 2003; Villamagna and Murphy, 2010). According to Brendonck *et al*. (2003), the roots and the leaves of water hyacinth plants offer an important substratum and habitat for colonization of macroinvertebrates.

The presence of aquatic alien species in freshwater systems is, therefore, currently of great concern to environmentalists, water resource and catchment managers, as well as hydrologists. Besides, invasive species proliferation is a substantial global change phenomenon that increasingly affects aquatic life, ecosystem functioning and productivity, ecological and hydrological processes, as well as human livelihoods (Schneider and Geoghegan, 2006; Burgiel and Muir, 2010). Invasion by free-floating plant mats is found to be a serious threat to freshwater ecosystems biodiversity (Janse and van Puijenbroek, 1998; Aloo *et al*., 2013). In tropical lakes, water hyacinth has dramatic negative impacts on fisheries and boat traffic (Gopal, 1987; Kateregga and Sterner, 2009). Literature shows that invasive water hyacinth species can cause severe ecological and economic impacts (Pimentel *et al*., 2005; Vila *et al*., 2011). Water hyacinth can disrupt native species' diversity through hybridization, ecosystem modifications and functioning (Rodriguez, 2006; Villamagna and Murphy, 2010; Stiers *et al*., 2011). The fact that it's mat-like in nature results in the concentration of micro-organisms around the plant roots and shoots, it can enhance an increase in pests and diseases, such as *schistosomiasis, filariasis, malaria* and *ancephalitis* (Spira *et al*., 1981; Gopal, 1987; Reddy and DeBusk, 1991; Muyodi, 2000).

Moreover, alien invasive plant species may alter the aquatic habitat structure, by creating a homogeneous habitat, thereby negatively affecting biological communities (Theel *et al*., 2008; Schultz and Dibble, 2012). Numerous water hyacinth management practices in previous years reported these environmental and economic challenges. Some of these practices largely focused on water hyacinth eradication through chemical, physical, or biological means; which have had little lasting success (Williams *et al*., 2005; Wilson *et al*., 2007). According to Williams *et al*. (2005), trends in population growth and economic development also suggest that the situation will be compounded in future, due to environmental and climate change, lack of actions taken towards the eradication of aquatic weeds and through high nutrient content in water. Therefore, accurate and urgent locational information is needed to understand the evolution of these weeds, and potentially vulnerable areas (Shekede *et al*., 2008). This information can aid in evaluating the efficiency of control measures and management practices currently in place.

The availability of automated, reliable and real time remote sensing data becomes permissible in addressing the spread of aquatic weeds, over freshwater bodies. Remote sensing of freshwater is gradually becoming an important alternative, especially in the light of increased water consumption and the current or projected impacts of climate change on this precious resource (Cavalli *et al*., 2009; Dube *et al*., 2015). Regardless of this, monitoring of aquatic macrophyte in freshwater ecosystem provides essential evidence for the development of proper mitigation and control measures, which can help to conserve both water quality and quantity (Dube *et al*., 2017b). Traditionally, aquatic weeds have been monitored, using conventional methods, which include repeated field-surveys, followed by chemical spraying as well as biological and physical removal (Dube *et al*., 2017b). Besides being spatially restricted, these techniques have been, however, found to be time-consuming and labour intensive (Ritchie *et al*., 2003). On the contrary, the availability of archival and real-time satellite data, dating back to the early 1970s, provides great prospects for spatio-temporal observations of aquatic weeds in a timely and cost-effective manner (Hestir *et al*., 2008; Shekede *et al*., 2008; Dube *et al*., 2014). Remote sensing can provide a spatial snapshot on areas that experience aquatic weeds infestation and potential vulnerable areas and/or to monitor response to management interventions.

Satellite remote sensing technologies can capture and instantaneously record earth surface information and provide a synoptic view of land surface characteristics and associated dynamics (Risser and Treworgy, 1985). Some of the current remote sensing imagery technologies have high spectral and spatial characteristics, which enable the enhanced monitoring of the spatial distribution and spread of invasive species. Thus, this enables researchers or managers to come up with an informed assessment of areas severely infested and provide timeous interventions (Shekede *et al*., 2008). In this review, we draw attention to new insights in the detection, mapping, and monitoring of invasive water hyacinth using multispectral remote sensing. Based on this background provided, this work sought to provide a detailed overview on the progress and development of remote sensing in detecting and mapping water hyacinth over space and time.

2.2 Literature search

To achieve these objectives, information was acquired from Earth Observation, GIS and Remote Sensing, and Water journals. During literature search, journal articles published in Institute for Scientific Information (ISI) international peer-reviewed journals were selected. Appropriate articles were primarily selected from recognised search engines, such as Google Scholar, SCOPUS and the ISI Web of Knowledge databases and other international recognised remote sensing and aquatic science journals. Supplementary journal articles were identified from appropriate literature reviews, as well as the associated reference lists through regressive reference list assessment. To achieve this, numerous keywords and expressions were used, and these included "remote sensing", "water hyacinth", "Landsat and aquatic weeds/ water hyacinth", "water hyacinth distribution", "mapping", "challenges", "ecology and geographical distribution", "detection", "sensors" and "spectral and vegetation indices".

2.3 Ecological impacts of water hyacinth

The spatial distribution and configuration of water hyacinth deteriorate aquatic life in freshwater ecosystem (Murkin and Kadlec, 1986; Meerhoff *et al*., 2006; Mironga *et al*., 2014). Ecologically, water hyacinth can impact zooplankton and phytoplankton productivity in freshwater ecosystems, modify surface water clarity and cause hypoxia or a decrease in the concentration of related and nutrients contaminants, such as nitrogen, phosphorous and heavy metals. The study by Mironga *et al*. (2014) showed that lake areas infested with water hyacinth exhibited significantly lower (α=0.005) zooplankton population, when compared to water hyacinth free-zones in Lake Naivasha, Kenya. This observation is further confirmed by the works of Chukwuka and Uka (2007) whose study also observed a significant (α=0.005) decline in the density of zooplankton population in water hyacinth infested areas in Awa reservoirs, Nigeria. The numerical effects of water hyacinth on zooplankton has been also found to have cascading effects on the population of aquatic organisms that rely on this alga e.g. fish (Mironga *et al*., 2014). Besides, the negative impacts it poses on aquatic food chains, water hyacinth tends to out-compete submersed vegetation and phytoplankton on nutrients and sunlight utilization (Mitchell, 1985).

Moreover, a severe ecological problem caused by water hyacinth invasion in freshwater ecosystems is mainly the changes in the structure, composition, productivity and functioning of aquatic ecosystem. The fact that water hyacinth covers freshwater ecosystems in the form of a blanket like layer, it therefore, inhibits sunlight penetration into the lower parts of the water body, minimizing the rate of photosynthesis for the submerged plants (Huang *et al*., 2007). This has serious implications on the diversity of aquatic life as it tends to create non-conducive and inhabitable ecological conditions (Wu *et al*., 2004). Literature shows that low oxygen conditions beneath the mats results in hypoxia and in some instances, create favourable breeding environment for diseases and pests i.e. *encephalitis, filariasis*, as well as mosquito vector of malaria and other related waterborne diseases. Furthermore, water hyacinth mats can reduce natural predation leading to increased abundance of certain species against others (Kateregga and Sterner, 2009). For instance, mats created by the invasive species can also hinder certain species from breeding, or nursery, and sometimes alter feeding grounds (Twongo and Howard, 1998). The presence of these aquatic weeds in freshwater ecosystems also compromises the quality and quantity of water, especially when they die-off and decay in copious quantities. This alone, creates anaerobic conditions and intensifies the release of poisonous gases that may be harmful to certain organisms in water. In addition, as the water hyacinth is composed by approximately 90% of water; evaporation rates increase (Gopal, 1987). In addition, its physical removal, disposal and decomposition pose serious health and environmental problems as these plants acts as an ecological scrubber of heavy metals and other pollutants.

2.4 Origin and geographical distribution of water hyacinth

Water hyacinth, which is botanically known as *Eichhornia crassipes* (Mart.) Solms-Laubach (Ogunye, 1988) is a member of the monocotyledonous family Pontederiaceae (Patel, 2012). It is an aquatic freshwater plant native to the Amazon basin and naturalized in the tropical and sub-tropical countries of South America (Penfound and Earle, 1948; Global Invasive Species Database, 2006). Water hyacinth (Figure 2.1) has leaves that are joined to broad, glossy, thick and ovate stalks, which are usually bulbous, long and spongy, with feathery roots). Its flowers are commonly purple-black in colour and have six petals. Under favourable growing conditions and environmental circumstances, some estimates suggest that water hyacinth can double its biomass through asexual reproduction in two weeks. Within a period of eight months, ten water hyacinth plants can reproduce 655,360 plants that can cover approximately half a hectare of the surface area (Gunnarsson and Petersen, 2007). Wilson *et al*. (2005)

indicated that nutrient concentration and increased Land Surface Temperatures (LST) are two of the most important aspects, influencing the growth and reproduction of water hyacinth species in open water bodies. So far, water hyacinth has spread to most of the tropical freshwater bodies throughout the world, and has been described as one of the most invasive aquatic weed on the planet (Cook, 1989; Ndimele *et al*., 2011; Havel *et al*., 2015). Figure 2.1, demonstrates how water hyacinth can chock freshwater bodies by inhibiting light penetration. The seriousness of these invasive species is demonstrated by the scale of invasion at global extent (±50 countries) (Figure 2.2). To date, water hyacinth has spread throughout Southeast Asia, the South-eastern United States, central and western Africa, Central America and Iberian Peninsula in southwestern Europe (Bartodziej and Weymouth, 1995; Martinez Jimenez and Gomez Balandra, 2007; Aguiar and Ferreira, 2013). If unabated, this will pose a severe problem to the already scarce freshwater resources.

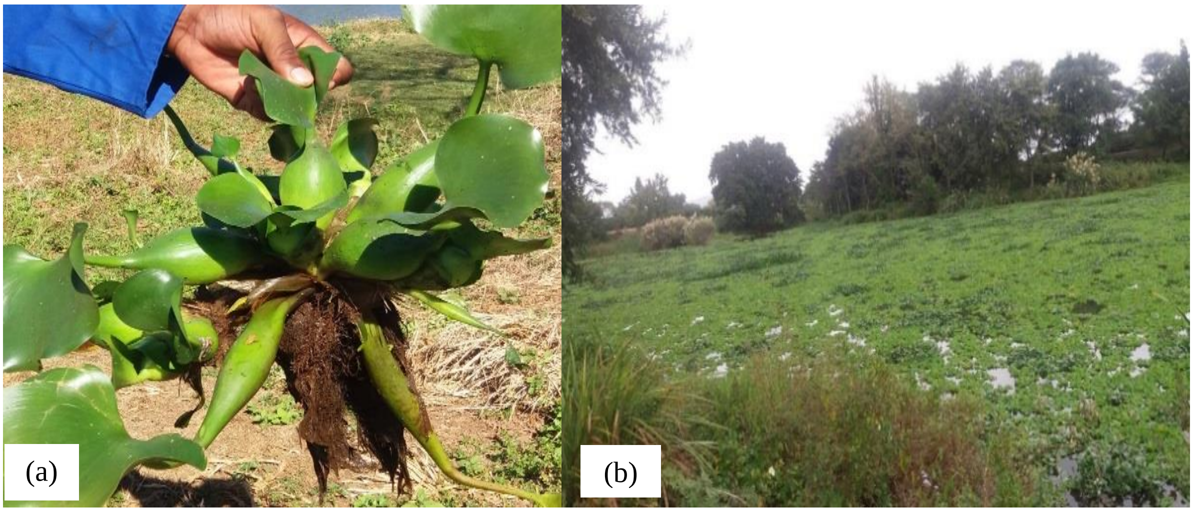

Figure 2.1: Typical water hyacinth species in Letaba river systems in Tzaneen, South Africa (Photograph credits: K.H Thamaga, 2017)

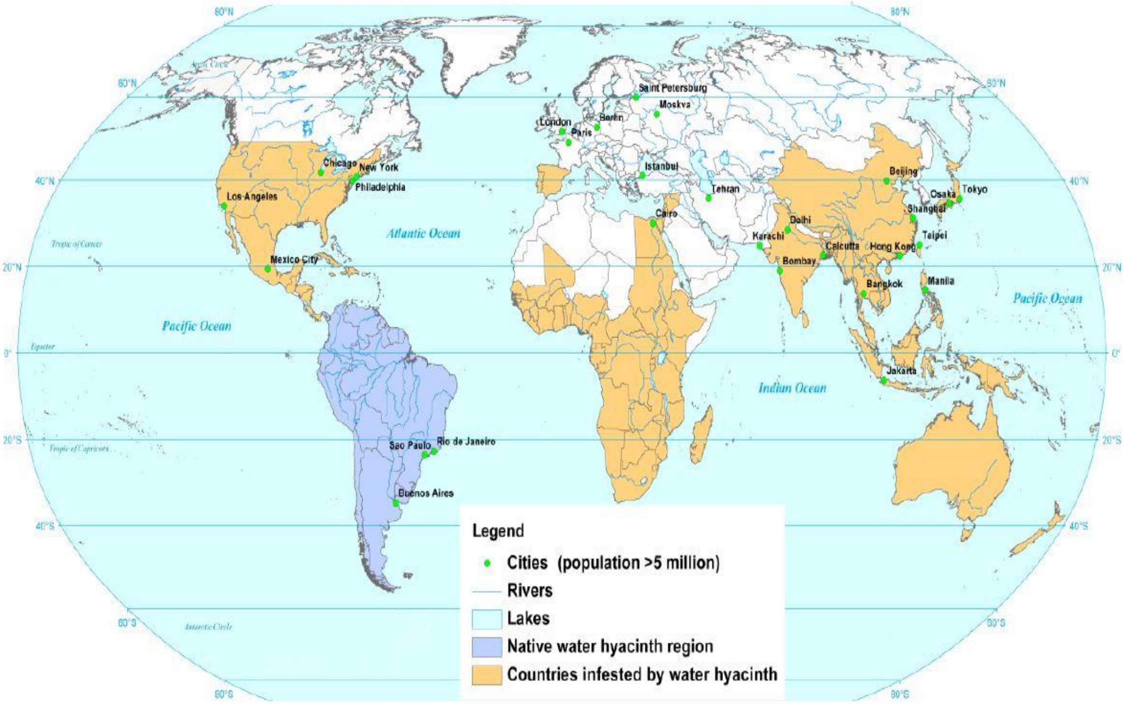

Figure 2.2: Global distribution of invasive water hyacinth (*E. crasspies*) (Téllez *et al*., 2008).

2.5 Remote sensing of water hyacinth

Over the past 30 years, many satellite borne sensors have been exploited to gather information on water hyacinth and its insight into the biological activity occurring within water bodies (Cavalli *et al*., 2009). Literature search published in remote sensing journals shows an increase on work done in mapping the spatial distribution of water hyacinth in lakes and dams (Figure 2.3). These studies demonstrate an exponential increase in the number of publications over the years with around 57 ISI articles published in remote sensing journals in the year 2014 alone. A linear regression plot (Figure 2.3) shows a strong positive correlation between remote sensing publications over time with a R^2 of 0.78.

The increase in the use of remote sensing data in mapping invasive species is linked to its ability to offer a variety of new applications that can quickly and synoptically monitor and manage large areas. For example, remote sensing has permitted a timely and inventory assessment of aquatic weeds, environmental hazards, natural resources and water quality monitoring. Satellite data can capture the spatial and temporal distribution of aquatic macrophytes in a timely and cost-effective approach (Hestir *et al*., 2008; Shekede *et al*., 2008; Dube *et al*., 2014). Furthermore, continual coverage of satellite sensors provides spatial data for both short and long-term monitoring, which is crucial in identifying and assessing the strengths of the control measures in place (Penatti *et al*., 2015). As such, the use of satellite imagery has proved to be a reliable primary data source and has become commonly used in ecological and environmental research (Aplin, 2005).

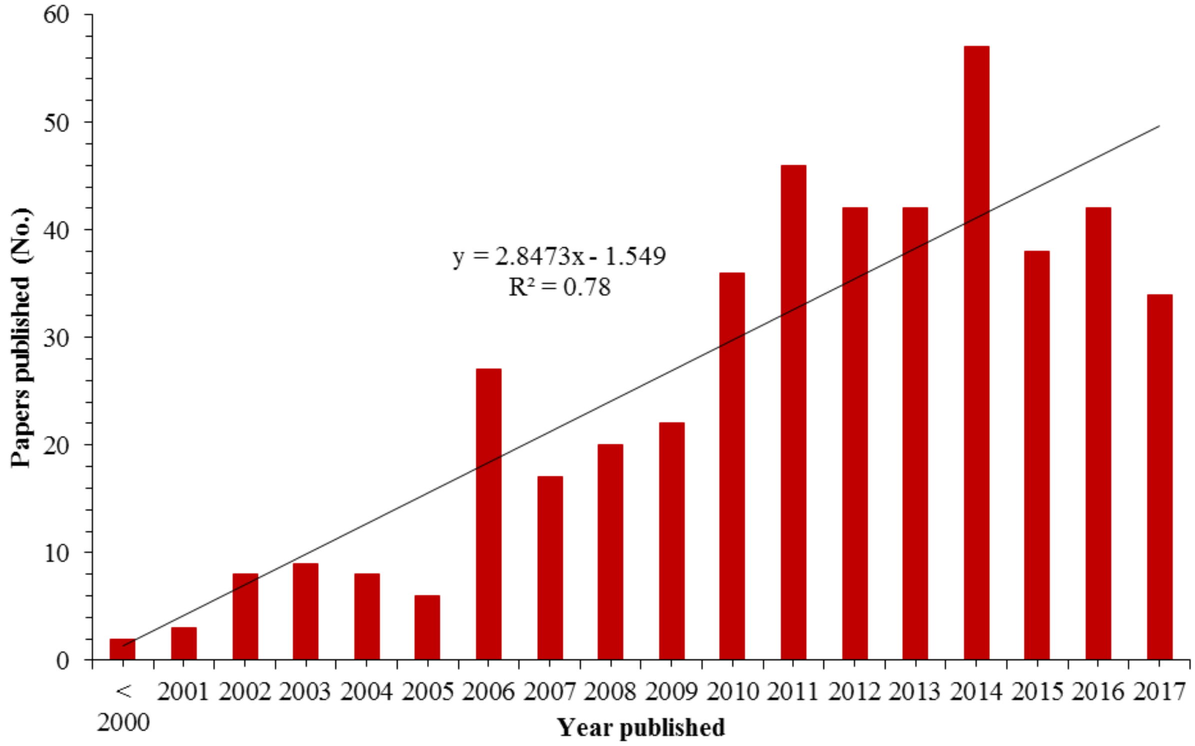

Figure 2.3: Number of remote sensing publications on water hyacinth over the years.

Remote sensing technologies have therefore been confirmed to be crucial in mapping land cover (e.g. water hyacinth, vegetation, grassland) and land use (e.g. farming, settlements) aspects, because of the availability of sensors that can provide high quality data (DeFries *et al*., 2004; Rindfuss *et al*., 2004). Hansen *et al.* (2006) for example derived a global land cover map from Advanced Very High-Resolution Radiometer (AVHRR) imagery using a decision tree (DT) based on a set of 41 metrics generated from five spectral channels and Normalized Difference Vegetation Indices (NDVI) for input. Hestir *et al*. (2008) also mapped water hyacinth using airborne hyperspectral data in the Californian delta, USA. Classification results of water hyacinth using decision tree approach produced a user accuracy of 51.4% and a producer accuracy of 61.9% respectively, as well as Kappa coefficient of 0.49. Furthermore, producer's accuracies of healthy water hyacinth and flowering hyacinth produced 86.5% and 44.9%, respectively. From the study, low accuracies produced by hyperspectral data can be attributed to the presence of mixed pixels. A study by Oyama *et al*. (2015) used Landsat 7 Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) shortwave infrared bands to differentiate surface cyanobacterial blooms and aquatic macrophytes in Lakes Kasumiguara, Inba-numa and Tega-muma (Figure 2.5) using the Floating Algal Index (FAI) and selected Landsat 7 TM, $NDWI_{4,5}$ and $NDWI_{2,5}$ to differentiate cyanobacterial blooms and macrophyte. Results of the study demonstrated the importance of merging FAI and $NDWI_{4,5}$ in the classification of lake areas. In addition, John and Kavya (2014) used multispectral and hyperspectral data to monitor aquatic macrophyte in Vembanad estuary in the western coast of Peninsular India. Spectral discrimination of aquatic macrophyte types (*Cabomba caroliniana, Eichhornia crassipes, Ischaemum travancorence, and Nymphaea pubescens*) species yielded an overall classification accuracy of 93.47% using spectro-radiometer. Furthermore, the study showed that WorldView-2 set of band combination (Red-Edge, Green, Coastal blue and Red-Edge, Yellow and Blue) yielded high overall classification accuracy of 100%. The study for the first time managed to map the spatial distribution of invasive aquatic macrophyte using unsupervised classification of WorldView-2 as well as PAN-sharpened WorldView-2 MSI (Figure 2.7). The modified Pan-sharpened image which enhanced the spectral resolution in mapping macrophyte communities showed identification of more land cover types at species level. The study highlighted the potential of multispectral and hyperspectral data in discriminating and mapping aquatic macrophyte cover types. However, the major challenge with these datasets is that they are costly, spatially and temporally restricted hence an increased number of studies that have applied broadband multispectral sensors, even though there is a gap in monitoring the spatial distribution of water hyacinth in a river scale.

Several studies have employed the use of multispectral remote sensing to identify invasive alien plant species (Carson *et al*., 1995; Mladinich *et al.*, 2006; Cuneo *et al*., 2009; Kimothi *et al*., 2010). Table 1.1 provides a detailed summary of remote sensing studies on mapping aquatic weeds. Literature reveals that, very few research works has been done to detect and map these species, especially using satellite data and this can be attributed to image acquisition costs as detailed in Table 1.2 and Figure 2.4, especially for commercial sensors (Dube *et al*., 2017b; Sarkar *et al*., 2017). In water scarce sub-Saharan African environments, little work has been done on this aspect and the same applies to other parts of the globe. The exceptions, include those by Dube *et al*. (2017a) who tested the detection and discrimination potential of the challenging water hyacinth (*E. crassipes*) in freshwater ecosystems, using new Landsat 8 satellite data in Lake Manyame of Zimbabwe, with an overall classification accuracy of 95%. Landsat 8 OLI sensor was found to be very useful to water related studies, due to the sensor's improved spectral, spatial, temporal and radiometric characteristics (Dube *et al*., 2017b). Similarly, Dube *et al*. (2017a) and Shekede *et al*. (2008) assessed the performance of the newly-launched Landsat 8 OLI and the Landsat series data in detecting and mapping the spatial configuration of water hyacinth in inland lakes of Zimbabwe, respectively. The analysis of variance (ANOVA) test was used to identify windows of spectral separability between water hyacinth and other land cover types over the study area. It was however, observed that the use of Landsat 8 OLI yielded high overall classification accuracy of 72%, when compared to Landsat 7 ETM+, which yielded lower overall of 57%. Therefore, the results of the study demonstrated the significance of the newly launched multispectral sensors in providing current information required for mapping the spatio-temporal distribution, and pattern of water hyacinth at a low or no cost over time and space. The results of this study bring new insights to the utilization of satellite imagery with high spatial coverage as well as readily available and up-to-date data at low cost in environmental applications. However, despite the reported outstanding performance of this new sensor, there is a need to test its applicability in tropical river systems, with narrow channels and mixed species. Also, it is crucial to compare its performance, with the 10 m high resolution sensors, such as Sentinel-2 MSI in mapping and monitoring invasive aquatic weeds at key phenological stages (Figure 2.6).

Satellite image acquisition at key phenological stages may assist in distinguishing between different invasive alien plant species. Since water hyacinth is an evergreen species, detecting their coverage will not be restricted by seasonal variation but largely hindered by the sensor's spatial and vegetation characteristics. Unlike the broadband multispectral data, with improved spectral and spatial resolution sensors, such as the 10 m Sentinel-2 MSI which have the capability to positively improve our understanding on the spatial distribution of water hyacinth, especially in smaller freshwater bodies where it was previously a challenging task with broadband multispectral sensors. Its application in vegetation (Harmel *et al*., 2017; Shoko and Mutanga, 2017; Sibanda *et al*., 2015; Veloso *et al*., 2017) has so far produced plausible results. The study by Dube *et al*. (2017a) revealed that, the latest Landsat 8 sensor with improved radiometric and other sensing characteristics have spectral bands that can uniquely discriminate water hyacinth from the co-existing species in lakes (Figure 2.4). This observation is in line with previous work on the application of Landsat 8 OLI and Worldview-2 in mapping invasive species in savanna rangelands. The study further showed that the use of Landsat 8 OLI raw spectral bands combined with derived NDVI vegetation indices significantly improved the detection and mapping of bracken fern.

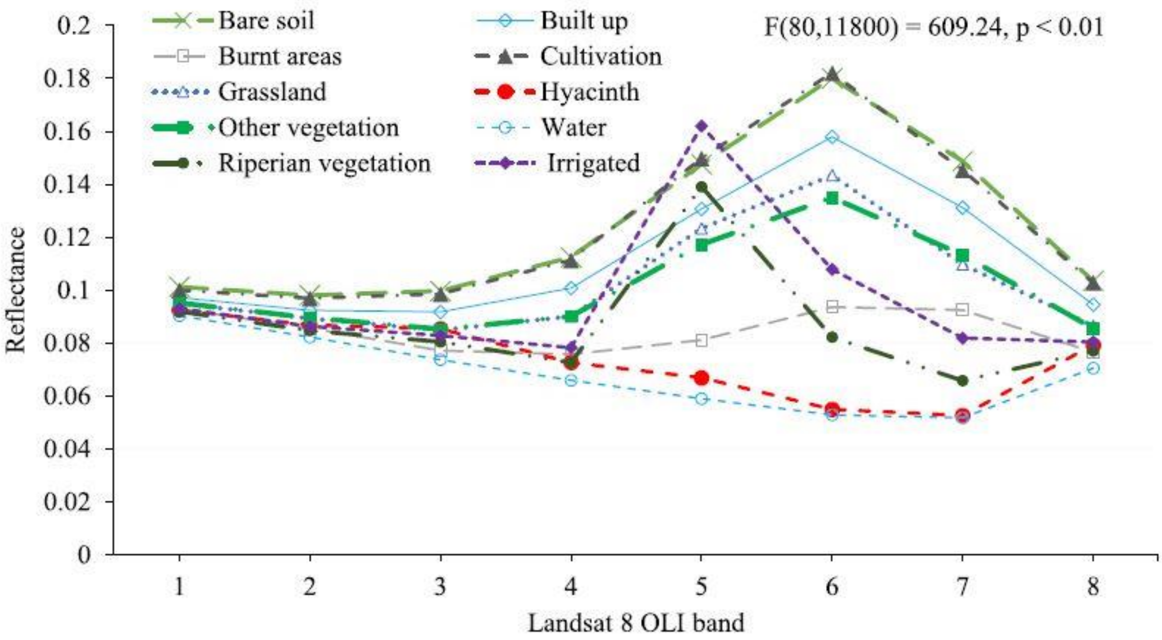

Figure 2.4: Remote sensing inherent spectral capabilities to different water hyacinth from other co-existing land cover types (Dube *et al*., 2017a).

2.6 Potential of remotely sensed derivatives in mapping the spatial distribution of water hyacinth invasion

Remote sensing technologies and their derivatives have since played a critical role in detecting, discriminating, mapping and monitoring the distribution of water hyacinth in large water bodies. Different spectral bands and vegetation indices from different sensors have been tested in mapping the spatial distribution of water hyacinth (Cheruiyot *et al*., 2014; Cho *et al*., 2008; Dube *et al*., 2017b). To mention just a few, Dube *et al*. (2017a) tested the detection and discrimination potential of the new Landsat 8 satellite data derived spectral and vegetation indices in mapping water hyacinth in freshwater ecosystems, in Lake Manyame of Zimbabwe. However, not all of these remotely sensed variables produced plausible performance in mapping its distribution. The interest in most of these indices lied in the improvement of classification accuracies (Asrar *et al*., 1984; Bariou *et al*., 1985; Qi *et al*., 1991; McNairn and Protz, 1993; Li *et al*., 2011; Vidhya *et al*., 2014).

Table 2.1: Summary of remote sensing applications in detecting and mapping aquatic weeds

Sensor (s)	Image analysis technique (s)	Results	Reference
MERIS	Maximum Peak Height algorithm	r^2 of 0.58 chl-a between 33 and 362.5 mg.m^{-3} error of 33.7%	Mark *et al.*, 2012
Landsat 8 OLI Landsat-7 ETM+	Variance test	Landsat 8 OLI has OA = 72% compared to Landsat-7 ETM+ yielded lower OA = 57%	Dube *et al.*, 2017b
Color-infrared (CIR) video imagery	Maximum likelihood classification	OA of 87.7%. Kappa= 0.828.	Everitt *et al.*, 1999
SPOT 5	Linear spectral unmixing (LSU) and spectral angle mapper techniques.	OCA =81%.	Schmidt and Witte, 2010
MERIS	Normalized Difference Vegetation Index (NDVI) slicing and maximum likelihood	Maximum likelihood with an ACA= 80% is better than NDVI slicing at 75%.	Cheruiyot *et al.*, 2014
HJ-CCD	Classification tree models	OA= 68.40% Kappa=0.6306,	Luo *et al.*, 2017
Landsat 5 TM	NDVI	linear relationship (r^2 =0.28) LAI: r^2 =0.66	Robles *et al.*, 2015
Landsat 8 OLI	Discriminant Analysis (DA) and Partial Least Squares Discriminant Analysis (PLS-DA).	OA= 95%	Dube *et al.*, 2017a
MERIS **Landsat 7**	NDVI and LSU	OA=87%; R^2=0.78; RMSE=0.13 OA=84%; R^2=0.73; RMSE=0.16	Cheruiyot *et al.*, 2013
Worldview-2 ASD spectroradiometer	PCA	-Unsupervised classification using the band combinations Red-Edge, Green, Coastal blue & Red-edge, Yellow, Blue produced 100%. -Band combinations NIR-1, Green, Coastal blue & NIR-1, Yellow, Blue yielded an accuracy of 82.35%.	John and Kavya, 2014
HyMap Hyperspectral	Spectral mixture analysis	Within Delta (51 ha) OA=93% for Brazilian waterweed OA=73% for water hyacinth Delta wide scale (177.000 ha) OA=29% for Brazilian waterweed OA=65% for water hyacinth	Underwood *et al.*, 2005

Notes: (OA= Overall Accuracy; ANOSIM = ANalysis Of SIMilarities; ACA= Average Classification Accuracy; CT= Classification Tree; PCA=Principal Components Analysis; LSU= Linear Spectral Unmixing)

Table 2.2: Remote sensing sensor specifications and associated acquisition cost per square metre (Adapted from Matongera *et al.*, 2016).

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

The NDVI has been found to positively correlate with plant health or vigour, with concentrated green pigments or active photosynthetic rates, due to a prominent level of reflectance in the near infrared (NIR) bands of the light spectrum (DeFries *et al*., 1999). The work by Penuelas *et al*. (1993) concluded that the Water Band Index (WBI), developed based on the ratio between the water band 970 nm and reflectance at 900 nm, is strongly correlated with relative plant water content. Using reflectance at 857 and 1241 nm, Gao (1996) developed the Normalized Difference Water Index (NDWI) in California, USA to estimate vegetation water content. The findings of the study showed that NDWI is less sensitive when compared to NDVI and it is therefore, beneficial in predicting freshwater stress in plant canopies and appraising invasive aquatic weed productivity. Further, Omute *et al*. (2012) used NDVI and numerous derivatives in monitoring water level and drought conditions of Lake Victoria. Cheruiyot *et al*. (2014) evaluated MERIS-based on aquatic vegetation mapping in Lake Victoria. In the study, two methods were applied, namely: NDVI slicing and maximum likelihood. From the results of the study, maximum likelihood produced 80% from average classification accuracy which was better than NDVI slicing at 75%. Although NDVI slicing and maximum likelihood produced larger errors over sparse vegetation, extent of the area and spatial resolution of the sensor, as well as methods applied influenced the overall classification accuracy.

Further investigations are however still required to understand vegetation indices derived from the new generation of satellite sensors, such as Landsat 8 OLI and Sentinel-2 MSI (Dube *et al*., 2017b). As such it is deemed one of the most potential tools capable to accurately provide timely spatial and site-specific weed information that can be converted into knowledge used for decision support systems. The strength of the latest remote sensing technologies as demonstrated in latest environmental applications are centred around their unique and robust capability to spectral discriminating different plant species based on the subtle difference in their biophysical and biochemical properties (Agjee *et al*., 2015; Dube *et al*., 2017b). For example, the study by Dube *et al*. (2017a), has demonstrated the ability of the new Landsat 8 to spectrally separate water hyacinth from other co-existing plant species (Figure 2.4). This capability alone has permitted the remote sensing community to further fully explore its potential and even extrapolate to large scale mapping to understanding aquatic weeds distribution and propagation rates, as well as growth stages the world over (Shekede *et al*., 2008; Dube *et al*., 2014; Giardino *et al*., 2015).

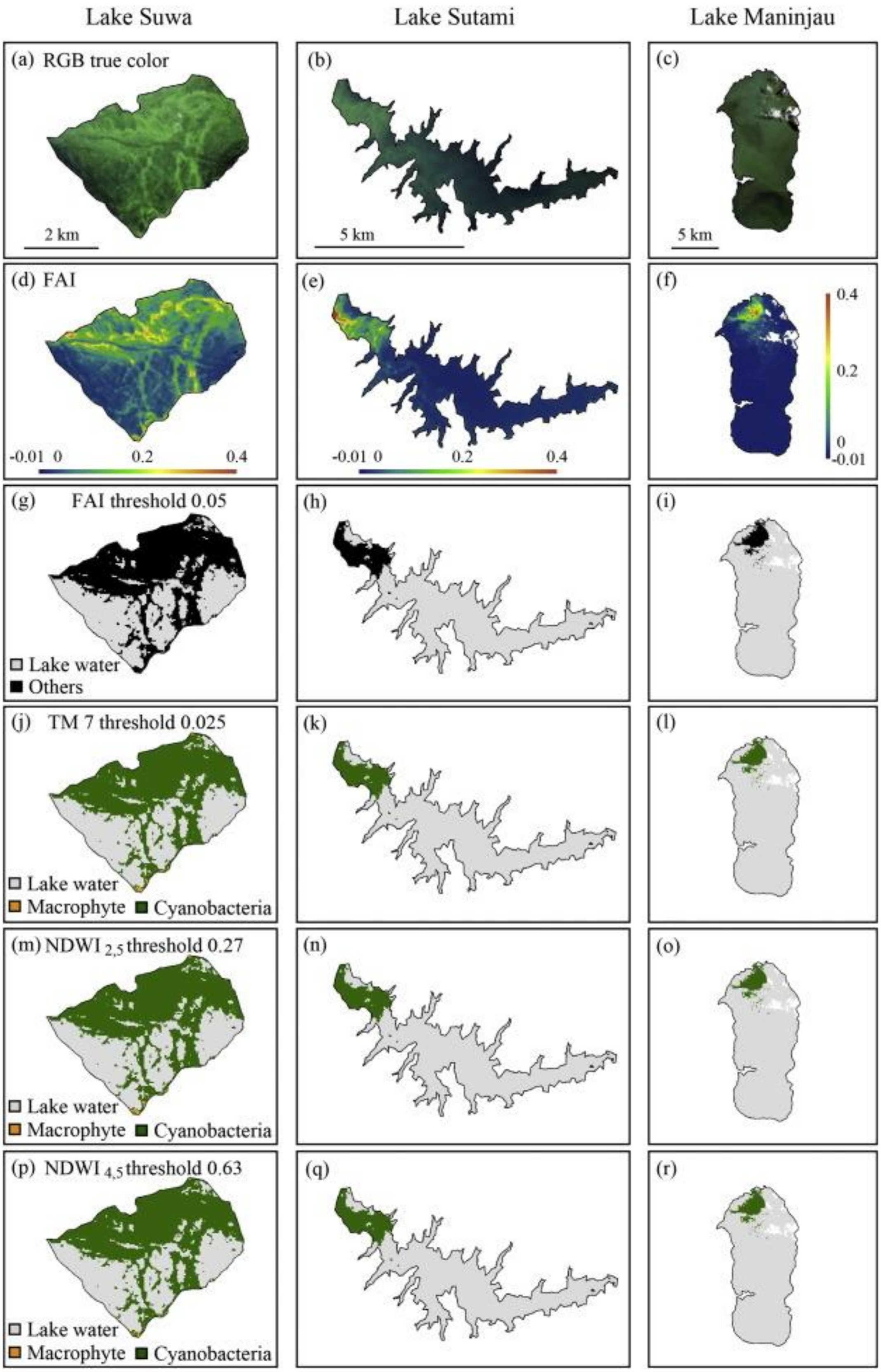

Figure 2.5: Landsat satellite imagery derived aquatic macrophytes in Suwa, Sutami and Maninjau lakes (Oyama *et al*., 2015).

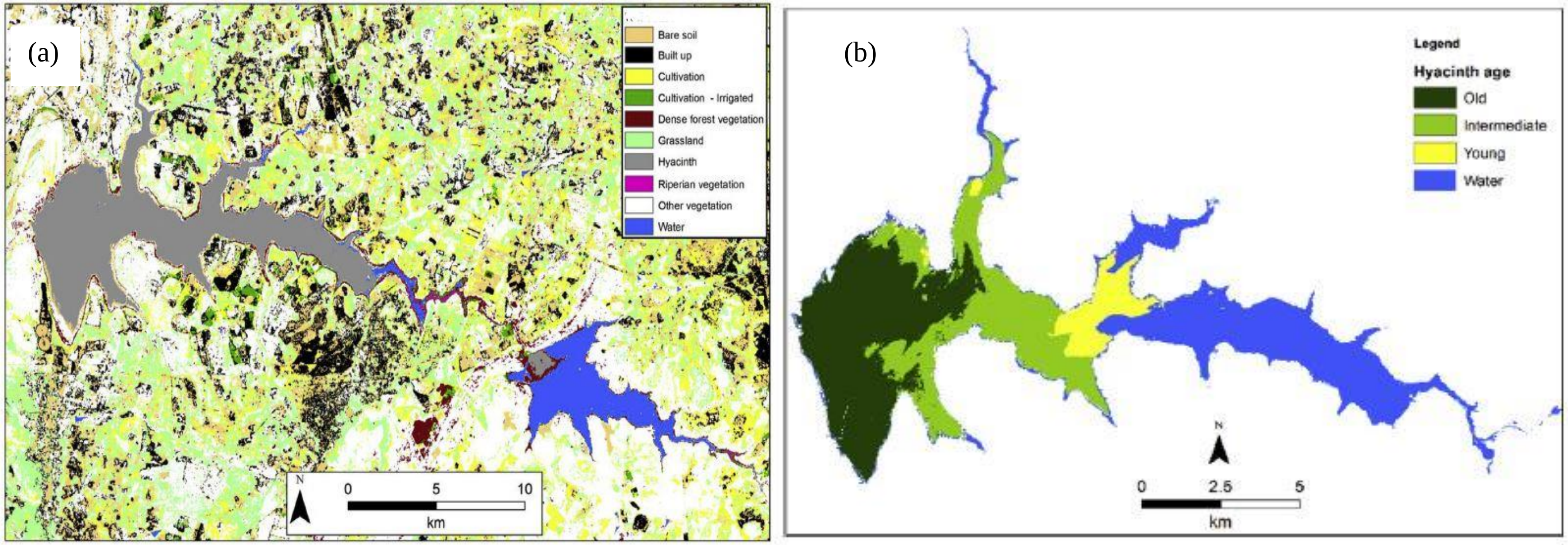

Figure 2.6: (a) Landsat 8 derived water hyacinth spatial distribution in Lake Manyame and Chivero and (b) in Lake Manyame (Dube *et al*., 2017).

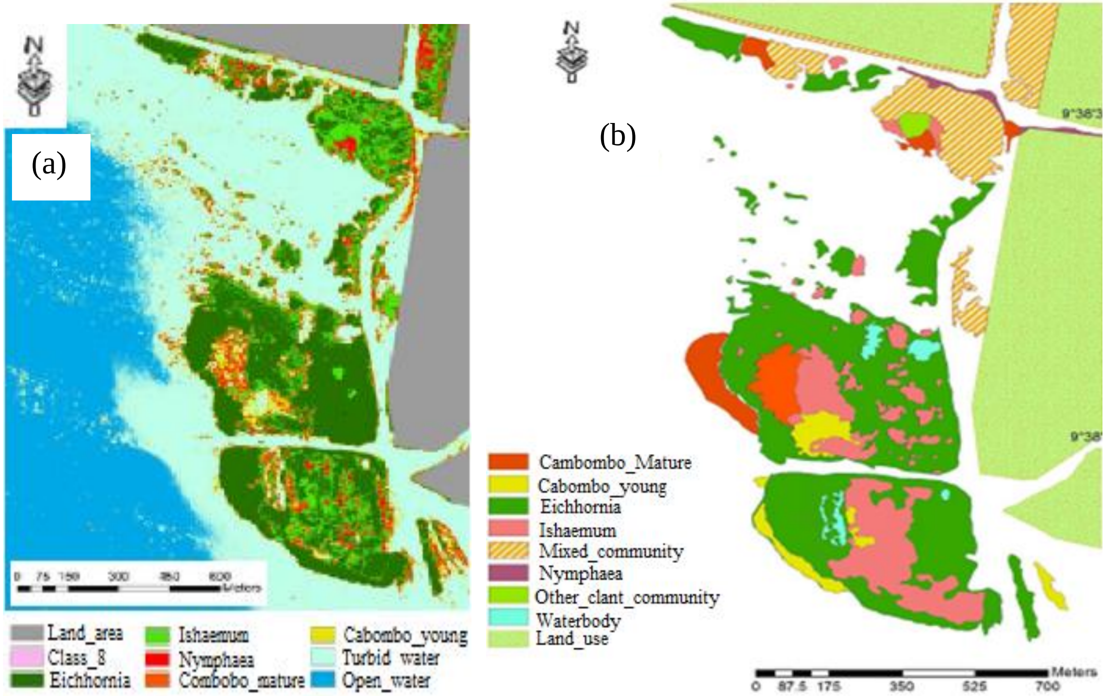

Figure 2.7: (*a*) The unsupervised classification of WorldView-2 imagery and (*b*) Aquatic macrophyte mapped through the Modified IHS PAN-sharpened WorldView-2 (John and Kayva, 2014).

2.7 Available water hyacinth classification algorithms

Spectral discrimination between vegetation types in complex environments is a challenging task, because different vegetation types have similar spectral signature (Xie *et al*., 2008). Applications of per pixel classifiers to images dominated by mixed pixels are often incapable of performing satisfactorily accurate classification (Zhang and Foody, 1998), due to poor spectral, temporal and spatial resolutions. In this case, complex environments such as rivers which require powerful techniques developed for remote retrieval to improve accuracies in discriminating vegetation types at plot level. Studies have demonstrated that classification accuracy can be greatly enhanced by applying expert knowledge and secondary data in extraction of land cover types (Shrestha and Zinck, 2001; Gad and Kusky, 2006). Maximum likelihood classifier (MLC) is typically stared as a classic and most extensively used supervised classification for satellite images resting on the statistical distribution pattern (Sohn and Rebello, 2002; Xu *et al*., 2005; Xie *et al*., 2008). A greater availability of remotely sensed data at higher spatial and spectral resolutions coupled with the development of machine learning algorithms could potentially improve classification accuracies (Abdel-Rahman *et al*., 2014; Adelabu *et al*., 2014). In this regard, three popular machine learning algorithms namely: Artificial Neural Networks (ANN), Random Forest (RF) and Support Vector Machines (SVM) have mainly been implemented for classifying vegetation stress (Agjee *et al*., 2015). These algorithms emerged as proxies to conventional parametric algorithms; however, they produce high classification accuracies, more accurate and capable of processing high datasets.

ANN is a non-parametric classifier that makes no assumptions about the distribution of the data (Dixon and Candade, 2008; Song *et al*., 2012), and it is useful in extracting vegetation-type information in dense vegetation canopies (Filippi and Jensen, 2006). ANN is computationally efficient, more resistant to noise and perform well with small training datasets (Song *et al*., 2012). Regardless of small training datasets, Berberoglu *et al*. (2000) used ANN, as well as texture analysis to classify land cover classes and they found that the accuracy could be 15% greater than the accuracy achieved, when using a standard per pixel MLC. However, a fuzzy classification approach is usually useful in mixed pixel areas and was investigated for the classification of suburban land cover from remote sensing imagery (Zhang and Foody, 1998), the study of medium-to-long term (approximately 10–50 years period) vegetation changes (Okeke and Karnieli, 2006). Xu *et al*. (2005) adopted DT derived from the regression approach to determine class proportions within a pixel to produce a soft classification, using Landsat ETM+ in New York. The study showed that DT produced higher results with overall classification accuracy of 74.45% as compared to maximum likelihood classifier (55.25%) and the supervised.

SVM's adopted the method of structural risk minimization for class member discrimination which minimizes the classification error on unseen data without making prior assumptions on the probability distribution of the data (Mountrakis and Ogole, 2011). This is advantageous as data acquired from remotely sensed imagery usually have unknown distributions (Mountrakis and Ogole, 2011). However, the performance of the SVM algorithm is sensitive to the choice of kernel function and the setting of its associated parameters (Song *et al*., 2012).

2.8 Challenges in remote sensing of water hyacinth

The robustness of remote sensing in sustenance to water hyacinth management has not been fully explored. While many satellite products are freely available, a significant proportion of products are not freely available (Turner *et al*., 2013). High-spatial resolution sensors, such as LIDAR, WoldView-2 and Quickbird with less than 5 m spatial resolution can accurately detect and map the invasive water hyacinth although not yet tested. However, their acquisition costs, lower temporal resolution and smaller swath width remains problematic in detecting and mapping the spatial distribution of water hyacinth at local and regional scale. Satellite remotely sensed data analysis can be expensive given logistical requirements (i.e. hardware, software, qualified specialists and training) for the processing and analysis of large data-sets. Altogether, costs can be considerable, and hampers the widespread application of satellite monitoring in applied ecology and management of invasive water hyacinth (Strand *et al*., 2007; Turner *et al*., 2013). Furthermore, free remote sensing products, open-source software solutions, such as QuantumGIS or GRASS are on the rise. Training opportunities and clear documentation is missing, and this complicates the use of open software application. But this is constantly changing with open-source software increasingly used for training across disciplines (Rocchini and Neteler, 2012).

Integration of inland data from ecologists, hydrologists and expert knowledge from remote sensing analysts is limited, leading to satellite remote sensing data frequently being underused and undervalued (Nagendra *et al*., 2013). Aquatic scientists, hydrologists and environmentalists would immensely benefit from application of remotely sensed data, particularly from active sensors or from high spatial resolution sensors. Nevertheless, these users often have limited access to remote sensing satellite imagery and the tools to process the images. Time between users' needs and the availability of satellite remote sensing can create hindrance in acquiring images that coincide with ground trothing. Invasive water hyacinth is often obscured in a setting of natural vegetation, water system, and are thus problematic to discriminate using moderate spatial or spectral resolution images.

The potential of satellite remote sensing to support hydrology and environmental management is likely to be best achieved when effective collaborations between experts in remote sensing and experts in water resources monitoring are developed. Such collaborative work is rare, due to (i) the scarcity of a shared interdisciplinary space to assist collaboration; (ii) semantic gaps and the lack of common frames of reference; (iii) issues arising from mixed spatial scales; (iv) logistical difficulties associated with information transfer and management; and (v) difficulties associated with defining research objectives that are rewarding and scientifically valuable to members of both disciplines (Pettorelli *et al*., 2014).

2.9 Possible future directions in remote sensing of water hyacinth

Although great progress has been made in sensors development in remote sensing and its application in mapping invasive water hyacinth distribution, it still remains a challenge. To the best of researcher's knowledge, there is a limited documentation based on the use of remote sensing datasets in mapping spatio-temporal distribution of invasive water hyacinth. Nonetheless, new developments in scientific exploration in remote sensing capabilities are now advocating for possible launching of innovative robust systems being established to manipulate biochemical and biophysical spectral data for vegetation mapping (Cochrane, 2000; Ustin and Gamon, 2010). There is a need for researchers to engage long-term monitoring and seasonal mapping of the aquatic weeds at a catchment scale (Matongera *et al*., 2017). Another future research challenge would be to test the use of new generation moderately fine spatial-resolution multispectral sensors (i.e. Landsat-8 and Sentinel-2), which are moderately cheap and readily available with strategically positioned spectral bands and improved temporal and radiometric properties. For instance, this is being applied in River Guadiana, this is a large river and it is impaired by storage reservoir in Southwestern Europe. More research work is needed to find the best variables (ancillary data) and predictive models that can be integrated with cheap, and sometimes free, multispectral datasets (Dube *et al*., 2016). In this regard, there is a need to put more emphasis on spectral decomposition of analysis since spatial and spectral resolution of multispectral remote sensing systems are now suitable for most water hyacinth assessments. For future research, acquired remote sensing data should be used as a problem solving and management tool. For this to be achieved, evolution of invasion water hyacinth and rapidity and direction of spread requires a detailed understanding of the impacts that climate, topography, soil, and anthropogenic factors have on invasive water hyacinth propagation and spread.

2.10 Conclusion

Literature shows that, the number of studies using remote sensing methods to estimate water hyacinth invasions are increasing. The majority of the available studies focused on mapping water hyacinth in large water bodies with little emphasis on small rivers. There is a need to increase the use of remote sensing which offers enhanced projections in detecting and mapping the spatio-temporal distribution of water hyacinth in these previously neglected water bodies, due to lack of appropriate spatial data. The arrival of freely and available satellite sensors, with a high revisit time, large coverage (swath-width), high radiometric, spatial and spectral resolution (Landsat 8 and Sentinel-2) is imperative in eradicating barriers restraining the rapid adoption of remote sensing technologies for the management of aquatic weeds. Since Sentinel-2 MSI data seem to provide promising potential in mapping water hyacinth in smaller water bodies, there is therefore a need for future research to evaluate the utility of models developed, using dataset, in mapping, monitoring and understanding seasonal water hyacinth growth dynamics in river systems. This information remains central if effective methods for their control are to be devised.

3. CHAPTER THREE

Testing two methods for mapping water hyacinth (*Eichhornia crassipes*) in the Greater Letaba river system, South Africa: Discrimination and mapping potential of the polar-orbiting Sentinel-2 MSI and Landsat 8 OLI sensors

This chapter is based on:

Thamaga K.H and Dube T., 2018. Testing two methods for mapping water hyacinth (*Eichhornia crassipes*) in the Greater Letaba river system, South Africa: Discrimination and mapping potential of the polar-orbiting Sentinel-2 MSI and Landsat 8 OLI sensors. *International Journal of Remote Sensing*, https://doi.org/10.1080/01431161.2018.1479796.

The research paper has been presented at:

- South African Society for Atmospheric Sciences (SASAS) conference, September 2017, **Polokwane, South Africa**
- 18th waterNET/WARFSA/GWP-SA Symposium, October 2017, **Swakopmund, Namibia**

Abstract

Early detection and mapping of the spatio-temporal distribution of invasive water hyacinth (*Eichhornia crassipes*) in inland hydrological systems are vital for a number of water resource management-related reasons. Field surveys, and current climate change projections (associated with longer dry-spells, and shortened rain seasons) have shown that climate change and the rapid spread of aquatic invasive species are increasingly affecting inland surface water availability in semi-arid regions of Southern Africa. It is upon this premise that accurate, reliable, and timely information on the spatio-temporal distribution and configuration of water hyacinth is required in tracing their evolution, and propagation in affected areas, as well as in potential vulnerable areas. This work, therefore, attempts to test two robust push-broom multispectral sensors: Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multi-Spectral Instrument (MSI) in identifying, detecting and mapping the spatial distribution and configuration of invasive water hyacinth in a river system. The results of the study show that water hyacinth in small reservoirs can be mapped with an overall accuracy of 68.44% and 77.56% using Landsat 8 and Sentinel-2 data, respectively. The results further demonstrated the blue, red, red edge (RE) 1, Short-wavelength infrared (SWIR)-1 and SWIR-2 of both satellite datasets as the critical and outstanding spectral regions in detecting and mapping water hyacinth from other land cover types. Overall, the study highlights the unexploited prospects of the new non-commercial multispectral sensors in monitoring invasive species infestation from inland surface waterbodies in semi-arid regions (i.e. smaller reservoirs).

Keywords: aquatic weeds; classification accuracy; eutrophication; mixed pixels; proliferation rates; semi-arid environments.

3.1 Introduction

Sub-Saharan Africa and other parts of the developing world currently face the largest wave of urban growth and industrial revolution in history (Mendes *et al.*, 2014). Amongst other factors, the fast-urban growth, together with the rural-to-urban migration, generates continuous expansion of slums (e.g. approximately 70% of African urban dwellers live in slums) which cannot cope with the provision of proper sanitation infrastructures (Potts, 2013; Krishna *et al.*, 2014; Rigg *et al.*, 2014; APHRC 2014). Chawira *et al.* (2013) noted that rural-to-urban migration and uncontrolled city growth have led to heavy urban water pollution (microbial and nutrient) via the discharge of poorly treated municipal wastewater in the freshwater ecosystem. Microbial and chemical freshwater pollution, end up being deposited in surrounding waterbodies leading to water eutrophication and the proliferation of aquatic weeds. Previous work shows that the spread of aquatic weeds in most freshwater bodies are linked to several land management practices (e.g. fertilizers or nutrients), as well as poor and uncontrolled discharge of sewage to river systems that create a conducive breeding ground for the growth of undesirable species (Chawira *et al.,* 2013; Giardino *et al.,* 2015). In addition to nutrient concentrations, the spatial distribution and spread of these species are also influenced by environmental factors, such as depth of the river, topography, type of soil substrates, water turbidity, as well as exposure to wind (Pearsall, 1920; Rorslett, 1984; Harvey *et al.*, 1987). Any changes in climatic conditions are most likely to alter the plant distribution and function (Shoko and Mutanga, 2017).

Aquatic weed infestation is one of the major environmental challenges globally, threatening the integrity and functioning of most hydrological ecosystems (Cheruiyot *et al.,* 2014). Moreover, the current projected climate change associated with longer dry-spells and shortened rain seasons coupled with the rapid spread of aquatic invasive species is likely to make inland water reservoirs in Southern Africa even much drier and scarce (Midgley *et al*., 2005). Continuous observation and monitoring of the proliferation of aquatic weeds are thus essential for proper water resource management and for the development of appropriate weed control strategies and prioritizations of most infested areas (Albright *et al.*, 2004). To date, this environmental problem has received limited attention from the responsible hydrologists, environmentalists, and researchers, due to either limited financial resources or the lack of technical expertise (Dube *et al.,* 2014), assurance in product accuracy and high-resolution satellite data continuity and, in some instances, the lack of government will or prioritization.

Despite the presence of these barriers, there are clear breakthroughs or inroads in remote sensing applications in water quality-related studies (Bresciani *et al.,* 2011; Bonansea *et al.,* 2015; Masocha *et al.,* 2017), wetland vegetation mapping (Huang *et al.,* 2014; Li *et al.,* 2015; Jin *et al.,* 2017), and aquatic invasive alien species, especially in large reservoirs (Dronova *et al.,* 2011). Unlike conventional field surveys, remotely sensed data are the key primary data source for mapping and monitoring the functioning and rate of invasion of hydrological systems, as well as identifying potential vulnerable areas, especially in developing countries, given the scarcity in ground data or lack of data access, due to institutional restrictions. Although there is limited appreciation of this technology by policy and decision makers in Africa, its relevance remains unquestionable.

Developing accurate, spatially explicit, fine-scale records on rates of invasions is a high priority (Panetta and Lawes, 2005). Therefore, remote sensing technologies emerge as a reliable approach in studying aquatic ecosystems. The availability of satellite data provides great potential for the spatial and temporal monitoring of aquatic weeds in a timely and cost-effective approach. Recent studies utilized remotely sensed data in monitoring lake conditions, due to their expansive nature (McCullough *et al.,* 2012; Hou *et al.,* 2017). Broadband multispectral sensors have demonstrated success in monitoring these areas (Dube *et al.,* 2014; Giardino *et al.,* 2015; Shekede *et al.,* 2008). However, little consideration has been paid in monitoring invasive water hyacinth in complex environments, such as smaller rivers, using these sensors. Satellite remote sensing of small freshwater systems has been limited by the sensing characteristics in terms of spectral, radiometric, temporal, and more importantly spatial (Hestir *et al.,* 2015). Past non-commercial satellite missions could not provide appropriate measurement resolutions needed to fully resolve freshwater ecosystem properties and processes (Hestir *et al.,* 2015). Due to the presence of mixed or ecological overlap of plant species in aquatic ecosystems, discriminating aquatic weeds from other aquatic plants remains a challenge, as it requires moderate to high spatial and spectral resolutions, in both visible and shortwave infrared regions (Hestir *et al.,* 2008). This problem is also supported by Cheruiyot *et al.* (2014) who stated that although multispectral remote sensing has the capability to detect and map alien plants, the weeds are often obscured in a backdrop of natural vegetation, making it difficult to be detected or even mapped at a fine-scale. In this case, sensors with high spatial, spectral, temporal and radiometric resolutions are needed on a broader scale for accurate ecological monitoring to understand water hyacinth distribution and to enhance management practices on both open and complex environments.

Although the previous satellite products have been associated with limitations in mapping aquatic invasive species; new crop of non-commercial sensors, e.g. Landsat 8 OLI and Sentinel-2 MSI, with improved sensing characteristics have demonstrated promising prospects in vegetation mapping (Fu, 2003; Zhang *et al.,* 2016). These sensors also show some potential for land use and land cover mapping (Kaufmann and Stern, 1997; Hassan *et al.,* 2016), biomass estimation (Yavaşl, 2016) and plant and crop disease monitoring (Hillnhutter and Mahleni, 2008; Dhau *et al.,* 2017). For instance, Shoko and Mutanga (2017) demonstrated the unique capability of the newly launched Sentinel-2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species with an overall classification accuracy of 90.41%. These sensors are therefore, perceived to provide new and invaluable opportunities for detecting, mapping, monitoring and understanding the proliferation of water hyacinth in smaller reservoirs – a previously challenging task with broadband multispectral satellite data. Refined sensing characteristics, which include the high spatial resolution (±10 m) and the presence of new and strategically positioned spectral wavebands red edge (RE); previously a characteristic of high resolution commercial sensors e.g. Worldview 2, Ikonos etc., brings with its unique improvements that could enable subtle detection and discrimination of aquatic weeds often obscured in the backdrop of natural vegetation. Besides, the greater and free availability of remotely sensed data at higher spatial and spectral resolutions coupled with the development of machine learning algorithms could potentially improve classification accuracies which maybe a great step towards water resource management (Peerbhay *et al.,* 2016). Therefore, this study sought to test the capability of Landsat 8 OLI and Sentinel-2 MSI sensors in detecting and mapping the spatial distribution and configuration of invasive water hyacinth (*Eichhornia crassipes)* in the Greater Letaba river system in Tzaneen, South Africa.

3.2 Materials and methods

3.2.1 Field survey and preprocessing

The capability of Landsat 8 OLI and Sentinel-2 MSI was tested in discriminating water hyacinth from other co-existing land cover types, such as bare land, plantation, and riparian vegetation, other vegetation, water, as well as built-up. Field data collection was conducted to record the location of water hyacinth and other land cover classes, at sub-metre accuracy, using Global Position System (GPS). Field data were collected from 24th June to 26th June 2017. Field data collection was achieved, using randomly generated sampling points across the river system, using the Hawths Analysis Tool in ArcGIS 10.4 software. A total of 329 points (47 points per land cover type) was generated and these were used to discriminate water hyacinth from other land cover types. Ground-truthing measurements coinciding with satellite image acquisition period were used. In this study, correspondence principle for image acquisition and ground-truthing measurements was set to three days. The period, allow for adequate matchups between ground-truth data and satellite imagery (Sriwongsitanon *et al*., 2011; Tebbs *et al*., 2013; Lamaro *et al*., 2013). Sites of recorded land cover types, using GPS were then imported into ArcGIS 10.4 software environment for classification purposes.

3.2.2 Remote sensing data acquisition and preprocessing

Sentinel-2 MSI and Landsat 8 OLI remotely satellite images were acquired to test the sensors' capability in discriminating water hyacinth from other vegetation cover types. Detailed spectral and spatial information on the satellite images used for analysis are presented in Table 3.1. Both cloudless satellite images covering the Greater Letaba river system were freely acquired from the online Landsat and Sentinel series archive manned by the United States Geological Survey (USGS) website (http://glovis.usgs.gov/web-link). The satellite images were acquired between 24th June to 26th June 2017 with two tiles of Landsat 8 OLI and six tiles of Sentinel-2 MSI covering the study area. Satellite images were then atmospherically corrected using Dark Object Subtraction (DOS1) model under Semi-Automated Classification (SCP) embedded in Quantum GIS (QGIS) 2.18.03 software. Pre-processing was done, using QGIS software to convert all the image bands into reflectance. We then resampled spectral bands of Sentinel-2 MSI from 20 m to 10 m using nearest neighbour resampling method. All tiles in both sensors were mosaicked using ArcGIS 10.4 to cover the extent of the study area. The 329 field sampled points were then overlaid on the layer-stacked reflectance images to extract the corresponding reflectance values. The extracted reflectance values per spectral band were then exported as a table in Microsoft excel. The data was then used to calculate spectral vegetation indices (Table 3.2). The selected indices were chosen based on their capabilities in improving vegetation spectral responses (Pahlevan and Schott, 2013; El-Askary *et al.*, 2014). For classification accuracy assessment, there is a disagreement between proportions of testing, as well as training sets of land cover types. Before proceeding with the analysis, the extracted spectral reflectance was randomly divided into 30% testing and 70% training sets, which is a requirement for all machine-learning algorithms (Adjorlolo *et al.,* 2013; Adelabu *et al.,* 2014; Sibanda *et al.,* 2015).

3.2.3 Water Hyacinth mapping using the Discriminant Analysis (DA)

A variety of classification algorithms have been developed and used to map the spatial distribution of invasive water hyacinth in the freshwater ecosystem. In this study, we used DA to test the capability of new generation sensors, Landsat 8 OLI and Sentinel-2 MSI data in mapping water hyacinth radiance from other land cover types. The choice of the model was based on its performance in classification as reported in previous studies (Sibanda *et al.,* 2015; Matongera *et al.,* 2017; Shoko and Mutanga, 2017). Fernandez, (2002) describe discriminant analysis as multivariate statistical classifier used to model group discrimination based on observed predictor variables of remote sensing in each observation into one of the groups.

Table 3.1: Sensors spectral and spatial characteristics of Landsat 8 OLI and Sentinel-2 MSI

Landsat 8 OLI			Santinel-2 MSI		
Band	**Band width**	**Resolution** (m)	**Band**	**Band width**	**Resolution** (m)
Blue	0.45– 0.52	30	Blue	0.49	10
Green	0.53 – 0.60	30	Green	0.56	10
Red	0.63 – 0.68	30	Red	0.67	10
NIR	0.85 – 0.89	30	RE 1	0.71	20
SWIR-1	1.56 – 1.66	30	RE 2	0.74	20
SWIR-2	2.10 – 2.30	30	RE 3	0.78	20
			NIR	0.84	10
			NIR narrow	0.87	20
			SWIR 1	0.16	20
			SWIR 2	0.22	20

NIR-Near infrared, SWIR-Shorter wave infrared, RE-red edge

Table 3.2: Landsat 8 OLI and Sentinel-2 spectral and vegetation indices retrieval

Index	**Formula**	**Reference**
NDVI	(NIR - Red)/(NIR + Red)	Tucker (1979)
NDWI	(Green - NIR)/(Green + NIR)	McFeeters (1996)
EVI	2.5 ((NIR - Red)/(1 + NIR + 6Red - 7.5Blue))	Huete *et al.*, 1997
SRI	(NIR/Red)	Jordan (1969)
SAVI	((NIR - Red) (1 + L))/(NIR2 + Red + L)	Huete (1988)
GI	Green/Red	Zarco-Tejeda *et al.*, 2005
GNDVI	(NIR - Green)/(NIR + Green)	Gitelson *et al*., (1996)
Clgreen	(NIR/Green) – 1	Gitelson *et al.*, 2002
ARVI	(NIR – (2*(Red – Blue)))/(NIR + (2*(NIR – Blue)))	Kaufman and Tanré, 1992
TVI	$\sqrt{(\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red}) + 0.5)}$	Deering e*t al.*, 1975
OSAVI	(NIR - Red)/(NIR + Red + 0.16)	Rondeaux *et al.*, 1996
RDVI	$\sqrt{(\mathrm{NDVI})(\mathrm{DVI})}$	Roujean and Breon, 1995
VGI	(Green - Red)/(Green + Red)	McFeeters (1996)
NG	Green/NIR + Red + Green	Sripada *et al.*, 2006
DVI	NIR – Green	Tucker, 1979

NDVI: normalized difference vegetation index; NDWI: normalized difference water index; EVI: enhanced vegetation index ; SRI: simple ratio index; SAVI: soil adjusted vegetation index; GI: greenness index; GNDVI: green normalized difference vegetation index; Clgreen: chlorophyll index green; ARVI: atmospherically resistant vegetation index; TVI: transformed vegetation index; OSAVI: optimized soil-adjusted vegetation index; RDVI: renormalized difference vegetation index ; VGI: vegetation greenness index; NG: normalised green**;** DVI: difference vegetation index

DA uses a linear function (assumes multivariate normality with equivalent covariance matrices) for classification criterion derived from individualities within a set group of covariance matrices. The observations classified within the group discriminate land cover types into categories based on a measure of generalized squared distance. The algorithm was therefore, used to classify and derive confusion matrices from the derived water hyacinth maps. The model converts reflectance data of land cover types at each waveband into several components that account for the difference in reflectance amongst land cover types (Sibanda *et al.,* 2015). The classification accuracy is formulated (confusion matrix) using an error matrix of predicted (classified) versus known (reference) occurrences of a target (Congalton, 1991). Confusion matrix yield estimates of an overall accuracy, user accuracy and producer accuracy and may also be used to calculate statistical measures of accuracy (i.e. Kappa statistics) (Congalton and Green, 1999; Foody, 2004). To test the capability of sensors in detecting spatial distribution of water hyacinth, Table 3.3 and Figure 3.1 illustrates analysis procedures that were implemented in this study. For example, three analytical experiments: (i) spectral bands; (ii) spectral vegetation indices and (iii) combined spectral and vegetation indices were applied in Microsoft XL STAT 2013 to generate classification accuracies (Overall, user and producer accuracy).

Table 3.3: Landsat 8 OLI and Sentinel-2 MSI experiments for water hyacinth

Data type	Sensors	Spectral Information	Analysis
Spectral bands (SB)	Landsat 8	Blue, Green, Red, NIR, SWIR-1 and SWIR-2	I
	Sentinel-2	Blue, Green, Red, Red edge(RE)-1, RE-2, RE-3, NIR, NIR narrow, SWIR-1 and SWIR-2	
Spectral vegetation indices (SVIs)	Landsat 8 Sentinel-2	NDVI, NDWI, EVI, SRI, SAVI, GI, GNDVI, Clgreen, ARVI, RVI, TVI, OSAVI, RDVI, VGI, NGI, DVI	II
SB + SVIs	Landsat 8	6 bands + 16 SVIs	III
	Sentinel-2	10 bands + 16 SVIs	

3.2.4 Statistical data analysis

Prior to statistical analysis, exploratory data analysis was done to understand the data. Analysis of Variance (ANOVA) was used to identify spectral separability of water hyacinth amongst other land cover types. We conducted ANOVA to test if there is significant difference (α = 0.05) between water hyacinth and other land cover types based on the derived spectral data for the two sensors. Windows of spectral separability based on both Landsat 8 OLI and Sentinel-2 MSI were used to test which band(s) can optimally discriminate water hyacinth from other land cover types.

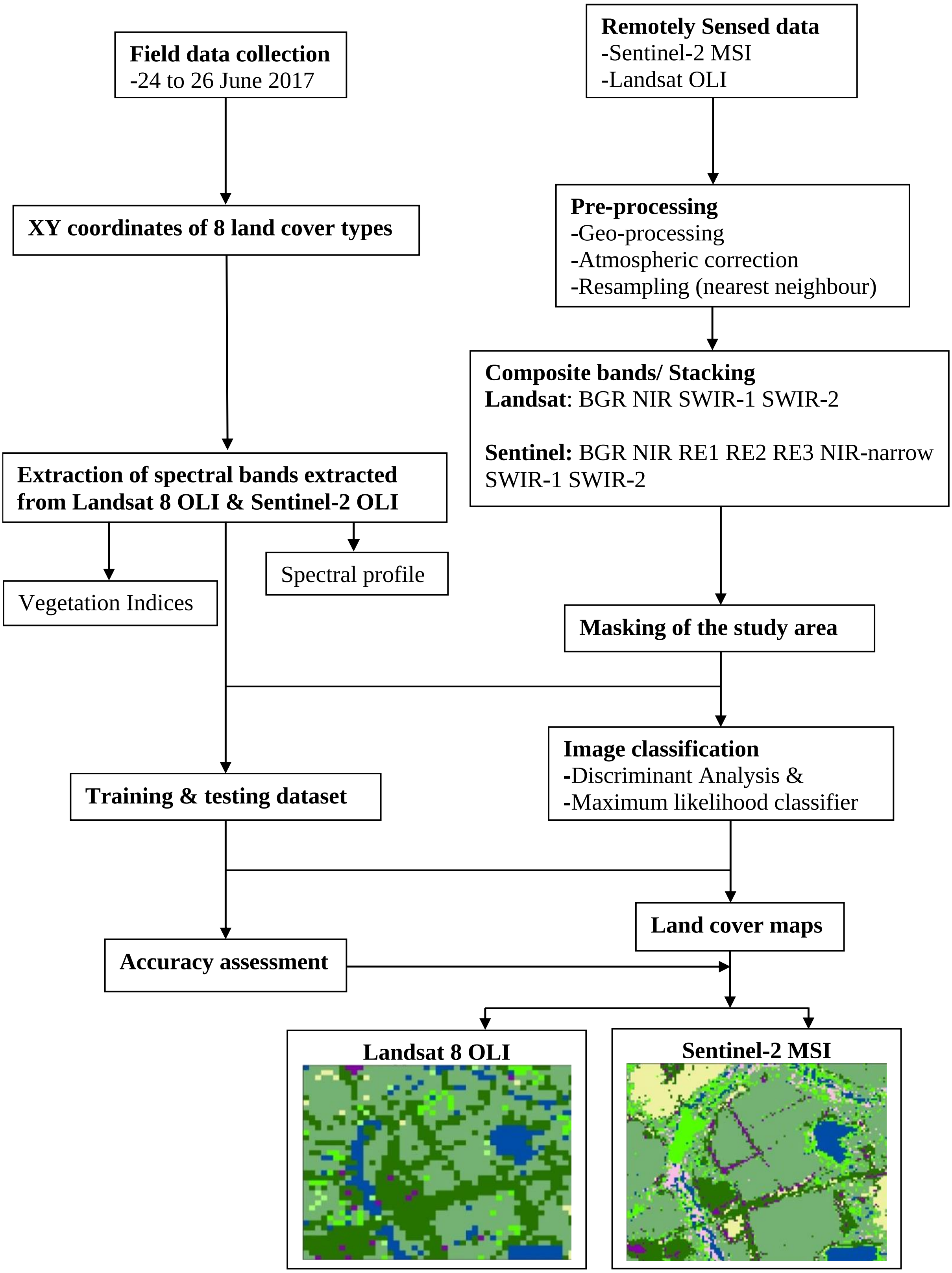

Figure 3.1: Flowchart of method

3.3 Results

3.3.1 Discriminating water hyacinth from other land cover types

Figure 3.2 illustrates the derived spectral profiles for water hyacinth and other land cover types considered in this study. The spectral profiles were derived using averaged Sentinel-2 MSI and Landsat 8 OLI derived spectral information (Figure 3.2(*a*, *b*)). Overall, the results show that water hyacinth can be discriminated from other land cover types, using the SWIR-2 spectral regions of Landsat 8 and blue, SWIR-1, as well as SWIR-2 of Sentinel-2. Sentinel-2 illustrates a clear window of spectral separability on the following bands: blue, RE 1, SWIR-1 and SWIR-2 compared to Landsat 8 OLI.

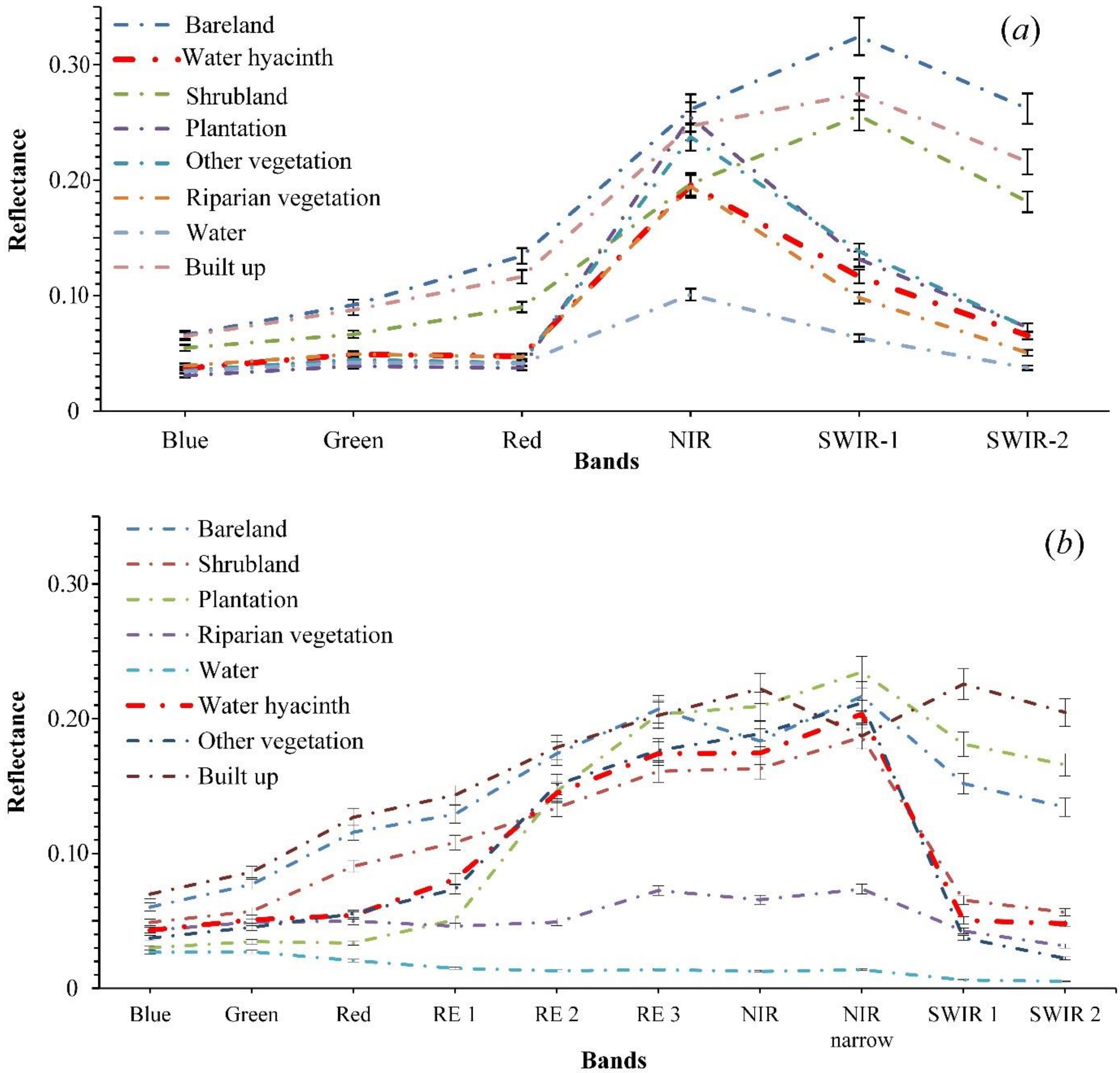

Figure 3.2: Averaged spectral reflectance for eight land cover types using (a) Landsat 8 OLI and (b) Sentinel-2 MSI sensors

3.3.2 Image classification Accuracies

3.3.2.1 Analysis I: Water Hyacinth classification using raw spectral data

Figure 3.3(*a*, *b*) illustrates classification accuracies of water hyacinth from other land cover types derived from Sentinel-2 MSI and Landsat 8 OLI datasets. It was observed that the Sentinel-2 MSI outperformed Landsat 8 OLI in discriminating water hyacinth producing an overall accuracy of 73% when compared to Landsat 8 OLI which yielded a slightly lower overall accuracy of 63.34%, with a deviation of 9.66% (Table 3.4). Furthermore, Sentinel-2 produced good user and producer accuracies, when compared to Landsat 8 OLI. For water hyacinth, Sentinel-2 yielded user accuracy of 78.56% and producer accuracy of 57.89% (Figure 3.3) when compared to Landsat 8 OLI that yielded low classification accuracies with user accuracy of 20% and producer accuracy of 35.67% (Figure 3.3). In comparison to other land cover types, the plantations produced low accuracy with 36.41% in Sentinel-2. Overall, Landsat 8 had the lowest user and producer accuracies as compared to Sentinel 2 sensor.

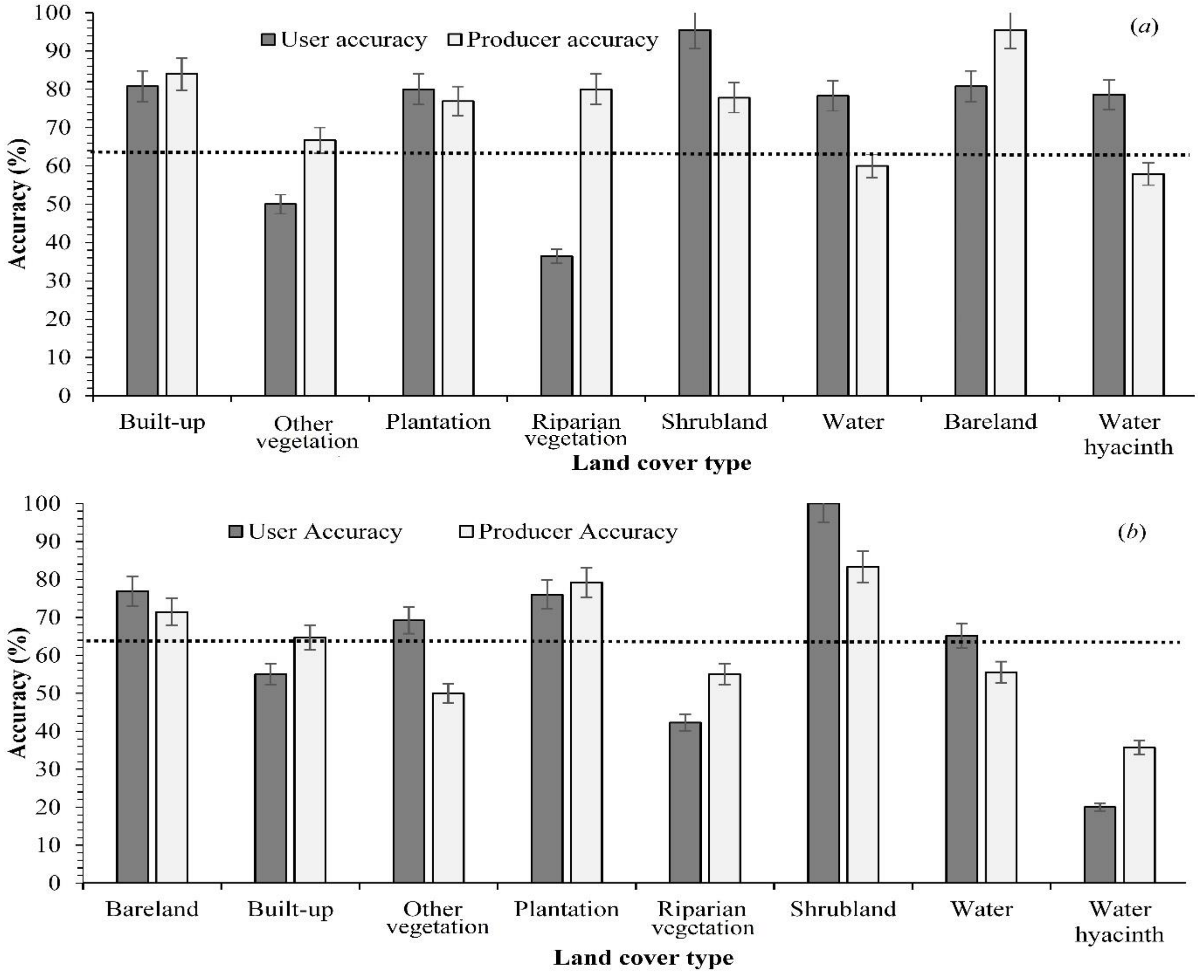

Figure 3.3: Classification accuracies of water hyacinth and other land cover types derived from (a) Sentinel-2 and (b) Landsat 8 spectral dataset. Dotted line represents good classification accuracies above 65% (Shoko and Mutanga, 2017).

3.3.2.2 Analysis II: Water Hyacinth classification using Landsat 8 and Sentinel-2 derived vegetation indices.

Water hyacinth classification accuracy using different spectral vegetation indices, demonstrated that the difference in sensors slightly improved performances when compared to the use of raw spectral bands. Figure 3.4(*a*, *b*) shows that Sentinel-2 outperformed Landsat 8 in discriminating water hyacinth from other land cover types producing an overall accuracy of 73.31% (Figure 3.6). On the other hand, Landsat 8 OLI derived spectral vegetation indices yielded overall accuracy of 65.53%. Compared to the first analysis (I), Landsat 8 OLI overall accuracy increased by 2.19% (Table 3.4) and by 0.31% for Sentinel-2. Furthermore, user and producer accuracies increased in both sensors, respectively (Figure 3.4). Regardless of the increase in user and producer accuracy of water hyacinth in both sensors, Landsat 8 OLI yielded lower accuracies with user accuracy of 40% and producer accuracy of 47.64%. When compared to other land cover types, plantation and shrub land produced higher classification of 100%.

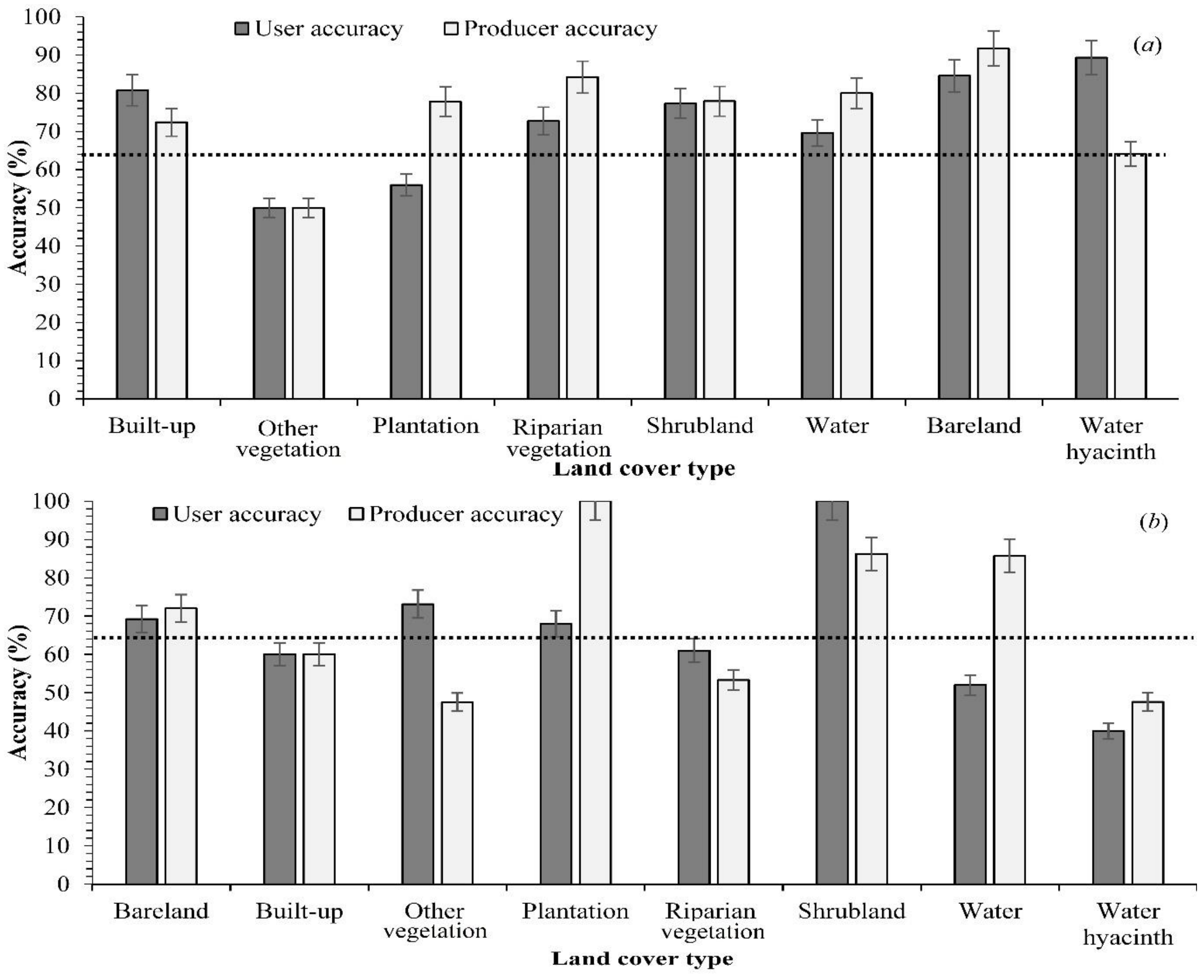

Figure 3.4: (a) Sentinel-2 and (b) Landsat 8 classification accuracies (%) for water hyacinth and other land cover types using derived vegetation indices.

3.3.2.3 Analysis III: Water Hyacinth classification using combined Landsat 8 and Sentinel-2 derived spectral bands and spectral vegetation indices.

Figure 3.5(*a*, *b*) illustrates the classification accuracy of water hyacinth based on integrated datasets of spectral bands and spectral vegetation indices derived from Landsat 8 and Sentinel-2, respectively. The combination of spectral bands and spectral vegetation indices produced satisfactory results for both sensors. For example, Sentinel-2 yielded an improved overall classification accuracy of 77.56% (Figure 3.6) and, when compared to analysis I, displays an overall improvement in accuracy of 4.56% and 4.25% from analysis II (Table 3.4). Although overall classification accuracy of Landsat 8 increased by 5.07% from Analysis I and 2.88% from Analysis II, the combined datasets produced overall accuracy of 68.41% (Figure 3.6). Integrated datasets produced user accuracy of 89.30% and producer accuracy of 61% for water hyacinth. When compared to analysis I, user accuracy increased by 10.74% whereas the producer accuracy increased by 3.11%, furthermore, when compared to analysis II, user and producer accuracy dropped by 3.11%. From the observation, water hyacinth produced lowest classification accuracies with user accuracy of 44% and producer accuracy of 50% using Landsat 8 OLI. Additionally, we compared the overall classification performance of the two sensors in mapping water hyacinth using *t*-test, and the results derived from *t*-test showed that there was significant difference (t=6.313, p<0.04) in their performances. The 10 m Sentinel-2 across all the analysis stages (I, II and III) outperformed the 30 m Landsat 8 sensor.

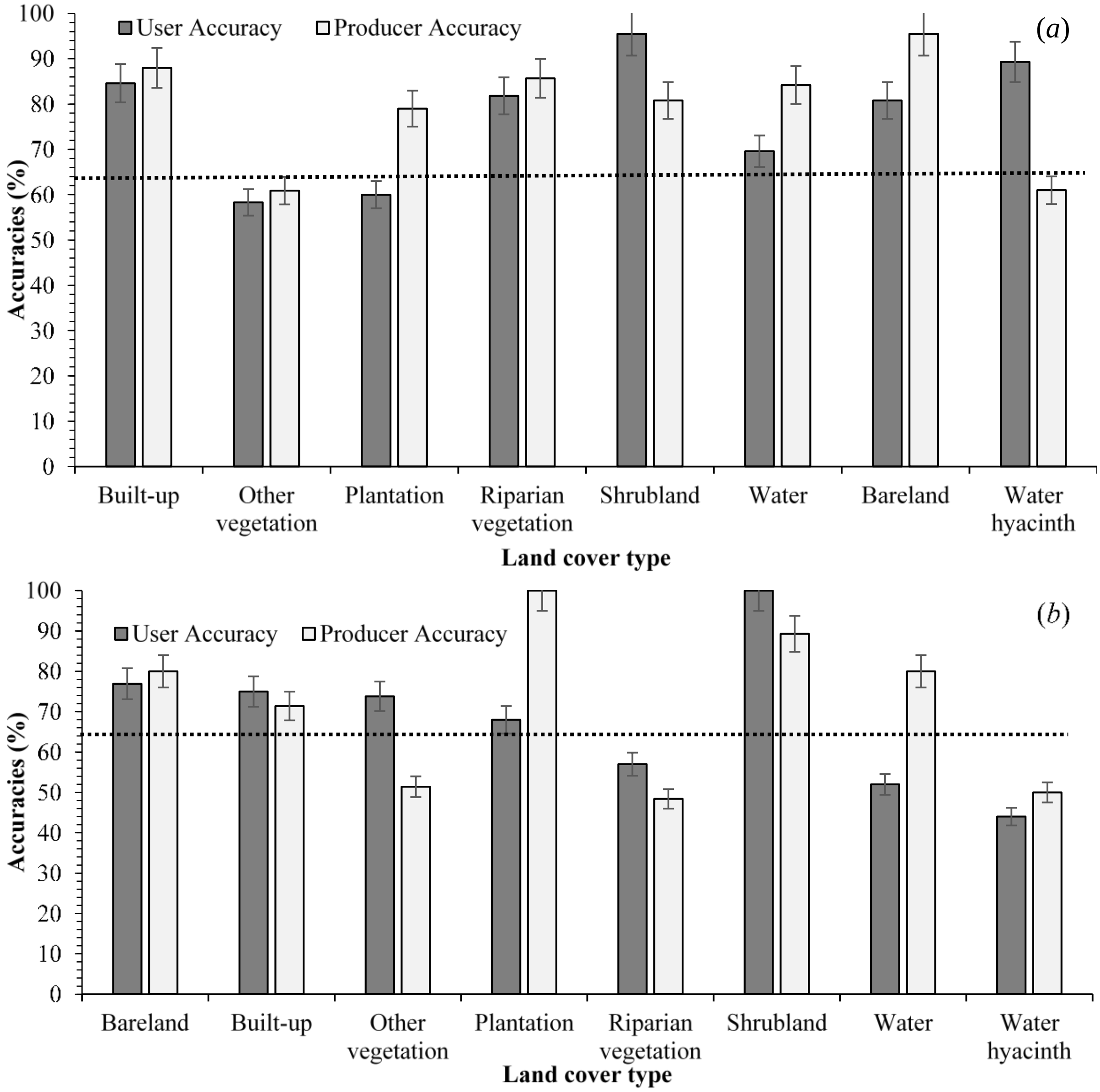

Figure 3.5: (*a*) Sentinel-2 and (*b*) Landsat 8 classification accuracies (%) for land cover types using combined spectral bands and spectral vegetation indices

Figure 3.6 illustrates the overall classification accuracies using a combined dataset (spectral bands and spectral vegetation indices) derived from Landsat 8 OLI and Sentinel-2 MSI imagery.

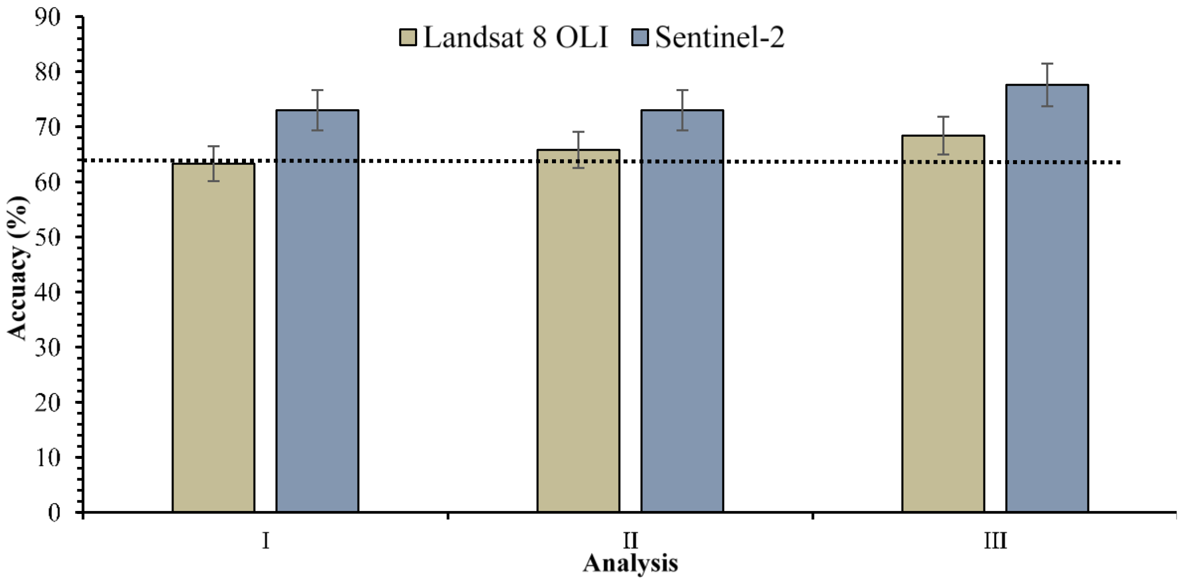

Figure 3.6: Combined spectral bands and spectral vegetation indices overall classification accuracies derived from Sentinel-2 MSI and Landsat 8 OLI

3.3.2.4 Capability of Landsat 8 OLI and Sentinel-2 sensors in mapping the spatial distribution of water hyacinth and other land cover types

Figure 3.7(*a*, *b*) illustrates the derived thematic maps showing land use and land cover revealing water hyacinth within the study area, using Landsat 8 OLI and Sentinel-2 MSI. Sentinel-2 MSI was capable of detecting and distinguishing most river portions affected by water hyacinth from other land cover types. On the other hand, 30 m Landsat 8 OLI comparatively to Sentinel-2 MSI did not detect and map certain area infested with water hyacinth.

Table 3.4: Deviation of classification accuracies between Sentinel-2 and Landsat 8

Sensor	Parameter	Accuracy (%)	Deviations in terms of accuracy (%)		
			I	II	III
Landsat 8 OLI	Bands	63.34	-	-2.19	-5.07
	VIs	65.53	±2.19	-	-2.88
	Bands + VIs	68.41	±5.07	±2.88	-
Sentinel-2 MSI	Bands	73	-	-0.31	-4.56
	VIs	73.31	±0.31	-	-4.25
	Bands + VIs	77.56	±4.56	±4.25	-

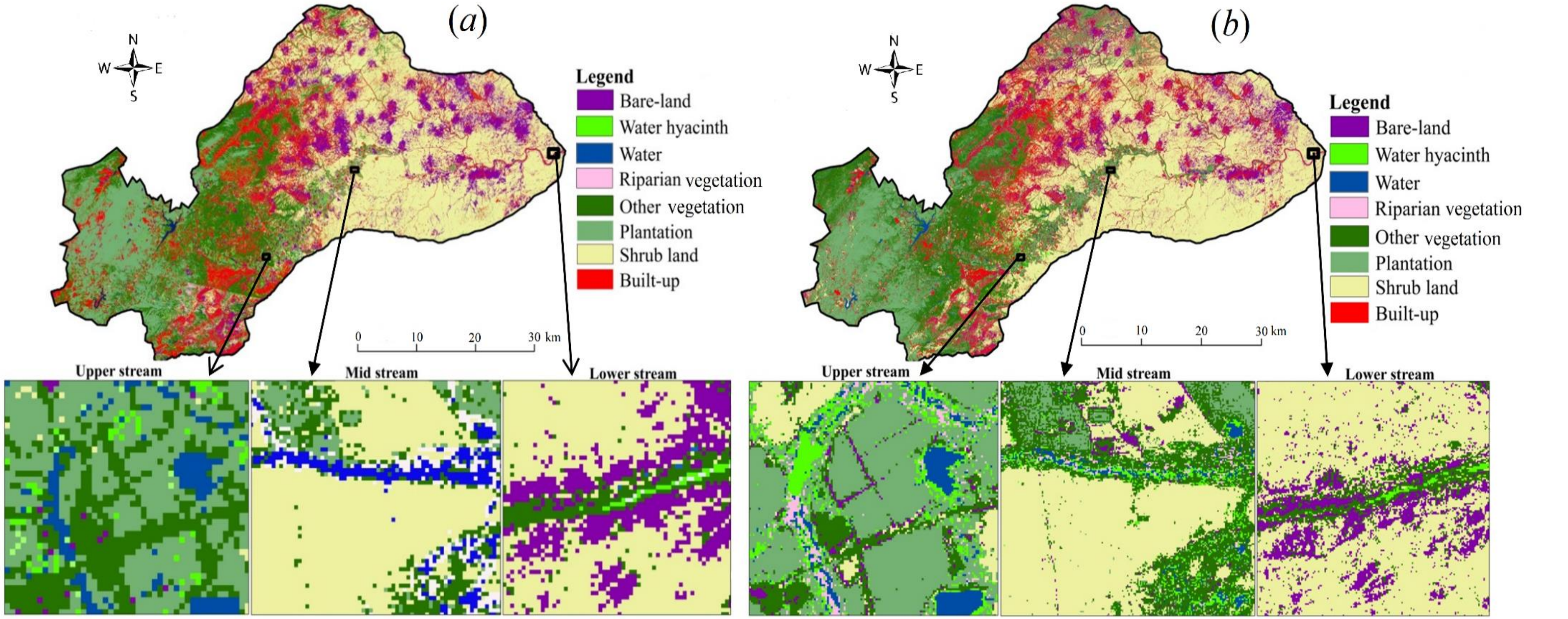

Figure 3.7: (*a*) Strength of Landsat 8 OLI and (*b*) Sentinel-2 MSI in mapping the spatial distribution of invasive water hyacinth and other land cover types

3.4 Discussion

The main aim of the study was to test the capability of new multispectral satellite data, Landsat 8 OLI and Sentinel-2 MSI sensors in detecting and mapping the spatial distribution of water hyacinth in freshwater ecosystem. The study proved that Sentinel-2 MSI outperformed Landsat 8 OLI in discriminating water hyacinth from other land cover types, such as water, plantation, built up areas, riparian vegetation, other vegetation, shrub land, as well as bare land. Besides, detecting and mapping the spatial distribution of water hyacinth is of importance in understanding its spatial pattern and extent before removal and management practices can take place. This information is critical to aquatic scientists, environmentalists, and hydrologists, as well as catchment managers, especially in complex environments. Management practices include biological control, furthermore, derived information will guide managers on how and where to start applying practices.

The outcome of this study confirmed the capability of newly launched Sentinel-2 MSI in detecting and mapping water hyacinth in freshwater system on a river scale, when compared to Landsat 8 OLI. Using spectral bands datasets of both sensors, Sentinel-2 achieved an overall classification accuracy of 73%, whereas Landsat 8 had an accuracy of 63.34%. Statistically, when compared to Sentinel-2, Landsat 8 had a magnitude of 9.66%, which clearly demonstrates the sensor's poor performance in mapping water hyacinth from the riverine and other related plants. The observed performance of Sentinel-2 MSI also confirmed by the recent study by Shoko and Mutanga, (2017) where they discriminated C3 and C4 grass functional types in the Drakensburg with high accuracy (85.45%). In their study, they concluded that the overall high classification was primarily attributed to the presence of more spectral bands, which provided more windows for spectral separability of specified land cover types. In contrast to other bands, the blue, red, RE and SWIR spectral regions played a key role in boosting spectral separability of water hyacinth from other land cover type. The selection of these bands can be attributed to the improved and unique sensitivity to plant biophysical and chemical properties (Dube and Mutanga 2015).

Furthermore, findings of this study showed that spectral vegetation indices derived from both sensors outperformed the overall performance of raw spectral bands in discriminating water hyacinth. For instance, the use of spectral vegetation indices for Sentinel-2 MSI yielded an overall accuracy of 73.31% whereas Landsat 8 OLI had an accuracy of 65.53%. More interestingly, Sentinel-2 MSI accuracy increased by 0.31% and by 2.19% for Landsat 8 OLI, when compared to raw spectral band reflectance. These findings are in line with various observations from literature (Motangera *et al*., 2017; Shoko and Mutanga, 2017), which shows that satellite derived vegetation indices provide one of the best possible ways to obtain the subtle vegetation biophysical parameters. Good classification accuracies from the use of spectral vegetation indices maybe linked to the strength of the Normalised Difference Vegetation Indices (NDVI). Liu and Huete, 1995; Díaz and Blackburn, 2003; Sibanda *et al.* (2015) reported that the performance of vegetation indices like NDVI could be attributed to its ability to suppress background effects much better than individual spectral bands. Such background effects include atmospheric impurities, soil or shadow backgrounds, as well as zenith angle of the sensor. Moreover, the outstanding performance of Sentinel-2 MSI may be attributed to its spatial resolution, a unique spectral band setting, which together with spectral vegetation indices offers an advantageous alternative than available broadband and low spatial resolution sensors, such as Landsat data.

The combined datasets (i.e. spectral bands and spectral vegetation indices) further proved its capability in discriminating water hyacinth from other land cover types. Although Sentinel-2 showed the supremacy in the discrimination process, both sensors produced overall classification accuracy within the range of 68.41% to 77.56%. Generally, Sentinel-2 MSI outperformed Landsat 8 OLI by a huge margin of 9.66%. The decrease in Landsat 8 OLI with 9.66% can be attributed to the sensor's challenges emanating from the spectral confusion of water hyacinth with other land cover types within the study area. Considering its 30 m spatial resolution requirements in a river scale (width between 8 to 60 m), the sensor was incapable of classifying water hyacinth from other land cover types in narrow environments. In contrary, width of the river and spatial resolution of Landsat 8 OLI resulted in the sensor's low sensitivity to water hyacinth hence slightly lower discrimination capabilities. Therefore, the observed capability of the newly launched Sentinel-2 MSI makes it a better and future alternative in discriminating and monitoring aquatic vegetation especially in a river system.

Overall, classification accuracies in both images increased and this was influenced by integration of spectral bands and spectral vegetation indices. Besides, combined dataset from the10 m Sentinel-2 MSI spatial resolution enhanced the sensor's potential to discriminate water hyacinth in the river systems. In this regard, results achieved in this study concur with research finding published by Matongera *et al.* (2017) who reported that combining spectral bands and spectral vegetation indices significantly improved the discrimination of bracken fern weeds. In addition, the work by Sibanda *et al.* (2015) also pointed on the value of combining spectral bands with spectral vegetation indices obtained from Sentinel-2 in quantifying grass above ground biomass treated with different fertilizer treatments. High results produced are due to the increased number of variables sensitive to plant biophysical properties.

Spatially, Sentinel-2 managed to depict the spatial distribution of water hyacinth along the course of river (upper, mid and lower stream). Furthermore, it can be seen in the Sentinel-2 image that in the upper and mid-stream water hyacinth has clogged this freshwater ecosystem. These findings are in line with the observed land use patterns within the area where it can be observed that alongside these selected sections of the river there are commercial agricultural farms practicing intensive farming. However, nutrients from commercial farms contribute in eutrophication that creates a conducive breeding ground for invasive species to thrive (Aboyeji, 2013; Galadima *et al.*, 2011; Carpenter and Biggs, 2009). Furthermore, the wide spread of water hyacinth can be influenced by nutrients washed into water system through runoff, as well as sewage disposal from upstream townships (Dube *et al*., 2017). Sewage spillage into open water bodies proliferates the biological oxygen strains to such a high level that all the available oxygen may be removed; subsequently, aquatic animals and even aquatic weeds can thrive or vice-versa, creating momentous distraction in the food chain (Aboyeji, 2013).

3.5 Conclusion

In this study, we tested two robust push-broom multispectral sensors: Landsat 8 and Sentinel-2 in identifying, detecting and mapping the spatial distribution and configuration of invasive water hyacinth in a river system. The findings of the study derived using DA demonstrated that newly launched Sentinel-2 MSI outperformed Landsat 8 OLI in mapping water hyacinth producing an overall classification accuracy of 77.56% compared to 68.44% for Landsat 8. Improved water hyacinth classification results were further observed from the integration of Sentinel-2 spectral bands and vegetation indices. Furthermore, the variable importance results demonstrated selected blue, RE 1, SWIR-1 and SWIR-2 bands as the most critical and outstanding spectral regions for detecting and mapping water hyacinth from other land cover types. The newly launched 10 m spatial resolution Sentinel-2 MSI sensor showed enhanced capability in detecting, mapping and monitoring the spatial distribution, configuration and invasion magnitude of invasive water hyacinth in a river scale.

4. CHAPTER FOUR

Mapping the seasonal dynamics of invasive water hyacinth (*Eichhornia crassipes*) in the greater Letaba river system using multi-temporal Sentinel-2 satellite data

Thamaga K.H and Dube T., 2018. Mapping the seasonal dynamics of invasive water hyacinth (*Eichhornia crassipes*) in the Greater Letaba river system using multi-date Sentinel-2 Multi-Spectral Instrument. *GIScience and Remote Sensing*, TGRS-S-18-00114. (**Manuscript under review**).

Abstract

In this study, we used multi-temporal 10 m Sentinel-2 Multi-Spectral Instrument (MSI) 2017 images to detect and map seasonal distribution and variations of water hyacinth in Greater Letaba river system in Limpopo Province, South Africa. Discriminant Analysis (DA), a multivariate statistical classifier which uses a discriminant or predictor function to classify land cover features into classes was applied to map the spatial distribution of water hyacinth and derive the classification accuracies namely; Overall Accuracy (OA), Producer Accuracy (PA), User Accuracy (UA) and kappa statistics. The derived water hyacinth maps showed that, approximately 63.82% and 28.34% of the river system was infested during the wet and dry seasons, respectively. The use of Specifically, Sentinel-2 derived spectral metrics (spectral bands in conjunction with vegetation indices) showed that, water hyacinth can be mapped at with an OA of 80.79% (wet season), and 79.04% (dry season) and a kappa coefficient of 0.764 and 0.724, respectively. Similarly, spectral bands (wet: 79.48% and dry: 75.98%) and vegetation indices (wet: 76.42% and dry: 74.42%) yielded slighter lower accuracies when compared to the use of the combined dataset. Findings of this study underscore the relevance of new satellite images in detecting and mapping the seasonal distribution of water hyacinth in river systems. Frequent revisit interval (5-day) and the improved spatial resolution of Sentinel-2 data provide new opportunities for seasonal monitoring of aquatic weeds.

Keywords: freshwater system; phenological change; remote sensing; seasonal dynamics; temporal mapping

4.1 Introduction

Water hyacinth (*Eichhornia crassipes*), which originates from the Amazon basin of Brazil, remains the most troublesome aquatic weed, both locally and globally (Holm *et al*., 1991; Mirongs, 2014; Thamaga and Dube, 2018). Its free-floating habit makes it a very effective competitor in newly invaded freshwater ecosystems (Pyšek and Richardson, 2010). Water hyacinth turns to outcompete other aquatic plant species and forms dense free-floating mats, which in many instances completely cover freshwater surfaces, such as lakes, rivers, wetlands and dams (Malik, 2007; Shekede *et al*., 2008). Its spatial distribution dominates and suppresses phytoplankton and submerged vegetation (Roijackers *et al.*, 2004). Furthermore, the uncontrolled expansion of water hyacinth is attributed to natural phenomenon, as well as the pervasiveness of eutrophication level in freshwater ecosystem (Law, 2007). The excessive growth of water hyacinth causes various environmental (or ecological) and socio-economic impacts, which threaten freshwater availability and quality (Getsinger *et al*., 2014; Hills and Coetzee, 2017). Water hyacinth thus pose serious threats to freshwater systems. For instance, the presence of these species in water can cause hypoxia, water quality deterioration (Ndimele *et al*., 2011; Mironga *et al*., 2011; Dube *et al*., 2014), change in macro-invertebrate species richness (Stiers *et al*., 2011), biodiversity loss (Villamagna and Murphy, 2010; Pyšek and Richardson, 2010; Khanna *et al*., 2011), as well as breeding ground for pests and vectors (Minakawa *et al*, 2008; Chandra *et al*., 2006; Borokini and Babalola, 2012). These dense mats further increase flood risk by obstructing water flows and irrigation system (Wilcock *et al*., 1999; Thouvenot *et al*., 2013), obstructs navigation (Holm *et al*., 1969) and impair recreational water activities, which decrease the quality of freshwater ecosystem (Halstead *et al*., 2003). In addition, water hyacinth chokes dams or lakes, resulting in the reduction of hydropower generation (Clayton and Champion, 2006), and promotes water loss through evapotranspiration.

Water hyacinth grows best in tropical and subtropical environmental conditions with optimal temperatures ranging between 25 and 27 °C, pH of 6-8 and eutrophic, still or slow-moving freshwater systems (Malik, 2007). Under favorable climatic conditions, water hyacinth can reproduce both vegetatively and sexually, by seeds produced in capsules under the base of each flower (Penfound and Earle, 1948). The species can grow and reproduce throughout the year, although flowering occurs mostly during spring and summer seasons (Tiwari *et al*., 2007). Growth rate of water hyacinth and risks in most open water bodies are driven by climate change and variability (i.e. rise in temperatures), high recharge from sewage disposal and nutrients through runoff from anthropogenic activities (Palmer *et al*., 2015; Pimentel *et al*., 2001). The propagation of these species and their threats to freshwater ecosystem requires immediate attention in terms of monitoring, to understand their spatial coverage and to put proper management practices in place. However, the use of field-data techniques in monitoring water hyacinth have proven otherwise as they are costly, time consuming, labour intensive and limited spatial coverage (Shekede *et al*., 2008; Dube *et al*., 2015). To ensure sustainable regional or catchment monitoring of freshwater ecosystem, cost effective information on the spread of water hyacinth is critical. Given the spatial extent and remoteness of water hyacinth, there is a pressing need for establishing the most suitable water hyacinth earth observation technologies with appropriate spatial and temporal scales and sufficient descriptive power to capture ecologically substantial weeds distribution in river systems. Multispectral remote sensing seem to emerge as the primary data source replacing field-data techniques. It provides a fast, cost-effective, and operative tool to detect and map the spatial distribution and spatial dynamics of water hyacinth across a broad geographical extent (Mironga 2004; Hestir *et al*., 2008; Dube *et al*., 2014). In this regard, remote sensing datasets can be utilised in diverse ways: for example, to identify areas at risk (Lodge *et al*., 2006), predict the distribution or patchiness (Bradley and Mustard, 2006) and estimate the impacts of water hyacinth. Remote sensing also allows temporal analysis of species distribution, due to its repeated coverage. Temporal mapping of water hyacinth can also enhance our understanding about their seasonal shifts. Furthermore, temporal information on the distribution of water hyacinth will open new avenues for scientific investigations, focusing on the modification of freshwater, climate change influence and anthropogenic activities surrounding open water systems.

Different types of satellite imagery have been applied extensively to study water hyacinth distribution and these include SPOT (Venugopal, 1998), MODIS (Fusilli *et al*., 2013), HyMap (Hestir *et al*., 2008), HJ-CCD (Luo *et al*., 2017), and Landsat TM, ETM+ or MSS (Dube *et al*., 2017). The study by Luo *et al*. (2017) demonstrated the capability of HJ-CCD images in mapping submerged aquatic vegetation species in the Taihu Lake. The study showed that satellite technologies can help to map submerged plants, with overall classification accuracy of 68.4%. Despite successful detection and mapping of submerged plants, the slightly lower accuracy was attributed to poor spatial resolution resulting in mixed pixels. On the other hand, Albright *et al*., (2004) used multi-temporal Landsat TM images to map water hyacinth infestation in Lake Victoria and associated river systems. Venugopal (1998), showed the usefulness of satellite images, e.g. SPOT in monitoring the infestation of water hyacinth in Bangalore, India. This study demonstrated that poor spatial resolution compromised the successful mapping of water hyacinth in water bodies. The major limitation with most studies on water hyacinth is bias on snapshot (*i.e.* single date) mapping. Single date species information limits an understanding on their temporal variability. Comprehensive information on the spatial distribution of water hyacinth and its annual and seasonal variability is critical in managing water resources (Molinos *et al*., 2015). The advent of new generation satellite sensors, such as Sentinel-2 MSI with improved sensing characteristics, offer new opportunities in understanding the distribution and spatial configuration of water hyacinth across seasons. This study therefore, sought to detect and map the spatio- temporal growth dynamics of water hyacinth in the Greater Letaba river system in Tzaneen, South

Africa, using multi-date Sentinel-2 satellite data. The sensor was chosen based on its technological advancement, such as an improved revisit interval (5days), unique spectral bands and refined spatial resolution, as well as its reported performance as demonstrated in literature. So far, Sentinel-2 MSI data has managed to provide valuable insights in C3 and C4 grass mapping (Shoko and Mutanga, 2017), crop monitoring (Campos-Taberner *et al*., 2016; Zhang *et al*., 2018), inland and sea water monitoring (Huang *et al*., 2018; Harmel *et al*., 2018), as well as agricultural mapping (Wang *et al*., 2013; Veloso *et al*., 2017).

4.2 Materials and methods

4.2.1 Field data collection

Reference data from the field was collected to complement remotely sensed data. Field data collection was done from the 24th June to 26th June 2017 for the dry season and 18th to 20th October 2017 for wet season. A Garmin GPS was used to collect x,y location of water hyacinth and other dominant land cover types in the area (bare land, built up, shrub-land, water, other vegetation, riparian vegetation, as well as plantation). A total of 329 points were randomly generated, using Hwath's Analysis Tool embedded in ArcGIS 10.4 software. Field data was used in the discrimination, mapping and validation of satellite derived water hyacinth of two seasons. Field data collection coincided with acquisition of remote sensing satellite images.

4.2.2 Image acquisition and preprocessing

In this study, six tiles (ortho-images in UTM/WGS84 projection) of cloudless Sentinel-2 MSI remote sensing data covering the entire study area were used. Dry and wet season satellite images (presented in Table 4.1) were downloaded from an online Sentinel Copernicus data hub. Before mapping water hyacinth, images were atmospherically corrected using the DOS1 technique in Quantum GIS 2.18.03 software. Selection of this technique was based on its performance as reported in literature (Pax-Lenney *et al*., 2001; Liu *et al*., 2017; Sepuru and Dube, 2018; Thamaga and Dube, 2018). The technique applies the darkest pixel in the scene as an estimate of atmospheric path radiance (Lp) in all bands, assuming that, the atmosphere is homogenous across the entire scene (Matthews *et al*., 2010). The atmospherically corrected images were further converted from radiance to reflectance values. For this study, 13 bands (presented in Table 4.2) from Sentine2 were used to achieve the aforementioned objective. These included the blue, green, red, NIR, red-edge (1, 2 and 3), NIR-narrow and SWIR (1 and 2). Band 1, 9 and 10 were excluded for analysis, due to their spatial resolution (60 m) and relevance for the detection of atmospheric features, such as aerosol and water vapour (Drusch *et al*., 2012; Hagolle *et al*., 2015). The spectral bands with a spatial resolution of 20 m were resampled to 10 m using the nearest neighbour resampling method in ArcGIS 10.4 software. This was done to ensure that all bands had a similar spatial resolution. Lastly, six scenes of Sentinel-2 images for each season were then layered and mosaicked in ArcGIS 10.4 software. A total of 329 sample points were then overlaid on the images to extract multi-values for further analysis (e.g. vegetation indices presented in Table 4.3). Zonal statistical tool was used to calculate areal coverage of water hyacinth

Table 4.1: Scenes of Sentinel-2 MSI used in the study for dry and wet season

Season	**Month**	**Scene**
Dry	June 2017	RT_T36KTV_20170625T081348
		RT_T36KUU_20170625T080542
		RT_T36KTU_20170625T081227
		RT_T35KRP_20170625T074618
Wet	October 2017	RT_T35KQP_20171019T074941
		RT_T36KTU_20171019T074941
		RT_T36KTV_20171019T074941
		RT_T36KTU_20171019T074941
		RT_T35KRP_20171019T074941

4.2.3 Data analysis

In this study we used Discriminant Analysis (DA) to map and assess the spatial variations of water hyacinth in the Greater Letaba River system, for the wet and dry seasons. DA is a multivariate statistical classifier, which uses a discriminant or predictor function to classify land cover features into classes, using a measure of generalized squared distance (Dube et al., 2017). The technique converts reflected data derived from satellite images into components that explain the variations in reflectance data amongst the land cover types. The algorithm offers cross-validated results with eigenvalue or variable scores that indicate the strength of a specific function in discriminating invasive water hyacinth from other dominant land cover classes. One of the assumptions of multivariate normality with equivalent covariance matrices is that the sample points are random, which was the case with land cover feature points used in this study. Besides, the algorithm applies the Box test (Chi-square and Fisher's F asymptotic approximation), Wilks's Lambda test (Rao's approximation), Mahalanobis distances, and Kullback's test to determine whether within-class covariance matrices were equal (Sibanda et al., 2015, Sepuru and Dube, 2018). These tests showed that there were significant differences (α = 0.05) among land cover classes within the matrices. The field data points were then randomly split into training (70%) and testing (30%), and computed by subtracting the two disagreements from a total of 100%, which is required for all machine learning algorithms (Adelabu *et al*., 2014; Adjorlolo *et al*., 2013; Sibanda et al., 2015). Three analytic sets of variables namely: (i) spectral bands, (ii) spectral vegetation indices and (iii) integrated spectral bands and spectral vegetation indices were used to derive confusion matrices and to compute overall accuracy (OA), user accuracy (UA), producer accuracy (PA) and kappa statistics.

Table 4.2: Sentinel-2 MSI sensor's spectral and spatial characteristics

Band	**Band no.**	**Central wavelength (nm)**	**Spatial resolution (m)**
Coastal aerosol	1	0.443	60
Blue	**2**	**0.490**	**10**
Green	**3**	**0.560**	**10**
Red	**4**	**0.665**	**10**
RE-1	**5**	**0.705**	**20**
RE-2	**6**	**0.740**	**20**
RE-3	**7**	**0.783**	**20**
NIR	**8**	**0.842**	**10**
NIR narrow	**8a**	**0.865**	**20**
Water vapour	9	0.945	60
SWIR Cirrus	10	1.375	60
SWIR 1	**11**	**1.610**	**20**
SWIR 2	**12**	**2.190**	**20**

*NIR-Near Infrared; SWIR-Shorter wave infrared; RE-red edge

Table 4.3: Sentinel-2 MSI spectral and Vegetation indices

Index	**Formula**	**Reference**
NDVI	(NIR - Red)/(NIR + Red)	Tucker (1979)
NDWI	(Green - NIR)/(Green + NIR)	McFeeters (1996)
EVI	2.5 ((NIR - Red)/(1 + NIR + 6Red - 7.5Blue))	Huete *et al.*, 1997
SRI	(NIR/Red)	Jordan (1969)
SAVI	((NIR - Red) (1 + L))/(NIR2 + Red + L)	Huete (1988)
GI	Green/Red	Zarco-Tejeda *et al.*, 2005
GNDVI	(NIR - Green)/(NIR + Green)	Gitelson *et al*., (1996)
Clgreen	(NIR/Green) – 1	Gitelson *et al.*, 2002
ARVI	(NIR – (2*(Red – Blue)))/(NIR + (2*(NIR – Blue)))	Kaufman and Tanré, 1992
TVI	$\sqrt{(\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red}) + 0.5)}$	Deering et *al.*, 1975
OSAVI	(NIR - Red)/(NIR + Red + 0.16)	Rondeaux *et al.*, 1996
RDVI	$\sqrt{(\mathrm{NDVI})(\mathrm{DVI})}$	Roujean and Breon, 1995
VGI	(Green - Red)/(Green + Red)	McFeeters (1996)
NG	Green/NIR + Red + Green	Sripada *et al.*, 2006
DVI	NIR – Green	Tucker, 1979

NDVI: normalized difference vegetation index; NDWI: normalized difference water index; EVI: enhanced vegetation index ; SRI: simple ratio index; SAVI: soil adjusted vegetation index; GI: greenness index; GNDVI: green normalized difference vegetation index; Clgreen: chlorophyll index green; ARVI: atmospherically resistant vegetation index; TVI: transformed vegetation index; OSAVI: optimized soil-adjusted vegetation index; RDVI: renormalized difference vegetation index ; VGI: vegetation greenness index; NG: normalised green**;** DVI: difference vegetation index

4.2.4 Accuracy assessment

Three analytically procedures were followed to discriminate water hyacinth from other land cover classes (Table 4.4). One-way Analysis of variance (ANOVA) was used to test for significant differences in seasonal distribution of water hyacinth, using spectral bands, vegetation indices, as well as integrated dataset (spectral bands and vegetation indices).

Table 4.4: Sentinel-2 MSI experimental measures of accuracy assessment for water hyacinth

Analysis	**Data type**	**Spectral information**
I	Spectral bands	Blue, Green, Red, Red edge(RE) 1, RE 2, RE 3, NIR, NIR narrow, SWIR-1 and SWIR-2
II	Vegetation Indices	NDVI, NDWI, EVI, SRI, SAVI, GI, GNDVI, Clgreen, ARVI, RVI, TVI, OSAVI, RDVI, VGI, NGI, DVI
III	SB + VIs	10 bands + 16 SVIs

4.3 Results

The results in figure 4.1 show the averaged spectral profiles for water hyacinth and other key land cover classes for the wet and dry season. It can be observed that, water hyacinth can be spectrally discriminated from other land cover types considered in this study mainly in the Red Edge (1, 2 and 3), NIR, NIR-narrow and SWIR (1 and 2) portions of the electromagnetic spectrum.

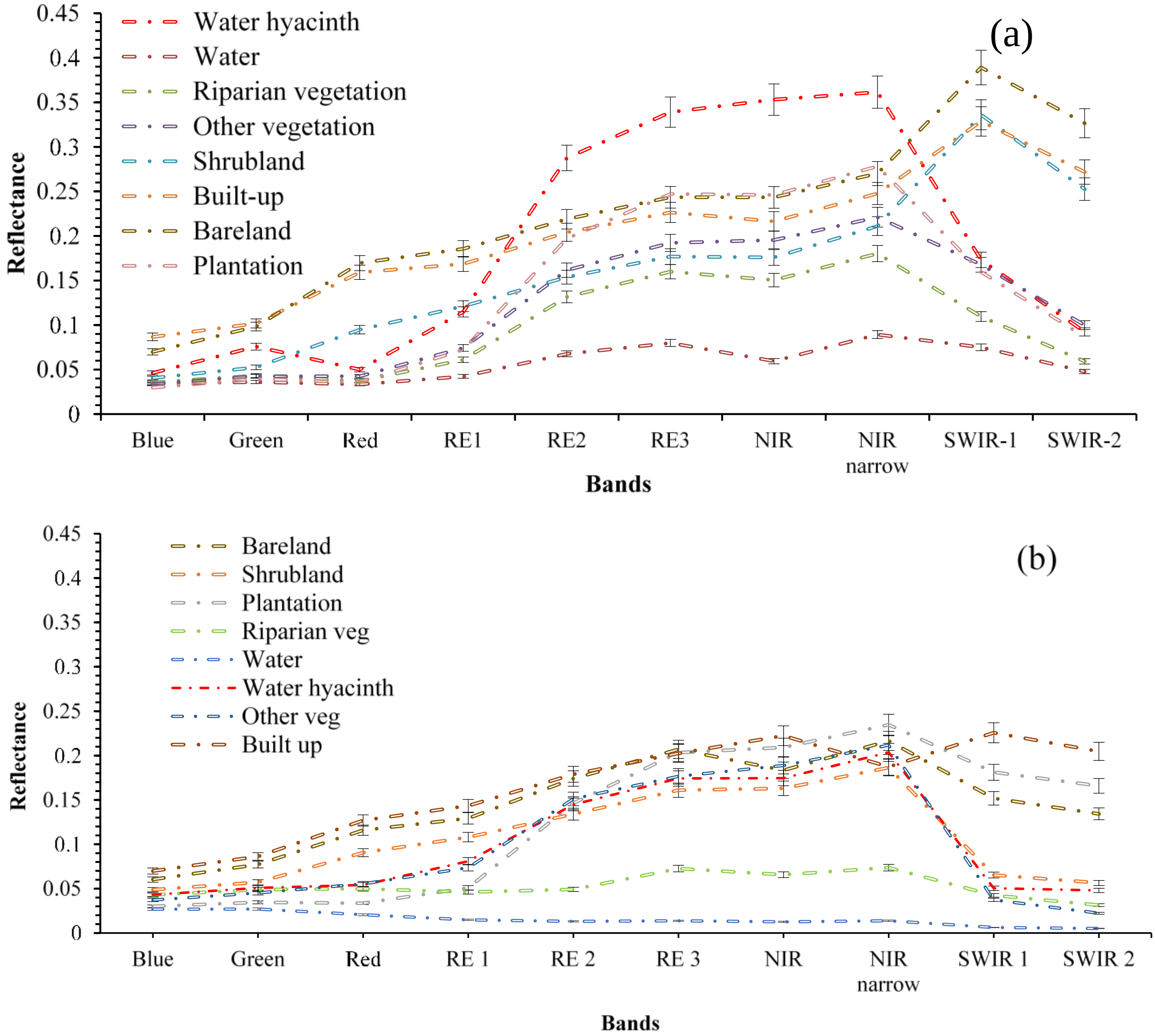

Figure 4.1: Averaged spectral reflectance derived from Sentinel-2 MSI (a) wet season and (b) dry season

4.3.1 Image analysis

4.3.1.1 Analysis I: Water hyacinth classification accuracies derived using raw spectral bands

Figure 4.2 shows classification accuracies derived using spectral bands as independent data for the dry and wet seasons. Spectral bands yielded an overall classification accuracy of 79.48% and 75.98% and kappa coefficients of 0.764 and of 0.724 for the wet and dry seasons, respectively. Although both seasons produced good classification accuracies derived using spectral bands, a slight deviation of 3.50% was observed (presented in Table 4.5). Furthermore, Sentinel-2 MSI managed to produce user accuracy and producer accuracy ranging from 44% to 100% of water hyacinth and other land cover classes for the two seasons. Wet season mapping results resulted in produced user and producer accuracies of 87.18% and 94.44% respectively. On the other hand, dry season classification resulted were achieved with user and producer accuracies of 84.62% and 66%, respectively.

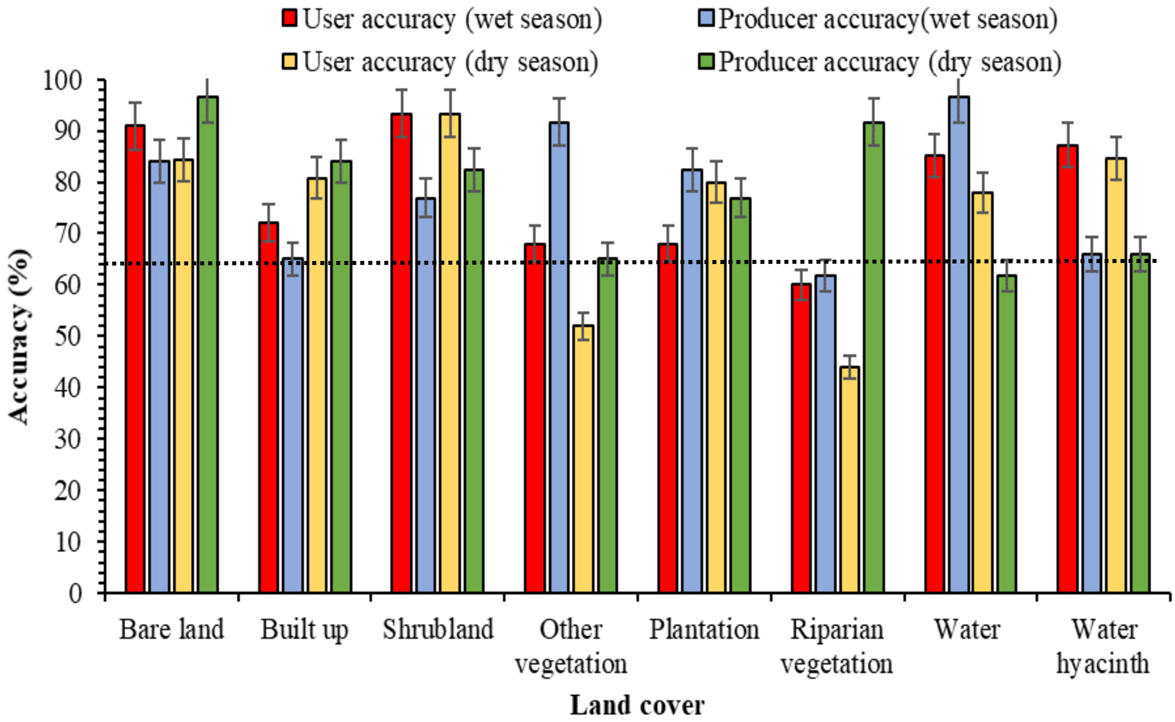

Figure 4.2: Classification accuracies of water hyacinth from other land cover types derived from dry and wet season using spectral bands as separate datasets. The line in dotted format represents satisfactory classification results above 65%.

4.3.1.2 Analysis II: Water hyacinth classification accuracies derived using spectral vegetation indices

The use of spectral vegetation indices as independent dataset in discriminating and mapping water hyacinth yielded OA of 76.42% (kappa coefficient of 0.706) and 74.42% (kappa coefficient of 0.708) for the wet and dry season, respectively (presented in Figure 4.3). Comparatively, the OA dropped by 3.06% in wet season and by 1.56% in dry season (presented in Table 4.5) when compared to the use of spectral bands alone. UA and PA were derived with improved accuracies for the two seasons. As illustrated in Table 6, high UA (87.18% and 89.74%) and PA (94.44% and 66.04%), were observed for wet and dry season, respectively.

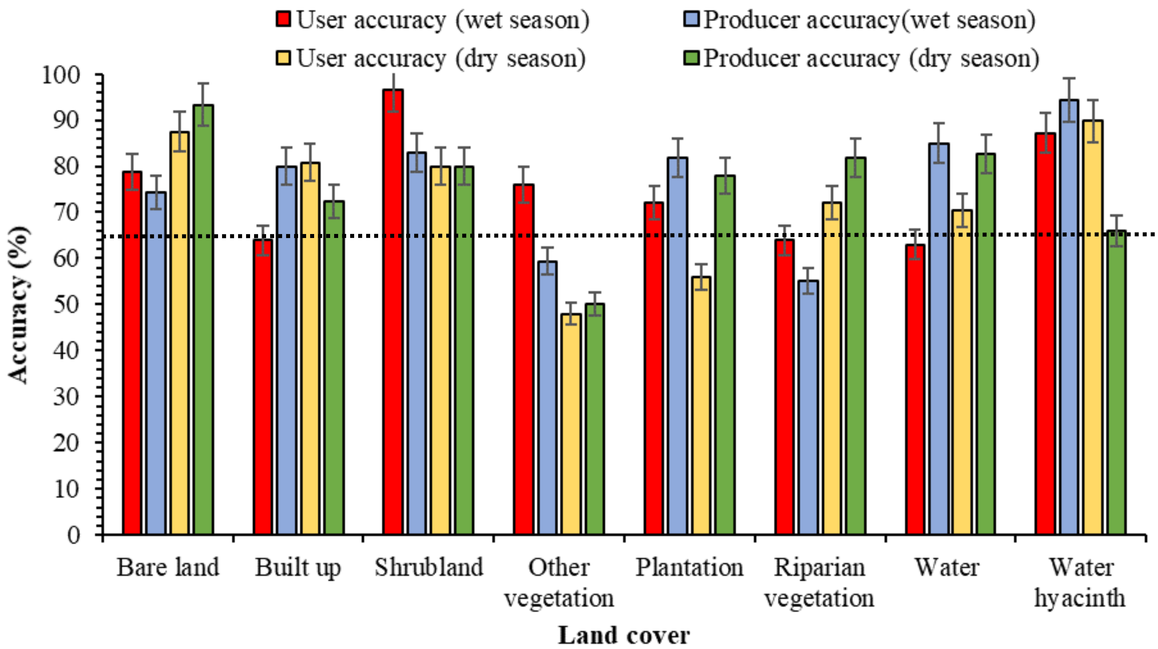

Figure 4.3: Classification accuracies of water hyacinth from other land cover classes derived from dry and wet season using vegetation indices

4.3.1.3 Analysis III: Water hyacinth classification accuracies derived using raw spectral bands and spectral vegetation indices.

The use of integrated dataset (spectral bands and vegetation indices) resulted in further improvement in the OA. The integrated dataset managed to achieve an OA of 80.79% (kappa coefficient of 0.780) during wet season compared to 79.04% (kappa coefficient of 0.759) in dry season (Figure 4.4). Similar results were observed for the PA and UA. In this case, water hyacinth was classified with high UA and PA of 84.62% and 94.29% in wet season, as well as 89.74% and 68.63% in dry season, respectively. Overall, analysis III yielded high UA and PA from when compared to analysis II and I.

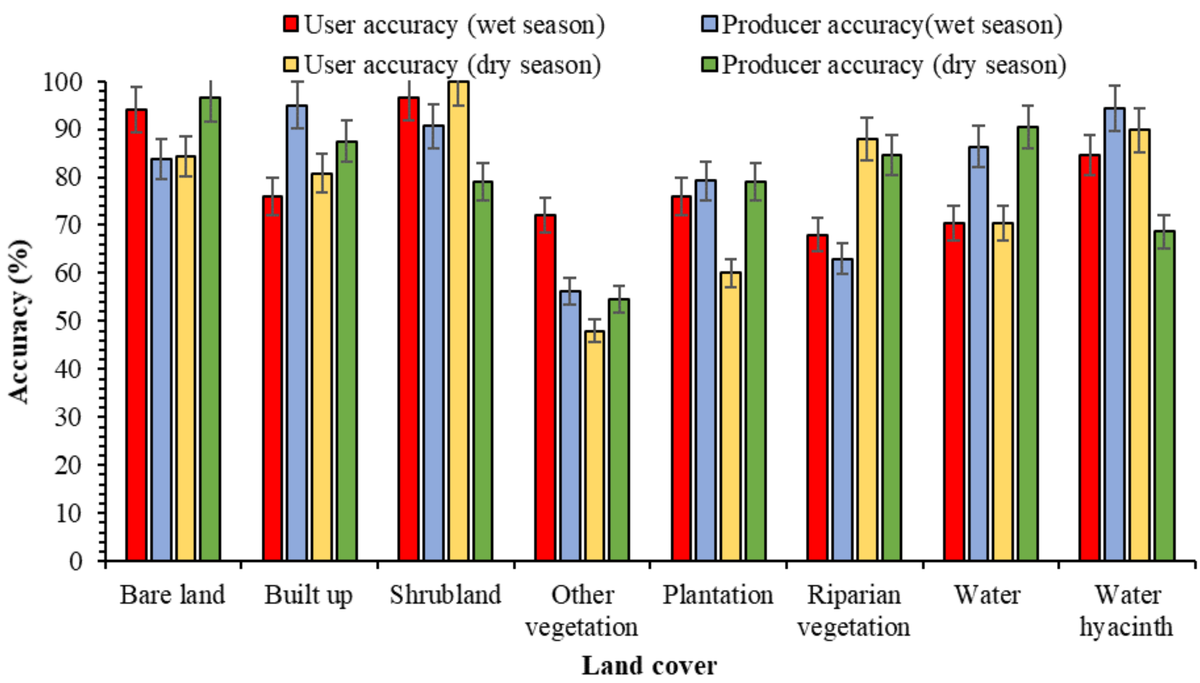

Figure 4.4: Classification accuracies of water hyacinth from other land cover types derived from dry and wet season using combined spectral bands and vegetation indices.

The overall classification accuracies illustrated in Figure 4.5 were achieved by using spectral bands (Analysis I), vegetation indices (Analysis II), as well as integrated (spectral bands and vegetation indices) dataset (Analysis III) derived from multi-seasonal Sentinel-2 MSI. Analysis of variance (ANOVA) showed that there was a significant difference amongst the accuracies derived from the three experiments i.e. (t=1.86, p<0.001) analysis I, analysis II (t=1.761, p<0.435) and analysis III (t=1.710, p<0.472).

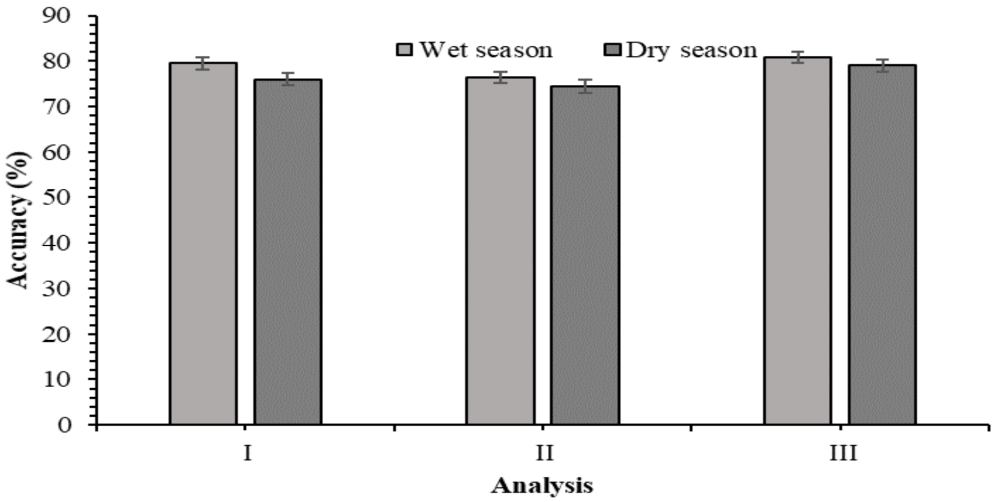

Figure 4.5: Overall classification accuracies derived using Sentinel-2 MSI variables.

Table 4.5: Magnitude of classification accuracies of wet and dry season derived from Sentinel-2 MSI

Season	**Parameter**	**Accuracy (%)**	**Deviations in terms of accuracy (%)**		
			I	**II**	**III**
wet season	Bands	79.48	-	-3.06	-1.31
	VIs	76.42	±3.06	-	-4.37
	Bands + VIs	80.79	±1.31	±4.37	-
Dry season	Bands	75.98	-	-1.56	-3.06
	VIs	74.42	±1.56	-	-4.62
	Bands + VIs	79.04	±3.06	±4.62	-

4.3.1.4 Seasonal mapping of the spatial distribution of water hyacinth

Figure 4.6 shows the derived water hyacinth spatial distribution maps for the two seasons. Overall, Sentinel-2 showed the capability of detecting and mapping seasonal distribution of water hyacinth. It was also observed that the spatial distribution of water hyacinth can be well depicted during the wet season than in the dry season. In the lower, mid and upper parts of the river, it can be seen that, had high coverage of water hyacinth in summer (wet season), than in dry season. For instance, in the wet season, water hyacinth covered (Figure 4.7) a surface area of 68.82% and 28.34% in dry season, with a deviation of 40.48%.

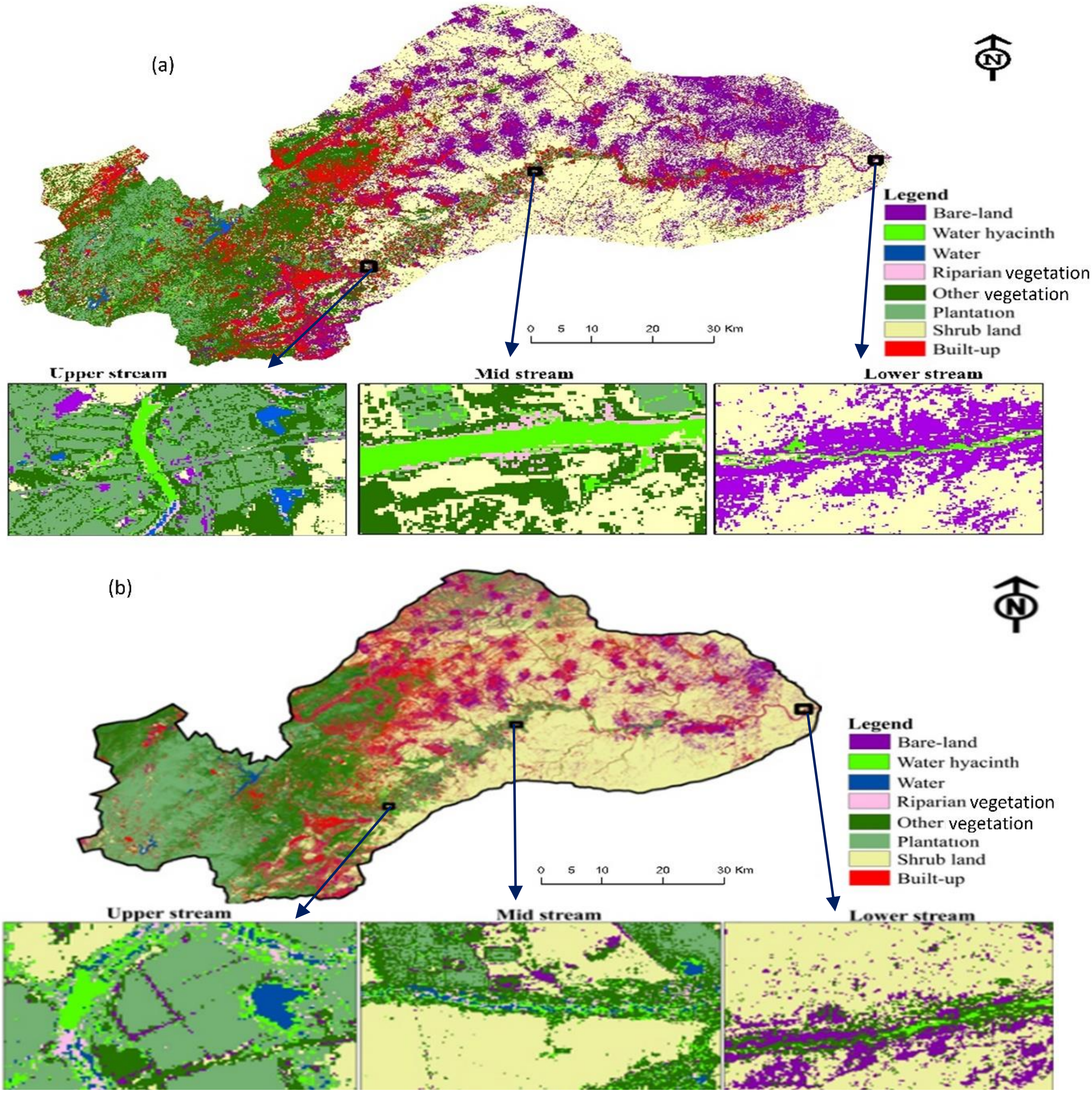

Figure 4.6: Seasonal maps derived using Sentinel-2 MSI (a) wet season and (b) dry season

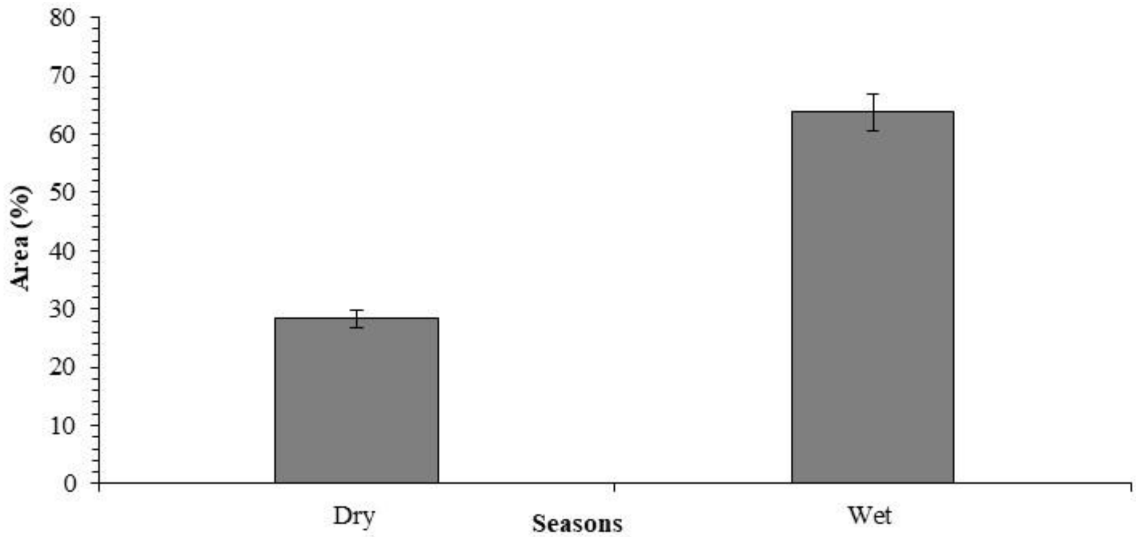

Figure 4.7: Spatial coverage of water hyacinth in the Greater Letaba river system

4.4 Discussion

The study sought to map the seasonal distribution of water hyacinth (*Eichhornia crassipes*) using Sentinel-2 MSI satellite data, in the Greater Letaba river system in Tzaneen, South Africa. This study demonstrated that Sentinel-2 MSI has the capability to obtain high accurate and reliable information on the seasonal distribution of water hyacinth. The results showed that the use of improved spatial and spectral resolution satellite in mapping water hyacinth provides critical information or input to water resource managers, especially in areas where there is a shortage of freshwater. Besides, seasonal mapping of these species gives a better view in understanding its spatial distribution and configuration required for frequent monitoring, assessment of infestation levels, sustainable remedial, eradication and effective management practices (Shekede *et al*., 2008; Thiemann and Kaufmann 2002; Ndungu *et al*., 2013; Dube *et al*., 2017). Sentinel-2 MSI demonstrated the capability of mapping water hyacinth in a river system. The study showed higher overall classification accuracy during wet season than dry season. The wet season is an optimal season where water hyacinth flowers and produces seeds under favourite climatic conditions (Kriticos, 2016).

The use of integrated dataset (spectral bands and vegetation indices) showed the highest capability of detecting and mapping the temporal distribution of water hyacinth in freshwater system with an OA of 80.79% in wet season compared to 79.04% in the dry season. Results produced from the use of integrated dataset are satisfactory with a deviation of 1.75%. In this regard, findings achieved using integrated dataset produced better results than those achieved in analysis I and II, furthermore, this concur with the work by Sibanda, (2014), Shoko and

Mutanga, (2017); Sepuru and Dube, (2018). The integrated data managed to produce high user and producer accuracies of 84.62% and 94.29% in wet season, as well as 89.74% and 68.63% in dry season. This illustrates the superiority of detecting the invasive water hyacinth during the wet and dry season. Findings of this study displayed seasonal variations in terms of mapping capabilities of Sentinel-2 MSI. This satellite data managed to produce OA of 76.42% during wet season and 74.42% in dry season using spectral vegetation indices.

Moreover, results derived from Sentinel-2 MSI showed the capability of detecting and mapping the spatial distribution of water hyacinth from other land cover classes of the study area in wet and dry season. For example, its 10 m spatial resolution accompanied by 10 spectral bands in the visible, NIR, SWIR and red edge showed the capabilities in discriminating water hyacinth from other land cover classes. The abovementioned influence the capability of the sensor in detecting and mapping spatial distribution of water hyacinth, which showed satisfactory results with an overall classification accuracy of 79.48% produced during wet season and 75.98% in dry season, derived from spectral bands datasets. Outcomes of this study concur with previous studies highlighting the capability of using Sentinel-2 MSI in aquatic or vegetation mapping related studies (Dube *et al*., 2017; Shoko and Mutanga, 2017). Seasonal variability in temporal distribution of water hyacinth showed that, the dry season had a deviation of ±3.50% in terms of accuracy when compared to the wet season results. The slightly poor performance from the dry season images can be attributed to the variability in nutrient load and weather conditions (Téllez, 2008; Waltham and Fixler, 2017). Extreme temperatures as a results of weather changes and flow dynamics fuel the spatio-temporal distribution of this species in freshwater (Thornton *et al*., 2014; Brierley and Kingsford, 2009).

The 10 m Sentinel-2 MSI showed its capability in detecting and mapping land cover classes identified in this present study. The generated maps evidenced the spatio-temporal variation of water hyacinth across the river system. Besides, it can be observed from the maps that the spatial pattern of water hyacinth in the upper, mid and lower stream differ seasonally. This is due to rainfall variability and water flow across the river system. The growth rate of water hyacinth during the wet season is higher when compared to that in winter (Bock, 1969; Rommens *et al*., 2003). Temperature rises and changes in the timing and amount of precipitation and runoff, as well as loads of nutrients from the surrounding farms, especially during wet season contributes to eutrophication, which accelerates growth of this species (Mangas-Ramírez and Elías-Gutiérrez, 2010; Kriticos and Brunel, 2016).

4.5 Conclusion

The present study focused on mapping the spatio-temporal distribution of water hyacinth in the river system during the wet and dry seasons, using Sentinel-2 MSI satellite data. The findings of this study showed that Sentinel-2 MSI satellite provide new opportunities for mapping and monitoring of seasonal distribution of water hyacinth in open water systems.

We conclude that:

- The findings showed that the wet season had high coverage of water hyacinth than the dry season.
- Sentinel-2 MSI with improved radiometric and spatial resolution managed to detect and map the seasonal distribution and spatial dynamics of water hyacinth in a river system.
- The use of combined spectral bands and vegetation indices improved the detection and mapping of water hyacinth when compared to the use of these datasets as standalone predictor variables.

Overall, the findings of this work provide new insights and critical on the usefulness of new generation sensors in monitoring aquatic water weeds and such findings can be key in decision making and policy development and draw remedial measures.

5. CHAPTER FIVE

SYNTHESIS

Remote Sensing of the spatio-temporal distribution of invasive water hyacinth in river systems

5.1 Introduction

The invasive aquatic weed, water hyacinth has been widely distributed throughout the tropical, subtropical and some warmer temperate regions of the world and has been categorised as problematic in freshwater ecosystems (Hill, 2003). Its rapid spread into freshwater ecosystems has the potential to destruct: aquatic life habitat, trap sunlight to penetrate through which results into killing of aquatic animals, obstructs navigation, impede recreation activities and reduces water quality (Shekede *et al*., 2008; Theel *et al*., 2008; Villamagna and Murphy, 2010; Schultz and Dibble, 2012). One of the critical tasks for proper management practices of invasive aquatic weeds is to understand their spatial extent and establish its severity. In this case, the accurate and estimation techniques that can precisely depict species information are required for mapping the spatial and temporal distribution and configuration of water hyacinth at a river scale. Although much has been done in mapping water hyacinth most of these studies focused on the snapshot analysis of water hyacinth distribution in large open waterbodies, such as dams and lakes, neglecting river systems. It is however, important to note that most of these rivers remain major primary water sources for the rural and small scale agricultural activities. Besides, the use of traditional methods suffered over time, due to lack of funding or limited logistics and instruments mandatory to harmonize research efforts (Zhang, 1998; Palmer *et al*., 2015).

The use of satellite images e.g. MODIS, Landsat TM/ETM+ has been on the rise recently in mapping and monitoring the invasion of water hyacinth in different locations. These sensors are somehow challenged in accurate detection and mapping of water hyacinth especially in complex environments due to sensors spatial resolution which lead to pixel mixing. This has led to poor identification or mapping of species resulting in poor management efforts or strategies in place. The key information on the progress, spatial extent, as well as proliferation rates of water hyacinth remains scarce, due to the lack of resources and high-resolution data (Shekede *et al*., 2008). However, the advancement in remote sensing recently i.e. Landsat 8 OLI and Sentinel-2 MSI with improved sensing characteristics as reported in biomass, Land use and water related studies provides new avenues for invasive species modelling (Carreiras *et al*., 2017; Veloso *et al*., 2017; Scharsich *et al*., 2017, Zhang *et al*., 2018; Toure *et al*., 2018; Yin *et al*., 2018). Therefore, new generation remote sensing is perceived to provide new opportunities for accurate detection, mapping and monitoring of aquatic weeds infestation in freshwater ecosystems at a local to global scale (Acklenson and Klemas, 1987). These sensors have improved sensors' characteristics (time revisit, spectral, spatial and radiometric resolution), which assumed to provide reliable and accurate results in detecting, mapping and monitoring of water hyacinth in complex environments. Hence, objectives of the study were:

1. To identify multispectral remote sensing variables that can optimally detect the spatial distribution of invasive water hyacinth in the Greater Letaba river system.
2. To map the spatial distribution of invasive water hyacinth in the river over time.

5.2.1 To identify multispectral remote sensing variables that can optimally detect the spatial distribution of invasive water hyacinth in the Greater Letaba river system.

This work aimed at testing two robust push-broom multispectral sensors: Landsat 8 OLI and Sentinel-2 MSI in detecting and mapping the spatial distribution and configuration of water hyacinth in a river system. The obtained results demonstrated that the blue, red, RE 1, SWIR-1 and SWIR-2 of both satellite datasets are the critical and outstanding spectral regions in detecting and mapping water hyacinth from other land cover types. Furthermore, the study showed that Sentinel-2 MSI outperformed Landsat 8 OLI, in detecting and mapping water hyacinth with the deficit of 9.66%. From the upper, mid and lower stream of the river system Landsat failed to accurately depict the spatial information of the species. Challenges results from the 30 m spatial resolution of the sensor and width of the river, which leads to mixed pixels or vegetation flush along the river system. In this regard, 10 m Sentinel-2 MSI with 10 spectral bands used in this study and 5-day revisit enhanced the sensors' capabilities in discriminating, detecting and mapping water hyacinth. The sensor's accurate mapping promotes its potential for long-term or continuous observation and monitoring the proliferation of water hyacinth in freshwater system thus critical for proper water resources management.

5.2.2 To map the spatial distribution of invasive water hyacinth in the river over time

The growth rate and risks associated with water hyacinth are perceived to vary in most open water systems, due to climatic and seasonal variability, high recharge of sewage disposal from urban areas and nutrients through runoff, as well as anthropogenic activities among other factors. However, little is known regarding the spatial distribution of water hyacinth in river systems and this makes management strategies to be complex. Use of single date spatial distribution information is not enough if these species are to be properly managed. This study therefore sought to detect and monitor seasonal distribution and variations of water hyacinth in Greater Letaba river system in Limpopo Province, South Africa, using multi-date 10 m Sentinel-2 MSI images. Sentinel-2 MSI offers several design features that may improve the classification accuracy of water hyacinth that can be mapped from multispectral satellite data. Findings demonstrated approximately 68.82% of the river system was infested with water hyacinth in wet and 28.34% in the dry season.

5.3 Conclusion

The main aim of the study was to map the spatio-temporal distribution of invasive water hyacinth in the Greater Letaba river system using remote sensing. Findings of this study highlighted the capabilities of multispectral remote sensing satellite imagery in terms of detecting and accurate mapping of water hyacinth. Based on the findings from objectives drawn in chapter 2, the following were obtained:

- Two satellite sensors (Landsat 8 OLI and Sentinel-2 MSI) showed their capabilities in terms of detecting, discriminating and mapping of water hyacinth in a rivers system. The 10 m Sentinel-2 MSI with improved spectral and spatial resolution however outperformed Landsat 8 OLI in mapping the distribution of water hyacinth.
- Remotely sensed derived variables demonstrated that, the use of integrated dataset (spectral bands plus vegetation indices) can improve water hyacinth classification accuracy than the use of these derivatives as independent dataset.
- Water hyacinth was found to be pronounced in the in wet season than in dry season. In wet season, water hyacinth covered a surface area of 68.82% and 28.34% in dry season.

5.4 Recommendations

The results obtained in the present study, provide insight in understanding the spatial distribution of water hyacinth and promote the utility of remote sensing to water or aquatic related scientists. These results provide new insights in remote sensing developments and their potential application in aquatic invasive species mapping in small water bodies- a previously challenging task with broadband multispectral sensors. There is therefore a need to shift towards the use of freely and readily available sensors with improved sensors characteristics. This study suggests the following recommendations for future research:

1. There is a need to map different water hyacinth species in the rivers instead of treating them as one species.
2. There is a need to determine the amount of water used by different water hyacinth species over time, this information will help to prioritize their removal and control strategies.
3. Although the study showed the capability of the sensors in accurate mapping of water hyacinth using new generation sensors, it will be of importance for future research to further estimate the amount of water loss from these species.
4. It is advisable for future research to studies determine the drivers of infestations. The information will be critical in understanding the environmental factors which favour the spread of water hyacinth and reduces freshwater quality.
5. Future studies need to explore the potential of detecting other pre-visual physiological indicators of vegetation stress such as chlorophyll Florence and leaf water content using remote sensing.
6. Furthermore, there is a need to study species nutrient enrichment.
7. Lastly, there is a need to explore the use of weevil as a biocontrol measure in causing damage on water hyacinth.

References

Abdel-Rahman, E.M., Mutanga, O., Adam, E. and Ismail, R., 2014. 'Detecting *Sirex noctilio* grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers'. *ISPRS Journal of Photogrammetry and Remote Sensing,* 88:48-59.

Aboyeji, O.O., 2013. "Freshwater Pollution in Some Nigerian Local Communities, Causes, Consequences and Probable Solutions." *Academic Journal of Interdisciplinary Studies,* 2(13):111.

Achankeng, E., 2003. Globalisation, urbanisation and municipal solid waste in Africa. In: *African Studies Association of Australasia and the Pacific Conference Proceedings – African on a Global Stage*. Available at http://www.ssn.flinders.edu.au/global/afsaap [accessed 13 June 2017].

Ackleson, S.G. and Klemas, V., 1987. Remote Sensing of submerged aquatic vegetation in lower Chesapeake Bay: a comparison of Landsat MSS to TM imagery. *Remote Sensing of Environment. 22: 235-248.*

Adelabu, S., Mutanga, O., Adam, E. and Sebego, R., 2014. 'Spectral discrimination of insect defoliation levels in Mopane woodland using hyperspectral data'. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 7:177-185.

Adjorlolo, C., Mutanga, O., Cho, M.A. and Ismail, R., 2013. "Spectral resampling based on user-defined inter-band correlation filter: C3 and C4 grass species classification." *International Journal of Applied Earth Observation and Geoinformation,* 21:535-544.

Africa Population and Health Research Center (APHRC)., 2014. Population and Health Dynamics in Nairobi's Informal Settlements. Report of the Nairobi Cross-sectional Slums Survey (NCSS) 2012. APHRC, Nairobi. http://aphrc.org/wp-content/uploads/2014/08/NCSS2-FINAL-Report.pdf.

Agjee, N., Mutanga, O. and Ismail, N., 2015. Remote sensing bio-control damage on aquatic invasive alien plant species. *South African Journal of Geomatics,* 4(4).

Aguiar, F.C.F. and Ferreira, M.T., 2013. Plant invasions in the rivers of the Iberian Peninsula, South-Western Europe - a review. *Plant Biosystems,* 147:1107-1119.

Albright, T.P., Moorhouse, T.G. and McNabb, T.J., 2004. "The rise and fall of water hyacinth in Lake Victoria and the Kagera River Basin, 1989-2001. *Journal of Aquatic Plant Management,* 42:73-84.

Aloo, P., Ojwang, W., Omondi, R., Njiru, J.M. and Oyungi, D., 2013. A review of the impacts of invasive aquatic weeds on the biodiversity of some tropical water bodies with special reference to Lake Victoria (Kenya). *Biodiversity journal,* 4(4):471-482.

Aplin, P., 2005. Remote sensing: ecology. *Progress on Physical Geography,* 29:104-113.

Asrar, G., Fuchs, M., Kanemasu, E.T. and Hatfield, J.L., 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat. *Agronomy Journal,* 76:300-306.

Babaeian, E., Homaee, M., Montzka, C., Vereecken, H., Norouzi, A.A. and van Genuchten, M. Th., 2016. Soil moisture prediction of bare soil profiles using diffuse spectral reflectance information and vadose zone flow modelling. *Remote Sensing of Environment,* 187:218-229.

Bariou, R., Lecamus, D. and Henaff, F., 1985a. Indices de végétation. Dossiers de télédétection, *Centre régional de télédétection, Université de Rennes 2, Rennes, France*, 80.

Bartodziej, W. and Weymouth, G., 1995. Waterbird abundance and activity on water-hyacinth and *Egeria* in the St-Marks River, Florida. *Journal of Aquatic Plant Management,* 33:19-22.

Bek, D., Nel, E. and Binns, T., 2017. Jobs, water or conservation? Deconstructing the Green Economy in South Africa's Working for Water Programme. *Environmental Development, 136-145.*

Berberoglu, S., Lloyd, C.D., Atkinson, P.M. and Curran, P.J., 2000. The integration of spectral and textural information using neural networks for land cover mapping in the Mediterranean. *Computers and Geosciences,* 26(4):385-396.

Binns, J.A., Illgner, P.M., Nel, E.L., 2001. Water shortage, deforestation: South Africa's Working for Water programme. *Land Degradation Development,* 12:341-355.

Bock, J.H., 1969. Productivity of the water hyacinth *Eichhornia crassipes* (Mart.) Solms. *Ecology Society of America,* 50(3):460-464.

Bonansea, M., Rodriguez, M.C., Pinotti, L. and Ferrero, S., 2015. "Using multi-temporal Landsat imagery and linear mixed models for assessing water quality parameters in Río Tercero reservoir (Argentina)." *Remote Sensing of Environment,* 158:28-41.

Borokoni, T. and Babalola, F., 2012. Management of invasive plant species in Nigeria through economic exploitation: lessons from other countries. *Management of Biological Invasions,* 3(1):45-55.

Breadly, B.A. and Mustard, J.F., 2006. Characterizing the landscape dynamics of an invasive plant and risk of invasion using remote sensing. *Ecological Application*, 16:1132-1147.

Brendonck, L., Maes, J., Rommens, W., Dekeza, N., Nhiwatiwa, T., Barson, M., Callebaut V., Phiri C., Moreau, K., Gratwicke, B., Stevens, M., Alyn N., Holsters, E., Ollevier, F. and Marshall, B., 2003. The impact of water hyacinth (Eichhornia crassipes) in a eutrophic subtropical impoundment (Lake Chivero, Zimbabwe). II. Species diversity. *Archiv Fur Hydrobiologie*, 158:389-405.

Bresciani, M., Giardino, C., Bartoli, M., Tavernini, S., Bolpagni, R. and Nizzoli, D., 2011. "Recognizing harmful algal bloom based on remote sensing reflectance band ratio." *Journal Application of Remote Sensing*, 5:053-556.

Brierley, A.S. and Kingsford, M.L., 2009. Impact of Climate Change on Marine Organisms and Ecosystems. *Current Biology*, 19(14):R602-R614.

Burgiel, S. and Muir, A., 2010. Invasive species, climate change and ecosystem-based adaptation: addressing multiple drivers of global change. *Global Invasive Species Programme (GISP).* Chicago (IL): University of Chicago Press.

Campos-Taberner, M., García-Haro, F.J., Camps-Valls, G., Grau-Muedra, F.N., Crema, A. and Boscheti, M., 2016. *Remote Sensing of Environment*, 187:102-118.

Carpenter, S.R. and Biggs, R., 2009. "Freshwaters: Managing Across Scales in Space and Time." *Springer Science*, doi: 10.1007/978-0-387-73033-29.

Carreiras, J.M.B., Quegan, S., Toan, T.L., Minh, D.H.T., Saatchi, S.S., Carvalhais, N., Reichstein, M. and Scipal, K., 2017. Coverage of high biomass forests by the ESA BIOMASS mission under defense restrictions. *Remote Sensing of Environment*, 196:154-162.

Carson, H.W., Lass, L.W., and Callihan, R.H., 1995. Detection of yellow hawkweed (Hieracium pratense) with high resolution multispectral digital imagery. *Weed Technology*, 9:477-483.

Cavalli, R.M., Laneve, G., Fusilli, L., Pignatti, S. and Santini, F., 2009. Remote sensing water observation for supporting Lake Victoria weed management. *Journal of Environmental Management*, 90:2199-2211.

Chandra, G., Ghosh, A., Biswas, D. and Chatterjee, S., 2006. Host plant preference of Mansonia mosquitoes. *Journal of Aquatic Plant Management*, 44:142-144.

Chawira, M., Dube, T. and Gumindoga, W., 2013. “Remote sensing based water quality monitoring in Chivero and Manyame lakes of Zimbabwe.” *Physics and Chemistry of the Earth Parts A/B/C,* 66:38-44.

Chen, Q., McRoberts, R.E., Wang, C. and Radtke, P.J., 2016. Forest aboveground biomass mapping and estimateion across multiple spatial scale using model-based inference. *Remote Sensing of Environment*, 184:350-360.

Cheruiyot, E., Menenti, M., Gerte, B. and Koenders, R., 2013. Accuracy and precision of algorithms to determine the extent of aquatic plants: Empirical sealing of spectral indices vs. spectral unmixing.

Cheruiyot, E.K., Mito, C., Menenti, M., Gorte, B., Koenders, R. and Akdim, N., 2014. Evaluating MERIS-Based Aquatic Vegetation Mapping in Lake Victoria. *Remote Sensing*, *6*:7762-7782.

Cho, H.J., Kirui, P. and Natarajan, N., 2008. Test of multispectral vegetation index for floating and canopy-forming submerged vegetation. *International Journal of Environmental Resources of Public Health*, 5:477-483.

Chukwuka, K.S. and Uka, U.N., 2007. Effects of water hyacinth (*Eichhornia crassipes*) infestation on zooplankton population in Awa Reservoir, Ibadan South-west Nigeria. *Journal of Biological Science,* 7(6):865-869.

Cilliers, C.J., Hill, M.P., Ogwang, J.M. and Ajuonu, O., 2003. Aquatic weeds in Africa and their control.

Clayton, J.S. and Champion, P.D., 2006. Risk assessment method for submerged weeds in New Zealand hydroelectric lakes. *Hydrobiologia,* 570:183-188.

Cochrane M., 2000. Using vegetation reflectance variability for species level classification of hyperspectral data. *International Journal on Remote Sensing*, 21:2075-2087

Coetzee, J.A., Jones, R.W. and Hill, M.P., 2014. ‘Water hyacinth, Eichhornia crassipes (Mart.) Solms-Laub. (Pontederiaceae), reduces benthic macroinvertebrate diversity in a protected subtropical lake in South Africa’. *Biodiversity and Conservation,* 23:1319-1330.

Congalton, R.G. and Green, K., 1999. Assessing the accuracy of remotely sensed data: Principles and practices. *Boca Raton: Lewis Publishers*.

Congalton, R.G., 1991. “A review of assessing the accuracy of classifications of remotely sensed data.” *Remote Sensing of Environment,* 37:35-46.

Cook, C.D.K., 1989. Origin, autecology, and spread of some of the world’s most troublesome aquatic weeds. In: Pieterse, A.H., Murphy, K.J. (Eds.), Aquatic Weeds: *The Ecology* *and Management of Nuisance Aquatic Vegetation*. Oxfrod University Press, New York, 31-38.

Cuneo, P., Jacobson, C.R. and Leishman, M.R., 2009. Landscape scale detection and mapping of invasive African Olive (*Olea europaea L. ssp. cuspidata Wall ex G. Don Ciferri*) in SW Sydney, Australia using satellite remote sensing. *Applied Vegetation Science,* 12:145-154.

De Troyer, N., Mereta, S.T., Goethals, P.L.M. and Boets, P., 2016. Water Quality Assessment of Streams and Wetlands in a Fast Growing East African City. *Water*, 8:123.

DEAT., 2001. State of the rivers report. http://soer.deat.gov.za/dm_documents/LimpopoLLtf4tA.pdf, Accessed 20 February 2017.

Deering, D.W., Rouse, J.W., Haas, R.H. and Schell, J.A., 1975. "Measuring "Forage Production" of Grazing Units from Landsat MSS Data." *Proceedings of the 10th International Symposium on Remote Sensing of Environment II,* 1169-1178.

DeFries, R.S, Townshend, J.R.G. and Hansen, M., 1999. Continuous fields of vegetation characteristics at the global scale. *Journal of Geophysical Research,* 104:16911-16925.

DeFries, R.S., Asner, G.P. and Houghton, R., 2004. Trade-offs in land-use decisions: towards a framework for assessing multiple ecosystem responses to land-use change. *Ecosystem Land Use Change,* 2:1-9.

Dhau, I., Adam, E., Mutanga, O. and Ayisi, K.K., 2017. "Detecting the severity of maize streak virus infestations in maize crop using *in situ* hyperspectral data." *Transections of the Royal Society of South Africa* 73(1):8-15.

Díaz, B.M. and Blackburn, G.A., 2003. "Remote sensing of mangrove biophysical properties: evidence from a laboratory simulation of the possible effects of background variation on spectral vegetation indices." *International Journal of Remote Sensing 24*(1):53-73.

Dixon, B. and Candade, N., 2008. 'Multispectral land use classification using neural networks and support vector machine: One or the other, or both?' *International Journal of Remote Sensing,* 29:1185-1206.

Dronova, I., Gong, P. and Wang, L., 2011. "Object-based analysis and change detection of major wetland cover types and their classification uncertainty during the low water period at Poyang Lake, China." *Remote Sensing of Environment* 115:3220-3236.

Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Labertini, P. and Martimort, P., 2012. Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment,* 120:25-36.

Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W. and Li, X., 2016. Water bodies' mapping from Sentinel-2 imagery with Modified Normalized Difference Water Index at 10-m spatial resolution produced by sharpening the SWIR band. *Remote Sensing,* 8:354.

Dube, T. and Mutanga, O., 2015. "Evaluating the utility of the medium-spatial resolution Landsat 8 multispectral sensor in quantifying aboveground biomass in uMgeni catchment, South Africa." *ISPRS Journal of Photogrammetry and Remote Sensing,* 101:36-46.

Dube, T., Gumindoga, W. and Chawira, M., 2014. "Detection of land cover changes around Lake Mutirikwi, Zimbambwe, based on traditional remote sensing classification techniques." *African Journal of Aquatic Science*, 39(1):89-95.

Dube, T., Mutanga, O. and Ismail, R., 2016. Quantifying aboveground biomass in African environments: A review of the trade-offs between sensor estimation accuracy and costs. *Topical Ecology,* 57(3).

Dube, T., Mutanga, O., Seutloali, K.E. and Shoko, C., 2015. Water quality monitoring in sub-Saharan African lakes: a review of remote sensing applications. *African journal of Aquatic Science,* 40(1):1-7.

Dube, T., Mutanga, O., Sibanda, M., Bangamwabo, V. and Shoko, C., 2017b. Testing the detection and discrimination potential of the new Landsat 8 satellite data on the challenging water hyacinth (*Eichhornia crassipes*) in freshwater ecosystems. *Applied Geography*, 84, 2017:112.

Dube, T., Mutanga, O., Sibanda, M., Bangamwabo, V. and Shoko, C., 2017. Evaluating the performance of the newly-launched Landsat8 sensor in detecting and mapping the spatial configuration of water hyacinth (Eichhornia crassipes) in inland lakes, Zimbabwe. *Physics and Chemistry of the Earth,* http://dx.doi.org/10.1016/j.pce.2017.02.015.

DWAF, 2007. Establishment of a pricing strategy for water use charges in terms of section 56(1) of the National Water Act, 1998. Department of Water Affairs and Forestry, Pretoria.

El-Askary, H., Abd El-Mawla, S., Li, J., El-Hattab, M. and El-Raey, M., 2014. "Change detection of corel reef habitat using Landsat-5 TM, Landsat 7 EMT+ and Landsat 8

OLI data in the Red Sea (Hurghada, Egypt).” *International Journal of Remote Sensing,* 35(6):2327-2346.

Everitt, J.H., Yang, G., Escobar, D.E., Webster, G.F., Lonard, R.I. and Davis, M.R., 1999. Using Remote Sensing and Spatial Information Technologies to Detect and Map Two Aquatic Macrophytes. *Journal of Aquatic Plant Management,* 37(2):71-80.

Fernandez, G.C., 2002. “Discrimination analysis, a powerful classification technique in data mining.” *Proceedings of the SAS Users International Conference,* 247-256.

Filippi, A.M. and Jensen, J.R., 2006. Fuzzy learning vector quantization for hyperspectral coastal vegetation classification. *Remote Sensing of Environment,* 100:512-30.

Foody, G.M., 2004. “Thematic map comparison: evaluating the statistical significance of differences in classification accuracy.” *Photogrammetric Engineering and Remote Sensing,* 70:627-633.

Fu, C., 2003. “Potential impacts of human-induced land cover change on East Asia monsoon.” *Global Planet Chang*e, 37:219-229.

Fusilli, L., Collins, M.O., Laneve, G., Palombo, A, Pignatti, S. and Santini, F., 2013. Assessment of the abnormal growth of floating macrophytes in Winam Gulf (Kenya) by using MODIS imagery time series. *International Journal Application of Earth Observation and Geoinformation,* 20:33-41.

Gad, S. and Kusky, T., 2006. Lithological mapping in the Eastern Desert of Egypt, the Barramiya area, using Landsat thematic mapper (TM). *Journal of African Earth Science,* 44:196-202.

Galadima, A., Garba, Z.N., Leke, L., Almustapha, M.N. and Adam, I.K., 2011. “Domestic Water Pollution among Local Communities in Nigeria - Causes and Consequences.” *European Journal of Scientific,* 52(4):592-603.

Gao, B. C., 1996. NDWI- a normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment,* 58(3):257-266.

Getsinger, K. D., Dibble, E. D., Rodgers J. H. and Spencer, D. F., 2014. Benefits of Controlling Nuisance Aquatic Plants and Algae in the United States. *Council on Agricultural Science and Technology,* Ames: 12.

Giardino, C., Bresciani, M., Valentini, E., Gasperini, L., Bolpagni, R. and Brando, V.E., 2015. Airborne hyperspectral data to assess suspended particulate matter and aquatic vegetation in a shallow and turbid lake. *Remote Sensing of Environment,* 157:48-57.

Gitelson, A.A., Kaufman, Y.J. and Merzlyak, M.N., 1996. "Use of a green channel in remote sensing of global vegetation from EOS-MODIS." *Remote Sensing of the Environment,* 58:289-298.

Gitelson, A.A., Viña, A., Ciganda, V., Rundquist, D.C. and Arkebauer, T.J., 2002. "Remote estimation of canopy chlorophyll content in crops." *Geophysical Research Letters,* 32:08-403.

Global Invasive Species Database, 2006. *Eichhornia crassipes* (aquatic plant). *International Union for the Conservation of Nature (IUCN),* Gland, Switzerland. Available at http://www.issg.org/database/species/ecology.asp?si=70 (accessed 24 April 2017).

Gopal, B., 1987. Aquatic Plant Studies 1. Water Hyacinth. *Elsevier Publishing, New York, USA.*

Gunnarsson, C.C. and Petersen, C.M., 2007. Water hyacinths as a resource in agriculture and energy production: A literature review. *Waste Management,* 27:117-129.

Hagolle, O., Sylvander, S., Huc, M., Claverie, M., Clesse, D., Dechoz, C., lonjou, V. and Poulain, V., 2015. SPOT-4 (Take 5): Simulation of Sentinel-2 Time Series on 45 Large sites. *Remote sensing,* 7(9):12242-12264.

Halstead, J.M., Michaud, J. and Hallas-Burt, S.H., 2003. Hedonic Analysis of effects of a non-native invader (Myriophyllum Heterophyllum) on New Hampshire (USA) lakefront properties. *Environmental Management*, 32:391-398.

Hansen, J., Sato, M., Ruedy, R., Lo, K., Lea, D.W. and Medina-Elizade, M., 2006. Global temperature change. *Proceedings of the National Academy of Sciences*, 103:14288-14293.

Hardoy, J.E. and Mitlin, D., 2001. Environmental problems in an urbanising world: *finding solutions in Africa, Asia, and Latin America*. Sterling, Virginia: Earths can Publications.

Harmel, T., Chami, M., Tormos, T., Reynaud, N. and Danis, P.A., 2017. Sunglint correction of the Multi-Spectral Instrument (MSI)-SENTINEL-2 imagery over inland and sea waters from SWIR bands. *Remote Sensing of Environment,* 204:308-321.

Harvey, R.M., Pickett, J.R. and Bates, R.D., 1987. "Environmental Factors Controlling the Growth and Distribution of Submersed Aquatic Macrophytes in Two South Carolina Reservoirs." *Lake and Reservoir Management,* 3:243-255.

Hassan, Z., Shabbir, R., Ahmad, S.S., Malik, A.H., Aziz1, N., Butt, A. and Erum, S., 2016. "Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan." *SpringerPlus,* 5:812.

Havel, J.E., Kovalenko, K.E., Thomaz, S.M., Amalfitano, S. and Kats, L.B., 2015. Aquatic invasive species: challenges for the future. *Hydrobiologia*, 750:147-170.

Hestir, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H. and Greenberg, J. A., 2008. Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. *Remote Sensing of the Environment,* 112:4034-4047.

Hestir, E.L., Brando, V.E., Bresciani, M., Giardino, C., Matta, E. and Villa, P., 2015. "Measuring freshwater aquatic ecosystems: The need for a hyperspectral global mapping satellite mission." *Remote Sensing of Environment,* 167:181-195.

Hill, M.P. and Coetzee, J., 2017, 'The biological control of aquatic weeds in South Africa: Current status and future challenges'. *Bothalia - African Biodiversity and Conservation,* 47(2): a2152.

Hill, M.P., 2003. The impacts and control of alien aquatic vegetation in South African aquatic ecosystems. *African journal of Aquatic Science*, 28(1):19-24.

Hillnhutter, C. and Mahleni, A.K., 2008. "Early detection and localisation of sugar beet diseases." *New approaches Gesunde Pflanzen,* 60 (4):143-149.

Holm, L.G., Plucknett, D.L., Pancho, J.V. and Herberger, J.P., 1991. The world's worst weeds: Distribution and biology. Kreiger Publishing Co., Malabar, FL.

Hou, X., Feng, L., Duan, H., Chen, X., Sun, D. and Shi, K., 2017. "Fifteen-year monitoring of the turbidity dynamics in large lakes and reservoirs in the middle and lower basin of the Yangtze River, China." *Remote Sensing of Environment,* 190:107-121.

Huang, C., Peng, Y., Lang, M., Yeo, I.Y. and McCarty, G., 2014. "Wetland inundation mapping and change monitoring using Landsat and airborne LiDAR data." *Remote Sensing of Environment,* 141:231-242.

Huang, X.Y., Lan, J.L., Su, M.X., Shi, H., Lin, K.M. and Zhu, Y.Q., 2007. Polymorphism of biological characteristics of *Eichhornia crassipes*. *Chinese Agricultural Science Bulletin,* 23(8):98-101.

Huete, A., Liu, H., Batchily, K.V. and Van Leeuwen, W., 1997. "A comparison of vegetation indices over a global set of TM images for EOS-MODIS." *Remote Sensing of the Environment,* 59:440-451.

Huete, A.R., 1988. "A soil-adjusted vegetation index (SAVI)." *Remote Sensing of the Environment,* 25:295-309.

Janse, J.H. and van Puijenbroek, P.J.T.M., 1998. Effects of eutrophication in drainage ditches. *Environment Pollution,* 102:547-552.

Jin, H., Huang, C., Lang, M.W., Yeo, I.Y. and Stehman, V.S., 2017. "Monitoring of wetland inundation dynamics in the Delmarva Peninsula using Landsat time-series imagery from 1985 to 2011." *Remote Sensing of Environment,* 190:26-41.

John, C.M. and Kavya, N., 2014. Integration of multispectral satellite and hyperspectral field data for aquatic macrophyte studies. *The international achieves of the photogrammetry, Remote Sensing and spatial information science,* 8:2014.

Jordan, C.F., 1969. "Derivation of leaf-area index from quality of light on the forest floor." *Ecology,* 50:663-666.

Kateregga, E. and Sterner T., 2009. Lake Victoria fish stocks and the effects of water hyacinth. *The Journal of Environment and Development,* 18:62-78.

Kaufman, Y. J. and Tanré. D., 1992. "Atmospherically Resistant Vegetation Index (ARVI) for EOS-MODIS." *IEEE Transactions on Geoscience and Remote Sensing,* 30(2):261-270.

Kaufmann, R.K. and Stern, D.I., 1997. "Evidence for human influence on climate from hemispheric temperature relations." *Nature,* 388:39-44.

Khanna, S., Santos, M.J., Ustin, S.L. and Haverkamp, P.J., 2011. An integrated approach to a biophysiologically based classification of floating aquatic macrophytes. *International Journal of Remote Sensing,* 32(4):1067-1094.

Kimothi, M.M., Anitha, D., Vasistha, H.B., Soni, P. and Chandola, S.K., 2010. Remote sensing to map the invasive weed, Lantana camara in forests. *Tropical Ecology,* 51:67-74.

Krishna, A., Siram, M., and Prakash, P., 2014. "Slum types and adaptation strategies: Identifying policy-relevant differences in Bangalore." *Environment and Urbanization,* 26(2):568-585.

Kriticos, D.J. and Brunel, S., 2016. Assessing and Managing the Current and Future Pest Risk from Water Hyacinth, (*Eichhornia crassipes*), an Invasive Aquatic Plant Threatening the Environment and Water Security. *Plos one,* 11(8): e0120054.

Lamaro, A.A., Mariñelarena, A. and Torrusio., S.E., 2013. "Water surface temperature estimate from Landsat 7 ETM+ thermal infrared data using the generalized single-channel method: case study of Embalse del Rió Tercero (Córdoba, Argentina)." *Advanced in Space Research,* 51(3):492-500

Law, R., 2007. Fisheries-induced evolution: present status and future directions. *Marine Ecology Progress Series,* 335:271-277.

Li, G., Lu, D., Moran, E. and Hetrick, S., 2011. Land-cover classification in a moist tropical region of Brazil with Landsat TM imagery. *International Journal of Remote Sensing,* 32(23):8207-8230.

Li, L., Chen, Y., Xu, T., Liu, R., Shi, K. and Huang, C., 2015. "Super-resolution mapping of wetland inundation from remote sensing imagery based on integration of back-propagation neural network and genetic algorithm." *Remote Sensing of Environment,* 164:142-154.

Liu, H.Q. and Huete, A., 1995. "A feedback based modification of the NDVI to minimize canopy background and atmospheric noise." *IEEE Transactions on Geoscience and Remote Sensing, 33*(2):457-465.

Lodge, D.M., Williams, S.L., MacIsaac, H., Hayes, K., Leung, B., Reichard, S., Mack, R.N., Moyle, P.B., Smith, M., Andow, D.A., Carlton, J.T. and McMichael, A., 2006. Biological invasions: recommendations for U.S. policy and management. *Ecological Applications*, 16:2035-2054.

Luo, J., Duan, H., Ma, R., Jin, X., Li, F., Hu, W., Shi, K. and Huang, W., 2017. Mapping species of submerged aquatic vegetation with multi-seasonal satellite images and considering life history information. *International Journal of Applied Earth Observation and Geoinformation,* 57:154-165.

Mabogunje, A.L., 2002. Poverty and Environmental degradation: Challenges within the global economy. *Environment*. 44:8-18.

Malik, A., 2007. Environmental challenge vis a vis opportunity: the case of water hyacinth. *Environment International,* 33:122-138.

Mangas-Ramírez, E. and Elías-Gutiérrez, M., 2010. Effect of mechanical removal of water hyacinth (*Eichhornia crassipes*) on the water quality and biological communities in a Mexican reservoir. *Aquatic Ecosystem Health and Management, 161-168.*

Mark, W.M., Stewart, B. and Lisel, R., 2012. A new algorithm for detecting trophic status (chlorophyll-a), cyanobacterial-dominanance, surface scums and floating vegetation in coastal and inland waters from MERIS. *The Applied Behavioural Ecology and Ecosystem Research Unit.*

Martinez Jimenez, M. and Gomez Balandra, M.A., 2007. Integrated control of *Eichhornia crassipes* by using insects and plant pathogens in Mexico. *Crop Protection,* 26:1234-1238.

Masocha, M., Murwira, A., Magadza, C.H.D., Hirji, R. and Dube, T., 2017. "Remote sensing of surface water quality in relation to catchment condition in Zimbabwe." *Physics and Chemistry of the Earth,* 100:1-6.

Matasci, G., Hermosilla, T., Wulder, M.A., White, J.C., Coops, N.C., Hobart, G.W. and Zald, H.S.J., 2018. Large-area mapping of Canadian boreal forest cover, height, biomass and other structure attributes using Landsat composites and lidar plots. Remote Sensing of Environment, 209:90-106.

Matongera, T.N., Mutanga, O., Dube, T. and Lottering, R.T., 2016. Detection and mapping of braken fern weeds using multispectral remote sensed data: a review of progress and challenges, *Geocarto International,* 1-16.

Matongera, T.N., Mutanga, O., Dube, T. and Sibanda, M., 2017. "Detection and mapping the spatial distribution of bracken fern weeds using the Landsat 8 OLI new generation sensor." *International Journal of Applied Earth Observation and Geoformation,* 57:93-103.

Matthews, M.W., Bernard, S. and Winter, K., 2010. Remote sensing of cyanobacteria dominant algal blooms and water quality parameters in Zeekoevlei, a small hypertrophic lake, using MERIS. *Remote Sensing of Environment,* 114(9):2070-2087.

McCullough, I.M., Loftion, C.S. and Sader, S.A., 2012. "High frequency remote monitoring of large lakes with MODIS 500 m imagery." *Remote Sensing of Environment,* 124:234-241.

McFeeters, S.K., 1996. "The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features." *International Journal of Remote Sensing,* 17:1425–1432.

McNairn, H. and Protz, R., 1993. Mapping corn residue cover on agricultural fields in Oxford County, Ontario, using Thematic Mapper. *Canadian Journal of Remote Sensing,* 19(2):152-159.

Meerhoff M., Fosalba C., Bruzzone C., Mazzeo N., Noordoven W. and Jeppesen E., 2006. An experimental study of habitat choice by Daphnia: plants signal danger more than refuge in subtropical lakes. *Freshwater Biology*, 51:1320-1330.

Meerhoff, M., Mazzeo, N., Moss, B. and Rodriguez-Gallego, L., 2003. The structuring role of free-floating versus submerged plants in a subtropical shallow lake. *Aquatic Ecology,* 37:377-391.

Mendes, A.P.F., Bertella, M.A. and Teixeira, F.A.P., 2014. "Industrialization in Sub-Saharan Africa and import substitution policy." *Brazilian Journal of Political Economy,* 34:1.

Midgley, G.F., Chapman, R.A., Hewitson, B., Johnston, P., de Wit, M., Ziervogel, G., Mukheibir, P., van Niekerk, L., Tadross, M., van Wilgen, B.W., Kgope, B., Morant, P.D., Theron, A., Scholes, R.J. and Forsyth, G.G., 2005. A status Quo, Vulnerability and Adaptation Assessment of the physical and socio-economic Effects of Climate Change in the Western Cape. Report to the Western Cape Government, Cape Town, South Africa. CSIR Report No. ENV-S-C 2005-073, Stellenbosch.

Minakawa, N., Sonye, G., Dida, G., Futami, K. and Kaneko, S., 2008. Recent reduction in the water level of Lake Victoria has created more habitats for Anopheles funestus. *Malaria Journal*, 7:119.

Mironga, J.M., Mathooko, J.M. and Onywere, S.M., 2011. Effects of water hyacinth infestation on the physico chemical characteristics of Lake Naivasha. *International Journal of Humanities and Social Science*, 2:103-113.

Mironga, J.M., Mathooko, J.M. and Onywere, S.M., 2014. "Effects of spreading patterns of water hyacinth (*Eichhornia crassipes*) on zooplankton population in Lake Naivasha, Kenya*". International Journal of Development and Sustainability*, 3(10):1971-1987.

Mitchell, D.S., 1985. Surface-floating aquatic macrophytes. In: *The Ecology and Management of African Wetland Vegetation P. Denny, editor. Dr. W. Junk Publishers, Dordrecht*, 109-124.

Mladinich, C.S., Bustos, M.R., Stitt, S., Root, R., Brown, K., Anderson, G.L. and Hager, S., 2006. The use of Landsat 7 Enhanced Thematic Mapper Plus for mapping leafy spurge. *Rangeland Ecology and Management*, 59:500-506.

Molinos, J.G., Viana, M., Brennan, M. and Donohue, I., 2015. Importance of Long-Term Cycles for Predicting Water Level Dynamics in Natural Lakes. *Plus one,* 10(3): e0119253.

Mountrakis, G.I. J. and Ogole, C., 2011. 'Support vector machines in remote sensing: a review'. *ISPRS Journal of Photogrammetry and Remote Sensing*, 66:247-259.

Murkin, H.R. and Kadlec, J.A., 1986. Relationships between waterfowl and macroinvertebrate densities in a Northern Prairie Marsh. *Journal of Wildlife Management*, 50:212-217.

Muyodi, F.J., 2000. Microbiological analysis of the waters of Lake Victoria in relation to the invasion of the water hyacinth, *Eichhornia crassipes* (Mart.) Solms: A case study of the lakeshores of Mwanza municipality. Ph.D thesis, University of Dares Salaam.

Nagendra, H., Lucas, R., Honrado, J.P., Jongman, R.H.G., Tarantino, C., Adamo, M. and Mairota, P., 2013. Remote sensing for conservation monitoring: assessing protected areas, habitat extent, habitat condition, species diversity, and threats. *Ecological Indicators,* 33:45-59.

Ndimele, P.E., Kumolu-Johnson, C.A. and Anetekhai, M.A., 2011. The invasive aquatic macrophyte, water hyacinth {*Eichhornia crassipes* (Mart.) Solm-Laubach: Pontederiaceae}: problems and prospects. *Research Journal of Environmental Sciences,* 5:509-520.

Ndungu, J., Augustijn, D.C.M., Hulscher, S.J.M.H., Kitaka, N. and Mathooko, J., 2013. Spatio-temporal variations in the trophic status of Lake Naivasha, Kenya. *Lakes and Reservoirs Science, Policy and Management for Sustainable Use*, 18(4):317-328.

Norah, M., Shumirai, Z., Zelma, M.L. and Upenyu, M., 2015. Impacts of Untreated Sewage Discharge on Water Quality of Middle Manyame River: A Case of Chinhoyi Town, Zimbabwe. *International Journal of Environmental monitoring and Analysis,* 3(3):133-138.

Ogunye, O., 1988. Water hyacinth - Nigerian experience. *In:* O.L.Oke, A.M.A.Imevbore & T.A.Farri (Eds.) Water Hyacinth Menace and Resource. *Proceedings of International Workshop, COSTED, Lagos.*

Ogwueleka, T. 2009. Municipal solid waste characteristics and management in Nigeria. *Iran Journal of Environ Health Science Engineering,* 6:173-80.

Okeke, F. and Karnieli, A., 2006. Methods for fuzzy classification and accuracy assessment of historical aerial photographs for vegetation change analyses. Part I: algorithm development. *International Journal of Remote Sensing,* 27:153-76.

Omute, P., Corner, R. and Awange, J.L., 2012. The use of NDVI and its derivatives for monitoring Lake Victoria's water level and drought conditions. *Water Resources Management,* 26(6):1591-1613.

Oyama, Y., Mantsushita, B. and Fukushima, T., 2015. Distinguishing surface cyanobacterial blooms and aquatic macrophytes using Landsat/TM and ETM+ shortwave infrared bands. *Remote Sensing of Environment*, 157:35-47.

Pahlevan, N. and Schott, J.R., 2013. "Leverage EO-1 to evaluate capability of new generation of Landsat sensors for coastal/inland water studies." *IEEE Journal Selected Topics in Applied Earth Observations and Remote Sensing,* 6(2):360-374.

Palmer, S.C.J., Kutser, T. and Hunter, P. D., 2015. Remote sensing of inland waters Challenges, progress and future directions. *Remote Sensing of Environment,* 157:1-8.

Panetta, F.D. and Lawes. R., 2005. "Evaluation of the performance of weed eradication programs: the delimitation of extent." *Diversity and Distributions,* 11: 435-442.

Patel, S., 2012. Threats, management and envisaged utilizations of aquatic weed *Eichhornia crassipes*: an overview. Rev. *Environment Science of Biotechnology,* 11:249-259.

Pearsall, W.H., 1920. "The Aquatic Vegetation of English Lakes." *Journal of Ecology,* 8(3):163-201.

Peerbhay, K.Y., Mutanga, O. and Ismail, R., 2016. "The identification and remote detection of alien invasive plants in commercial forest: An Overview." *South African Journal of Geomatics,* 5:1.

Penatti, N.C., Almeida, T.I.R.d., Ferreira, L.G., Arantes, A.E. and Coe, M.T., 2015. Satellite based hydrological dynamics of the world's largest continuous wetland. *Remote Sensing of Environ*ment, 170:1-13.

Penfound, W.T. and Earle, T.T., 1948. The biology of the water hyacinth. *Ecological Monographs,* 18:447-472.

Penuelas, J., Blanchard, B. and Blanchard, A., 1993. Assessing community type, plant biomass, pigment composition and photosynthetic efficiency of aquatic vegetation from spectral reflectance. *Remote Sensing of Environment,* 46:110-118.

Pettorelli, N., Safi, K. and Turner, W., 2014. Satellite remote sensing, biodiversity research and conservation of the future. *Philosophical Transactions of the Royal Society B,* 369:20130190.

Pimentel, D., Lach, L., Zungiga, R. and Morrison, D., 2001. Update on the environmental and economic costs associated with alien invasive species in the United States. *Ecological Economics*, 52:273-288.

Potts, D., 2013. Rural–Urban and Urban–Rural Migration Flows as Indicators of Economic Opportunity in SubSaharan Africa: What do the data tell us? Migrating Out Of Poverty Working Paper 9. *Migrating Out of Poverty Consortium, University of Sussex, Brighton.* http://migratingoutofpoverty. dfid.gov.uk/files/file.php?name=wp9-potts-rural-uban-and-urban-rural-migation-flows. pdf&site=354

Price, K.P., 1993. Detection of soil erosion within pinyon-juniper woodlands using Thematic Mapper (TM) data. Remote Sensing of Environment, 45(3):233-248.

Pyšk, P. and Richardson, D.M., 2010. Invasive species, environmental change and management, and health. *Annual Review of Environment and Resources,* 35:25-55.

Qi, J., Moran, M.S., Huete, A.R., Jackson, R.D. and Chehbouni, A., 1991. View-atmosphere soil effect on vegetation indices derived from SPOT images. *Proceedings of the 5th International Symposium Physical Measurements and Signatures in Remote Sensing,* 2:785-790.

Reddy, K.R. and DeBusk, W.F., 1991. Decomposition of water hyacinth detritus in eutrophic lake water. *Hydrobiologia*, 211:101-109.

Rigg, J., Nguyen, T. and Luong, T., 2014. “The Texture of Livelihoods: Migration and Making a Living in Hanoi.” *The Journal of Development Studies,* 50(3):368-382.

Rindfuss, R.R., Walsh, S.J., Turner, B., Fox, J. and Mishra V., 2004. Developing a science of land change: challenges and methodological issues. *Proceedings of Natural Academic Science USA*. 101:13976-13981.

Risser, P.G. and Treworgy, C.G., 1985. Overview of ecological research data management. Research data management in the ecological sciences, Columbia, University of South Carolina Press.

Ritchie, J.C., Zimba, P.V. and Everitt, J.H., 2003. Remote sensing techniques to assess water quality. *Photogrammetry Engineering of Remote Sensing*, 69:695-704.

Robles, W., Madsen, J.D. and Wersal, R.W., 2015. Estimating the Biomass of Water hyacinth (*Eichhornia crassipes*) Using the Normalized Difference Vegetation Index Derived from Simulated Landsat 5 TM. *Invasive Plant Science and Management*, 8(2):203-211.

Rocchini, D. and Neteler, M., 2012. Let the four freedoms paradigm apply to ecology. *Trends in Ecology and Evolution*, 27:310-311.

Rodriguez, L.F., 2006. Can invasive species facilitate native species? Evidence of how, when, and why these impacts occur. *Biological Invasions*, 8:927-939.

Roijackers R., Szabo S. and Scheffer M., 2004. Experimental analysis of the competition between algae and duckweed. *Archiv Fur Hydrobiologie*, 160:401-412.

Rommens, W., Maes, J., Dekeza, N., Inghelbrecht, P., Nhiwatiwa, T., Holsters, E., Ollevier, F., Marshall. B. and Brendonck, L., 2003. The impact of water hyacinth (*Eichhornia crassipes*) in a eutrophic subtropical impoundment (Lake Chivero, Zimbabwe). I. water quality. *Archiv fur Hydrobiology*, 158(3):373-388.

Rondeaux, G., Steven, M. and Baret, F., 1996. “Optimization of Soil-Adjusted Vegetation Indices”. *Remote Sensing of Environment*, 55:95-107.

Rorslett, B., 1984. “Environmental Factors and Aquatic Macrophyte Response in Regulated Lakes.” *Aquatic Botany,* 19:199-220.

Roujean, J.L. and Breon. F.M., 1995. “Estimating PAR absorbed by vegetation from bidirectional reflectance measurements.” *Remote Sensing of Environment,* 51:375-384.

Sarkar, S., Franz, B.A., and Balasubramanian, He. J., 2017. Sentinel-2 Multi-Spectral Instrument (MSI) data processing for aquatic science applications: Demonstration, and validations. *Remote Sensing of the Environment*, 201:47-56.

Scharsich, V., Mtata, K., Hauhs, M., Lange, H. and Bogner, C., 2017. Analysing land cover and land use change in the Matobo National Park and surroundings in Zimbabwe. *Remote Sensing of Environment*, 194:278-286.

Schmidt, M. and Witte, C., 2010. "Monitoring aquatic weeds in a river system using SPOT 5 satellite imagery", *Journal of Application Remote Sensing*, 4(1):043-528.

Schneider, L. and Geoghegan, J., 2006. Land abandonment in an agricultural frontier after a plant invasion: the case of bracken fern in southern Yucatán, Mexico Agriculture. *Resource Economic Review*, 35(1):167.

Schultz, R. and Dibble, E., 2012. Effects of invasive macrophytes on freshwater fish and macroinvertebrate communities: the role of invasive plant traits. *Hydrobiologia*, 684(1):1-14.

Selman, M., Greenhalgh, S., Díaz, R. and Sugg, Z., 2008. Eutrophication and hypoxia in coastal areas: A global assessment of the state of knowledge. *World Resources Institute Policy Note*, No, 1. Washington D.C. 6.

Sepuru, T.K. and Dube, T., 2018. Understanding the spatial distribution of eroded areas in the former rural homelands of South Africa: Comparative evidence from two new non-commercial multispectral sensors. *International Journal of Applied Earth Observations and Geoinformation*, 69:119-132.

Shanab, S., Shalaby, E., Lightfoot, D. and El-Shemy, H., 2010. Allelopathic effects of water hyacinth (*Eichhornia crassipes*). *PLoS One*, 5(10):1320.

Shekede, M., Kusangaya, S. and Schmidt, K., 2008. Spatio-temporal variations of aquatic weed abundance and coverage in Lake Chivero, Zimbabwe. *Physics and Chemistry of the Earth, Parts A/B/C,* 33:714-721.

Sheng, Y., Song, C., Wang, J., Lyons, E.A., Knox, B.R., Cox, J.S., 2016. Representative lake water extent mapping at continental scale using multi-temporal Landsat-8 imagery. *Remote Sensing of Environment*, 185:129-141.

Shoko, C. and Mutanga, O., 2017. Examining the strength of the newly-launched Sentinel-2 MSI sensor in detecting and discriminating subtle differences between C3 and C4 grass species. *ISPRS Journal of Photogrammetry and Remote Sensing*, 129:32-40.

Shrestha, D.P. and Zinck, J.A., 2001. Land use classification in mountainous areas: integration of image processing, digital elevation data and field knowledge (application to Nepal). *International Journal Application of Earth Observation and Geoinformation,* 3:78-85.

Sibanda, M., Mutanga, O. and Rouget, M., 2015. "Examining the potential of Sentinel-2 MSI spectral resolution in quantifying above ground biomass across different fertilizer treatments." *ISPRS Journal Photogrammetry of Remote Sens*ing, 110:55-65.

Sohn, Y. and Rebello, N. S., 2002. Supervised and unsupervised spectral angle classifiers. *Photogrammetric Engineering and Remote Sensing,* 68(12):1271-1282.

Song, X., Duan, Z. and Jiang, X., 2012. 'Comparison of artificial neural networks and support vector machine classifiers for land cover classification in northern China using SPOT-5 HRG image'. *International Journal of Remote Sensing,* 33:3301-3320.

Sotolu, A.O., 2013. Management and Utilization of Weed: Water Hyacinth (*Eichhornia crassipes*) for Improved Aquatic Resources. *Journal of Fisheries and Aquatic Science,* 8:1-8.

Spira W.M., Huq A., Ahmed Q.S. and Saeed Y.A., 1981. Uptake of *Vibrio cholerae* biotype eltor from contaminated water by water hyacinth (*Eichhornia crassipes). Application Environment of Microbiolology,* 42:550-553.

Sripada, R.P., Heiniger, R.W., White, J.G. and Meijer, A.D., 2006. "Aerial color infrared photography for determining early in-season nitrogen requirements in corn." *Agronomy Journal,* 98:968-977.

Sriwongsitanon, N., Surakit, K. and Thianpopirug, 2011. S., "Influence of atmospheric correction and number of sampling points on the accuracy of water clarity assessment using remote sensing application." *Journal of Hydrology,* 401(3-4):203-220.

Stiers, I., Crohain, N., Josens, G. and Triest, L., 2011. Impact of three aquatic invasive species on native plants and macroinvertebrates in temperate ponds. *Biological Invasions,* 13:2715-2726.

Strand, H., Hüoft, R., Strittholt, J., Miles, L., Horning, N., Fosnight, E. and Turner, W., 2007. Sourcebook on Remote Sensing and Biodiversity Indicators. *Secretariat of the Convention on Biological Diversity, Montreal,* 32:203.

Tebbs, E.J., Remedios, J.J. and Happer D.M., 2013. "Remote sensing of chlorophyll-a as a measure of cynobacterial biomass in Lake Bogoria, a hypertrophic, saline-alkaline, Flamingo Lake, using Landsat 7 ETM+". *Remote Sensing of Environment,* 135:92-106.

Téllez, T.R., de Rodrigo López, E.M., Granado, G.L., Pérez, E.V., López, R.M. and Guzmá, J.M.S., 2008. The Water Hyacinth, *Eichhornia crassipes*: an invasive plant in the Guadiana River Basin (Spain). *Aquatic Invasions,* 3(1):42-53.

Thamaga, K.H. and Dube, T., 2018. Remote sensing of invasive water hyacinth (*Eichhornia crassipes*): A review on applications and challenges. *Remote Sensing Applications: Society and Environment,* 10:36-46.

Theel, H.J., Dibble, E.D. and Madsen, J.D., 2008. Differential influence of a monotypic and diverse native aquatic plant bed on a macroinvertebrate assemblage; an experimental implication of exotic plant induced habitat. *Hydrobiologia,* 600:77-87.

Thiemann, S. and Kaufmann, H., 2002. Lake Water Quality Monitoring Using Hyperspectral Airborne Data-A Semiempirical Multisensory and Multitemporal Approach for the Mecklenburg Lake District, Germany. *Remote Sensing of Environment,* 81:228-237.

Thornton, P.K., Ericksen, P.J., Herrero, M. and Challinor, A., 2014. Climate variability and vulnerability to climate change: a review. *Global Change Biology,* 20(11):3313-3328.

Thouvenot, L., Haury, J. and Thiebaut, G., 2013. A success story: water primroses, aquatic plant pests. *Aquatic Conservation,* 23:790-803.

Tiwari, S., Dixit, S. and Verma, N., 2007. An effective means of biofiltration of heavy metal contaminated water bodies using aquatic weed *Eichhornia crassipes*. *Environmental Monitoring* and *Assessment,* 129:253-256.

Toft, J.D., Simenstad, C.A., Cordell, J.R. and Grimaldo, L.F., 2003. The effects of introduced water hyacinth on habitat structure, invertebrate assemblages and fish diets. *Estuaries,* 26(3):746-758.

Toure, S.I., Stow, D.A., Shih, H., Weeks, J. and Lopez-Carr, D., 2018. Land cover and land use change analysis using multi-spatial resolution data and object-based image analysis. *Remote Sensing of Environment*, 210:259-268.

Tucker, C.J., 1979. “Red and photographic infrared linear combinations for monitoring vegetation.” *Remote Sensing of the Environment,* 8:127-150.

Turner, W., Buchanan, G., Rondinini, C., Dwyer, J., Herold, M., Koh, L.P., 2013. Satellites: make data freely accessible. *Nature,* 498:37.

Turpie, J.K. Marias, C. and Blighaut, J.N., 2008. The working for water programme: Evolution of a payments for ecosystem services mechanism that addresses both poverty and ecosystem service delivery in South Africa. *Ecological Economics,* 65:788–798.

Twongo, T. and Howard G., 1998. Ways with weeds. *New Scientist*, 159:57-57.

Underwood, E.C., Mulitsch, M.J., Greenberg, J.A., Whiting, M.L., Ustain, S.L. and Kefauver, S.C., 2005. Mapping invasive aquatic vegetation in the Sacramento-San Joaquin Delta using Hyperspectral imagery. *Environmental Monitoring and Assessment,* 121:47-64.

Ustin, S. L. and Gamon, J. A., 2010. Remote sensing of plant functional types. *New Phytologist,* 186(4):795-816.

van Wilgen, B.W. and Wannenburgh, A., 2016. Co-facilitating invasive species control, water conservation and poverty relief: achievements and challenges in South Africa's Working for Water programme. *Current Opinion in Environmental Sustainability*, 19:7-17.

Veloso, A., Mermoz, S., Bouvet, A., Le Toan, T., Planells, M., Dejoux, J.F. and Ceschia, E., 2017. Understanding the temporal behaviour of crop using Sentinel-1 and Sentinel-2-like data for agricultural applications. *Remote Sensing of Environment,* 1999:415-426.

Venugopal, G., 1998. Monitoring the effects of biological control of water hyacinth using remotely sensed data: a case study of Bangalore, India. *Singapore Journal of Tropical Geography*, 19(1):91-105.

Vidhya, R., Vijayasekaran, D., Ahamed Farook, M., Jai, S., Rohini, M. and Sinduja, A., 2014. Improved classification of Mangroves health status using hyperspectral remote sensing data. The International Archives of the photogrammetry, *Remote Sensing and Spatial Information Sciences,* 8:2014.

Vila, M., Espinar, J.L., Hejda, M., Hulme, P.E., Jarošik, V., Maron, J.L., Pergl, J., Schaffner, U., Sun, Y. and Pyšek, P., 2011. Ecological impacts of invasive alien plants: a meta-analysis of their effects on species, communities and ecosystems. *Ecology Letters,* 14:702-708.

Villamagna, A.M. and Murphy, B.R., 2010. Ecological and socio-economic impacts of invasive water hyacinth (*Eichhornia crassipes*): a review. *Freshwater Biology,* 55:282-298.

Waltham, N.J. and Fixler, S., 2017. Aerial Herbicide Spray to Control Invasive Water Hyacinth (*Eichhornia crassipes*): Water Quality Concerns Fronting Fish Occupying a Tropical Floodplain Wetland. *Tropical Conservation Science, 10:1-10.*

Wang, C., Hunt Jr, E.R., Zhang, L. and Guo, H., 2013. Phenology-assisted classification of C3 and C4 grasses in the U.S. Great Plains and their climate dependency with MODIS time series. *Remote Sensing of Environment,* 138:90-101.

Wilcock, R.J., Champion, P.D., Nagel, J.W. and Croker, G.F., 1999. The influence of aquatic macrophytes on the hydraulic and physic-chemical properties of a New Zealand lowland stream. *Hydrobiologia,* 416:203-214.

Williams, A.E., Duthie, H.C. and Hecky, R.E., 2005. Water hyacinth in Lake Victoria: Why did it vanish so quickly and will it return? *Aquatic Botany,* 81:300-314.

Wilson, J.R., Ajuonu, O., Center, T.D., Hill, M.P., Julien, M.H., Katagira, F.F., Neuenschwander, P., Njoka, S.W., Ogwang, J. and Reeder, R.H., 2007. The decline of water hyacinth on Lake Victoria was due to biological control by *Neochetina spp*. *Aquatic Botany,* 87:90-93.

Wilson, J.R., Holst, N. and Rees, M., 2005. Determinants and patterns of population growth in water hyacinth. *Aquatic Botany,* 81:51-67.

Wu, H.Y., Bao, W.K., Wang, A. and Cao, W.P., 2004. The environmental effects of alien species water hyacinth. *World Sci-technology Resource Development*, 26(2):25-29.

Xie, Y., Sha, Z. and Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology,* 1(1):9-23.

Xu, M., Watanachaturaporn, P., Varshney, P. K. and Arora, M. K., 2005. Decision tree regression for soft classification of remote sensing data. *Remote Sensing of Environment,* 97(3):322-336.

Yavaşl, D.D., 2016. "Estimation of above ground forest biomass at Muğla using ICESat/GLAS and Landsat data." *Remote Sensing Applications: Society and Environment*, 4:221-218.

Zarco-Tejada, P.J., Berjón, A., López-Lozano, R., Miller, J.R., Martín, P., Cachorro, V., González, M.R. and de Frutos, A., 2005. "Assessing vineyard condition with hyperspectral indices: Leaf and canopy reflectance simulation in a row-structured discontinuous canopy." *Remote Sensing of Environment,* 99:271-287.

Zhang, C., Denka, S., Cooper, H. and Mishra, D.R., 2018. Quantification of sawgrass marsh aboveground biomass in the coastal Everglades using object-based ensemble analysis and Landsat data. *Remote Sensing of Environment*, 204:366-379.

Zhang, J. and Foody, G.M., 1998. A fuzzy classification of sub-urban land cover from remotely sensed imagery. *International Journal of Remote Sensing,* 19:2721-2738.

Zhang, X., Wu, S., Yan, X. and Chen, Z., 2016. A global classification of vegetation based on NDVI, rainfall and temperature. *International Journal of Climatology,* doi: 10.1002/joc.4847.