Mapping and monitoring the spatial distribution of *Eichhornia crassipes* (water hyacinth) in the Hartbeespoort Dam, South Africa, using remote sensing data.

by

Galaletsang Latoya Keebine (754634)

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Supervisor: Dr Elhadi Adam

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Declaration – Plagiarism

I, Galaletsang Latoya Keebine, declare that this research report is my own unaided work. It is being submitted to the Degree of Master of Science in Geographical Information Systems and Remote Sensing to the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

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Signature of Student

28 **day of** May **2019 at** the University of the Witwatersrand

Abstract

The rapid spread of *Eichhornia crassipes* (water hyacinth) has caused negative ecological, economic and social impacts in warm tropical and sub-tropical countries globally. The invasive taxa of *Eichhornia* species are presently listed among 100 of the most undesired species globally. However, the absence of current information about the temporal and spatial dispersion of water hyacinth infestation has deterred the control and monitoring efforts employed against the weed. Thus, monitoring and detection of water hyacinths are crucial in order to provide trustworthy and precise information about the spatial dispersal and the level of water hyacinth infiltration into native environments.

This study investigates the ability of Sentinel-2 MSI and Landsat-8 OLI imagery for mapping the spatial extent of the water hyacinth invasion in the Hartbeespoort Dam, North West Province, South Africa, using the random forest classifier. Images utilised in this study were acquired within a period of 24 hours of each other; 26 October 2018 and 27 October 2018, respectively. Both sensors, Sentinel-2 MSI and Landsat-8 OLI, similarly achieved high overall accuracies of 93.13% and 89.88% respectively. Although, Sentinel-2 MSI was better at distinguishing water hyacinth from other LULCC in the area, as shown by the 91.75% producers accuracy for water hyacinth, whereas the delineation of water hyacinth from the Landsat-8 OLI imagery achieved a moderately high 80.41% producers accuracy. The study additionally utilised historical Landsat 7 ETM+ data and change detection analysis to infer on the success of physical control measures previously employed against the weed in the dam for 2007 and 2009. The change detection statistic showed that the physical control of water hyacinth is to an extent successful, but requires a long-term implementation to avoid greater re-infestation of water by water hyacinth.

The result not only demonstrates that Sentinel-2 MSI and Landsat-8 OLI imagery are able to detect and correctly delineate water hyacinth distribution from other LULCC but that the multispectral sensors do so with high-accuracy. Moreover, they indicate the possibility of monitoring water hyacinth infestations on a regular basis, by integrating data from various sensors. The high accuracies provide an opportunity for the mapping of the spatial extent of the intrusive alien plants to be performed on a regular basis utilising freely available data of high quality. The restoration of ecological functions and processes, by physically controlling water hyacinth invasion, through *Metsi A Me* programme and *Working for Water* programme is plausible and a functional long-term strategy.

Dedication

I dedicate this dissertation to the two special women in my life; my mother and sister, Mmabakwena Keebine and Bothobile Modise. It is your unwavering love, encouragement and support (emotionally, mentally, physically and financially) that have enabled me to continue making strides in this world. This accomplishment would not have been possible without you and for that I say thank you and I love you.

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To Percerverance Khumalo and Tinobakashe Ncube, I thank you for your jokes, willingness to assist me and moral support. It is your presence that ensured my sanity during late nights in the GIS lab.

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List of Abbreviations

CART	Classification and regression trees
CSIR	Council for Scientific and Industrial Research
DA	Discriminant Analysis
DWAF	Department of Water Affairs and Forestry
DWS	Department of Water and Sanitation
ESA	European Space Agency
ETM+	Enhanced Thematic Mapper Plus
FLAASH	Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube
GISS	Generic Impact Scoring System
HDRP	Hartbeespoort Dam Remediation Programme
IUCN	International Union for Conservation of Nature
LULCC	Land Use Land Cover Class
MSI	Multispectral instrument
MSS	Multispectral sensor
N	Nitrogen
NASA	National Aeronautics and Space Administration
NIR	Near-infrared
OLI	Optical Land Imager
OOB	Out-of-bag
P	Phosphorus
PLS-DA	Partial Least Squares Discriminant Analysis
RF	Rand Forest
RS	Remote Sensing
RSA	Republic of South Africa
SPOT	Satellite Probatoire d'Observation de la Terre
SWIR	Shortwave infrared
TOA	Top-of-atmosphere
USGS	United States Geological Survey
WASA	Wind Atlas of South Africa
WWF-SA	World Wildlife Fund – South Africa

CHAPTER ONE

INTRODUCTION

1.1 General Introduction

Invasive vegetation species are plants that are non-native to the environments they inhibit, which are becoming increasingly problematic as a growing global phenomenon (Scanes, 2018). They are characterised by aggressive growth rates and rapid infiltration of their new environment (Asner *et al*., 2008; Xu *et al*., 2012; Rogers, 2018; Scanes, 2018). Rogers (2018) further defines invasive alien plant species as self-sustaining organisms able to produce reproductive offspring, and due to their rapid growth, can cover large areas of land very quickly. Invasive alien species are primarily introduced to foreign regions by humans, either intentionally or accidentally (Rands *et al*., 2010; Xu *et al*., 2012; Downey and Richardson, 2016; Rogers, 2018; Scanes, 2018).

Eichhornia crassipes (Mart.) Solms, commonly referred to as water hyacinth, is an invasive alien freshwater weed. *Eichhornia crassipes* is of the Pontederiaceae family, under the *Eichhornia* genera; *Eichhornia* has eight species of freshwater plants, water hyacinth included in it (Barrett, 1988; Patel, 2012). Water hyacinths are native to the Amazon basin of Brazil, South America (Villamagna and Murphy, 2010; Patel, 2012; GEAS, 2013; Güereña *et al*., 2015; Nguyen *et al*., 2015; Thamaga and Dube, 2018). Water hyacinth was intentionally spread across five continents by humans as an ornamental species to embellish water bodies (Villamagna and Murphy, 2010; Patel, 2012; Nguyen *et al*., 2015). Water hyacinths are listed among the most invasive macrophytes that are distributed extensively globally; having been recognized amidst the 100 most burdensome invasive species by the International Union for Conservation of Nature (IUCN) (IUCN, 2004; Téllez *et al*. 2008; Thamaga and Dube, 2018). Additionally, water hyacinth has been identified by several authors as being 1 of the 10 most invasive macrophyte universally (Patel, 2012; Nguyen *et al*., 2015; Thamaga and Dube, 2018).

Water hyacinth has negative impacts on ecosystems, social activities, and the livelihoods of affected communities (Villamagna and Murphy, 2010). The presence of water hyacinths can cause water bodies to be hypertrophic; these water bodies have very high nutrient concentrations of phosphates and nitrates (DWAF, 2007; Fanie, 2016). These nutrient concentrations promote the growth and spread of eutrophication (Villamagna and Murphy, 2010; Thamaga and Dube, 2018). Eutrophication is the gradual and natural process of water ageing that is however intensified and accelerated by high nutrient loadings (Villamagna and Murphy, 2010; Thamaga and Dube, 2018). Thus eutrophication is a precondition of the hypertrophic state of waters, as it promotes the growth and spread of water hyacinth (Patel, 2012; GEAS, 2013). Water hyacinth invasions can lead to an increase in the presence of reptiles and mosquitoes, a decrease of fish populations, and the blockage of waterways due to the agglomeration of the species on water surfaces (Villamagna and Murphy, 2010; Patel, 2012). This invasive weed asphyxiates the water along with other organisms in their proximity as a result of the formation of water hyacinth mats on the surface of the water (Villamagna and Murphy, 2010; Patel, 2012; Thamaga and Dube, 2018). The water hyacinths mats are dense, impenetrable and interlocked (Bicudo *et al*., 2007; Patel, 2012). These cause a decrease in not only dissolved oxygen levels, but in the growth and spread of phytoplankton and zooplankton production (Bicudo *et al*., 2007; Villamagna and Murphy, 2010; Patel, 2012; Thamaga and Dube, 2018). Decreased dissolved oxygen levels have the ability to act as a catalyser in the release of phosphorus from sediments (Villamagna and Murphy, 2010; Patel, 2012). Phosphorus concentrations, in turn, accelerate and promote the growth of water hyacinth invasions (Bicudo *et al*., 2007). A reduction in the quantity of phytoplankton and zooplankton in aquatic ecosystems is detrimental for fish, as they ~~phytoplankton and zooplankton~~ are natural food organism for fish (Villamagna and Murphy, 2010; Thamaga and Dube, 2018).

Over the last decades, numerous efforts have been employed globally through policy implementations and conservation management techniques, as an attempt to minimise the negative influences of invasive species infestations (Genovesi *et al.*, 2015). Remote sensing (RS) is one such strategy, it has been greatly utilised by ecologists and conservation managers for the monitoring and mapping of invasive plant species (Hestir *et al*., 2008; Palmer *et al*., 2015; Dube *et al*., 2017; Murray *et al*., 2018). According to Palmer *et al* (2014), the increased utilisation of remote sensing is a result of ~~remote sensing~~ it surpassing conventional monitoring approaches. Remote sensing is not only cost effective compared to conventional monitoring approaches, but more reliable in providing accurate information for mapping vegetation (Mureriwa *et al*., 2016; Adam *et al*., 2017). Traditional methods of vegetation monitoring, on the other hand, are primarily site based (Godínez-Alvarez *et al*., 2009). This means that the methods are prone to biases, as the accuracy, precision, and sensitivity of the results are highly dependent on the researcher (Carlsson *et al*., 2005; Godínez-Alvarez *et al*., 2009; Lawley *et al*., 2016). Traditional monitoring methods, moreover, have a tendency to be limited in terms of cost, encompassing tremendous amounts of fieldwork that can be time-consuming, revisit periods, and spatial coverage (Palmer *et al*., 2014). Remote sensing has varying spatial resolutions (from < 1m to > than 1km), fixed revisit periods and spectral abilities beyond the visible region, characteristics conventional water hyacinth conservative mapping approaches lack (ITC, 2014; Palmer *et al*., 2014).

Detecting, monitoring, and mapping water hyacinth have the potential to reduce the prevalence of the species, with the end goal being to eradicate, and reverse the ecological damage on natural resources (Dube *et al*., 2017). Undertaking the aforementioned tasks will ensure the conservation of biological diversity and the restoration and preservation of affected ecosystems (Dube *et al*., 2017). There are various control methods which have been implemented in an attempt to control water hyacinth invasion in Europe, Malawi, Tanzania, USA, and Zimbabwe (GEAS, 2013). These methods include: i) biological control, which includes the introduction of insects that feed on the plant; ii) chemical control, which entails spraying herbicides and pesticides such as Glyphosate on the plants, and; iii) physical control, which is the removal of the plant, either manually or utilising mechanical devices (Wittenberg and Cock, 2001; Villamagna and Murphy, 2010).

1.2 Problem statement

The Republic of South Africa (RSA) is categorised as a water-stressed country (WWF-SA, 2017; Donnenfeld *et al*., 2018; Kapangaziwiri *et al*., 2018). The country receives, on average, rainfall of approximately 490 mm per annum (WWF-SA, 2016; WWF-SA, 2017; Mettetal, 2019). This is 40% lower than the world's averaged rainfall of 814 mm per annum (WWF-SA, 2016; WWF-SA, 2017). Rainfall is a pivotal component for water availability in RSA, as it is responsible for replenishing freshwater resources (Oberholster and Ashton, 2008; WWF-SA, 2016; WWF-SA, 2017). Freshwater resources that are used for human and environmental consumption in RSA include rivers, dams, and groundwater (WWF-SA, 2016; WWF-SA, 2017). Dams provide the majority, 90%, of the water with only 10% being sourced from groundwater (Oberholster and Ashton, 2008; WWF-SA, 2017; Mettetal, 2019). The agricultural, municipal, and industrial sectors account for 90% of dam water use with respective consumptions of 63%, 26% and 11% (WWF-SA, 2016; WWF-SA, 2017; Donnenfeld *et al*., 2018). Thus dam water management is of great importance to the country.

Dams are valuable due to their direct link to the country's socio-economic status (WWF-SA, 2017; Mettetal, 2019). Water management encompasses, but is not limited to, pollution control, environmental protection and flood management (Lee *et al*., 2018).

Managing water resources has been a challenging undertaking for water managers (Oberholster and Ashton, 2008; Kapangaziwiri *et al*., 2018). The rapid increase in population and economic activities has influenced the accelerated decline of water quality countrywide (Ashton *et al*., 2008; Oberholster and Ashton, 2008; WWF-SA, 2016; Donnenfeld *et al*., 2018). The growing population in RSA is straining the available water resources, hence the efficient management of this valuable resource is becoming increasingly challenging (Ashton *et al*., 2008; Oberholster and Ashton, 2008; WWF-SA, 2016). The increase in population has also largely promulgated the agricultural, mining, urban, and industrial sectors - causing a further increase in water consumption (Ashton *et al*., 2008; WWF-SA, 2016). WWF-SA (2016) has identified sewage effluents, industrial discharge, agricultural run-off, acid mine drainage, and poor sanitation in informal and rural settlements as prevalent water contamination sources. The aforementioned effluents result in excess nitrogen and phosphate nutrient loadings in water bodies (Venter, 2004; DWAF, 2007; WWF-SA, 2016). The high nutrient loadings promote and stimulate the growth of algae and aquatic plants, such as water hyacinth (Harding, 2004; Wilson *et al*., 2005; Villamagna and Murphy, 2010).

The discharge of effluents from wastewater treatment plants, agricultural activities and other human influences on the Jukskei River have resulted in the increase of water hyacinth invasion in the Hartbeespoort Dam (Harding, 2004; Waaigras, 2015; Rimayi *et al*., 2018). The Jukskei River discharges into the Crocodile River, water hyacinth discharges directly into the Hartbeespoort Dam (Rimayi *et al*., 2018). The Hartbeespoort Dam was built in the 1900s as an impoundment for irrigation water as well as a source of freshwater for the surrounding communities (Harding, 2004; Venter, 2004). Over the last decades, the dam has become a hub for recreational activities, a prime property location, and a tourist attraction, in addition to being a natural water source (Harding, 2004). The Jukskei River is located downstream of the Hartbeespoort Dam in Johannesburg, the water quality has greatly been deteriorated by anthropogenic activities (Waaigras, 2015; Rimayi *et al*., 2018). Thus there is an extensive distribution of the aggressive invader (water hyacinth) in the Hartbeespoort Dam (Figure 1).

All three previously mentioned control methods (biological, chemical and physical) have been employed, in several instances, as efforts to reduce the spatial distribution of water hyacinth in RSA's inland waters (Harding, 2004; Besaans, 2011; Hill and Coetzee, 2017). Bio-control of water hyacinth introduces known natural consumers of the invasive weed into an environment, to mitigate the distribution of water hyacinth (Hill and Coetzee, 2017). Biological control has been the most employed method of water hyacinth in RSA, since its inception in 1973 (; GAES, 2013; Hill and Coetzee, 2017). Physical control of water hyacinth requires the manual or mechanical harvesting of water hyacinth (Besaans, 2011; Hill and Coetzee, 2017). This technique of control is nonetheless labour intensive and expensive (Besaans, 2011; Hill and Coetzee, 2017). Chemical control of water hyacinth utilises chemical herbicides, they are cheaper to employ than physical control measures, to eradicate water hyacinth (Villamagna and Murphy, 2010). However, chemical control affects biological control agents similarly deployed against the weed (Hill *et al*., 2012; GEAS, 2013).

Sentinel-2 Multispectral Instrument (MSI), as well as Land Remote Sensing Satellite-8 (Landsat-8) Operational Land Imager (OLI) imagery, will be utilised for mapping the spatial extent of water hyacinth currently invading the Hartbeespoort Dam waters. Landsat-8 OLI and Sentinel-2 MSI are new generation sensors that provide data freely and possess imagery with a fine spatial resolution of 10 meters and medium spatial resolution of 30 meters, respectively. The spectral resolution of the Sentinel-2 MSI is inclusive of the red edge band (Ramoelo *et al*., 2015). The use of the red edge band in the classification of vegetation species has proven to be essential, thus this study will test if the inclusion of the red edge is of any significance in the mapping of water hyacinth (Ramoelo *et al*., 2015). Red edge is defined as the region of abrupt change in the leaf reflectance between the spectral regions of 680 nm and 780 nm due to the combined effects of strong chlorophyll absorption in red wavelengths and high reflectance of in the near-infrared (NIR) wavelengths due to leaf internal scattering (Mutanga *et al*., 2012; Ramoelo *et al*., 2015). Furthermore, the Sentinel-2 imagery capability's to detect and discriminate water hyacinth have not been fully explored~~,~~ in South Africa.

The efficient management of this aquatic weed asserts for current and precise information on its spatial distribution. This research intends to map water hyacinth that is currently invading the dam, illustrating the spatial extent of the invasive aquatic weed. Consequently, this study will test the ability of Sentinel-2, in comparison to that of Landsat-8 OLI, to accurately discriminate and map the water hyacinth from other land use and land cover types in and around the Hartbeespoort Dam. This will provide a quantitative estimation of water hyacinth distribution in the dam and consequently, aid in the identification of areas within the dam that are highly encroached by this invasive species. Furthermore, this study will make use of change detection methods to assess the success of the physical control measures employed against the weed, in an attempt to mitigate its spread, utilising historical Landsat imagery.

The results of the study will be utilised to advice water resource managers on the various drivers that propagate the sprawl of water hyacinth. Mapping of water hyacinth is essential for policymakers and conservation managers as it provides a quantitative estimate of water hyacinth and provides visual illustrations on the spread of water hyacinth on water bodies.

Figure 1: Water hyacinth infestation in the Hartbeespoort Dam (Author, 2018).

1.3 Aims and Objectives

1.3.1 Aims

The primary aim of this research is to examine the ability of Sentinel-2 MSI and Landsat-8 imagery in mapping the spatial distribution of water hyacinth in the Hartbeespoort Dam. Furthermore, this research aims to assess the success of control measures that have previously been used to mitigate the spread and reduce the abundance of water hyacinth, by using multi-temporal remote sensing data.

1.3.2 Objectives

The specific objectives of this research report are to:

1. Compare the use of Sentinel-2 MSI and Landsat-8 OLI imageries in mapping and quantifying the spatial distribution of water hyacinth in the Hartbeespoort Dam, using the Random Forest (RF) classifier.
2. Assess the success of physical control measures of water hyacinth in Hartbeespoort Dam using Landsat multi-temporal data.

CHAPTER TWO

LITERATURE REVIEW

2.1 INVASIVE SPECIES

Invasive species are organisms found in foreign regions with the ability to rapidly reproduce and infiltrate their new environments (Xu *et al*., 2012). Plant invaders are listed among the key pressures which are exacerbating the loss of biodiversity (Rands *et al.*, 2010; Genovesi *et al*., 2015). This has resulted in accelerated efforts from ecologists, conservationists, and governments, globally, to control further spread of non-native plant species that threaten the ecological integrity of new environments they enter into (Xu *et al*., 2012; Rogers, 2018; Scanes, 2018). Invasive alien species are primarily introduced to foreign regions by humans, either intentionally or accidentally (Rogers, 2018; Scanes, 2018).

Invasive exotics pose a major threat globally to economies, ecological systems, and societies (Patel, 2012; Mostert *et al*., 2017; Kganyago *et al*., 2018). Genovesi *et al* (2015) estimated the overall economic loss of €12 billion in Europe in 2009, due to the encroachment of invasive species. Similarly, in 2013, R6.5 billion was the approximated financial contribution by South Africa towards the control of invasive alien species (GEAS, 2013). Invasive plants tend to degrade environments by reducing biological diversity, changing ecosystem structure and functions, altering nutrient cycles and deteriorating water quality (Rands *et aI*., 2010; Downey and Richardson, 2016; Paul and Kar, 2016; Kganyago *et al.*, 2018).

2.1.1 Water Hyacinth

Water hyacinth, botanically known as *Eichhornia crassipes* (Mart.) Solms belongs to the family Pontederiaceae (Barrett, 1998). Water hyacinth originates from the Amazon basin and Ecuador regions of Brazil, South America (Parsons *et al*., 2001; Villamagna and Murphy, 2010; Patel, 2012). The introduction of water hyacinth across the tropical, subtropical, and warm temperate regions of Africa, Asia, Australia, Europe, and North America was a deliberate act by humans (Parsons *et al*., 2001; Patel, 2012; Nguyen *et al*., 2015). Humans introduced water hyacinth as an ornamental species to adorn inland water bodies (Villamagna and Murphy, 2010; Patel, 2012; Nguyen *et al*., 2015). The large blue, purple and violet flowers of water hyacinth, along with their glossy leaves, and bulbous petioles attributed to the popularity of water hyacinth as an ornamental species (Figure 2) (Patel, 2012; GEAS, 2013). The vast global distribution of water hyacinth was identified among the most abundantly spread invasive aquatic plants in the world (Thamaga and Dube, 2018). Furthermore, water hyacinth was listed amid 100 burdensome invasive species globally by IUCN (Lowe *et al*., 2000; Téllez *et al*. 2008; Villamagna and Murphy, 2010).

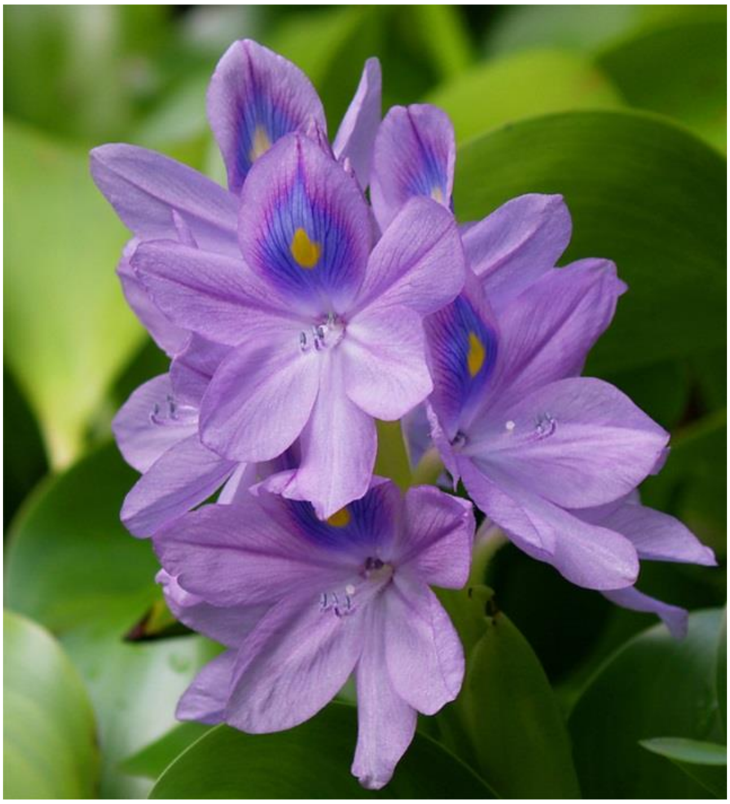


Figure 2: Mature water hyacinth flower (Source: Karin De Coeyer, 2007; Available from https://www.treknature.com/gallery/photo148614.htm, accessed 23 January 2019)

Water hyacinth reproduces rapidly and creates dense, interlocking mats above water bodies (Figure 3) (Kushwaha, 2012; Thamaga and Dube, 2018). The ability of water hyacinth to reproduce both sexually and asexually attributes to its ability to propagate at high rates (Villamagna and Murphy, 2010; Patel, 2012). The sexual reproduction of water hyacinth is through stolons, while seed dispersal is the asexual reproductive method of this invasive plant (Patel, 2012). The presence of the dense water hyacinth mats interferes with waterways, disrupt the functioning of aquatic ecosystems, and create ideal conditions for disease-carrying vectors (Parsons *et al*., 2001; Perna and Burrows, 2005; Villamagna and Murphy, 2010; Kushwaha, 2012). These cause a disturbance in the everyday economic, social and ecological activities of water hyacinth infested waters (Parsons *et al*., 2001; Perna and Burrows, 2005;

Villamagna and Murphy, 2010). Such disruptions in the functioning of water bodies include decreased boating navigability and access, hindrance of water supply systems and drainage canals, and decreased fish populations (Parsons *et al.*, 2001; Perna and Burrows, 2005; Villamagna and Murphy, 2010). Water hyacinth similarly disrupts the ecological processes of water bodies. It decreases dissolved oxygen concentrations and limits the productivity of phytoplankton while creating ideal conditions for diseases and exacerbating their carriers (Parsons *et al*., 2001; Villamagna and Murphy, 2010; Kushwaha, 2012).

Figure 3: Dense. interlocked water hyacinth mats in the Hartbeespoort Dam (Author, 2018).

Lindsey and Hirt (1999) state that the harvesting of water hyacinth has the potential to significantly enhance ecological, economic and social aspects in communities. The authors list water purification, animal fodder, fertiliser, and paper production as some of the beneficial uses of water hyacinth. These findings were further reiterated by Villamagna and Murphy (2010) who stated that water hyacinth has important ecological and socio-economic properties, even though it is an invasive species.

2.1.2 Water hyacinth in South Africa

Water hyacinth was first introduced to South African waters in 1908 as an ornamental plant in the Cape Flats (Stent, 1913; Besaans, 2011). Since its introduction, water hyacinth has become highly invasive in the country (Figure 4) (Hill and Olckers, 2001; Pérez *et al*., 2011). Majority of the water hyacinth infestations in South African waters is concentrated in the Eastern Cape, KwaZulu-Natal, Mpumalanga and Western Cape provinces (Hill, 2003). Nonetheless, water hyacinth populations are evidently present in all the other provinces of the country excluding the Northern Cape Province (Figure 4) (Hill, 2003). The New Years Dam

(Eastern Cape), Vaal River (Gauteng), and Isipingo River (KwaZulu-Natal) have been the focus of several studies due to the prevalence of water hyacinth in these systems (Hill, 2003; eThekwini Municipality, 2013).

The spread and rapid invasion of water hyacinth in RSA were largely exacerbated by high levels of eutrophication, the plant's rapid reproductive rates and the absence of the species natural enemies (Besaans, 2011). The high levels of eutrophication were aggravated by the construction of dams, nutrient-rich agricultural run-off, and effluents from sewage and industries (Besaans, 2011; Hill and Olckers, 2001).

Water hyacinth degrades water quality and aquatic ecosystems (Hill, 2003). Hill and Coetzee (2017) identified water hyacinth as an aquatic species with the most impact on aquatic ecosystems, from seven other invasive aquatic plants. The authors work utilised the generic impact scoring system (GISS) scoring a total of 43 to water hyacinth. Ashton *et al* (1979) stated that water hyacinth invasion in the Hartbeespoort Dam covered 60% of the dams surface area, with an approximated area cover of 1200 ha. Furthermore, in the 1990s the intrusive water hyacinths heavily invaded the Nselani River in the KwaZulu-Natal Province of South Africa (eThekwini Municipality, 2013). The water hyacinth infestation in the Nselani River was propagated by effluent discharge from sewerage water treatment plants (eThekwini Municipality, 2013). The upgrade of the sewerage water treatment plant drastically decreased the invasion of water hyacinth, through the reduction of effluents deposited into the river (eThekwini Municipality, 2013).

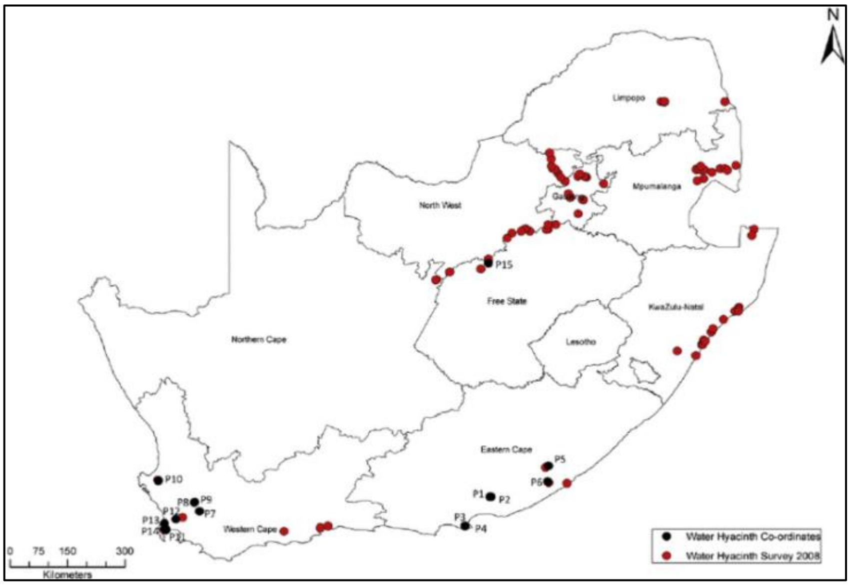


Figure 4: The red dots indicate the distribution of water hyacinth in South Africa (Source: Pérez *et al*., 2011).

2.2 Factors that propagate the sprawl of water hyacinth

Several authors (DWAF, 2007; Villamagna and Murphy, 2010; Güereña *et al*., 2015; Nguyen *et al*., 2015; Thamaga and Dube, 2018) have identified the following factors as the natural drivers of water hyacinth growth and sprawl:

- Temperature
- pH levels
- Solar radiation

Water hyacinth growth is optimum in the presence of daylight, between temperatures of 25°C and 30° C, and in fairly neutral waters, with pH levels ranging between 6 and 8 (Wilson *et al*., 2005; DWAF, 2007; Nguyen *et al*., 2015). Photosynthetic day length (solar radiation) is required by the water hyacinth for biomass production (Güereña *et al*., 2015). Thus the ideal growth period of water hyacinth is during the day, especially during summer months, when the solar radiation is at its peak (DWAF, 2007).

Similarly, several authors (Harding 2004; DWAF, 2007; Villamagna and Murphy, 2010; Güereña *et al*., 2015; Thamaga and Dube, 2018) have identified the following factors as the anthropogenic drivers of water hyacinth growth and sprawl:

- Wastewater treatment plant discharges into catchments.
- Washed surface pollution such as animal waste, litter, and sewer spillages into the dam.
- Poor up-keep of sanitation systems water hyacinth result in overflows and leaks during rainstorms.
- Agricultural runoff (fertilisers are washed into the dam during rainstorms).
- Informal washing in the rivers.

The anthropogenic determinants of water hyacinth constitute high levels of nutrient concentrations in dams, such as nitrogen (N) and phosphorus (P) (Güereña *et al*., 2015). These nutrients are continually deposited in dams and enrich the water with dissolved nutrients. The dissolved nutrients are inevitably taken up by the water hyacinth, resulting in the rapid expansion of the weed across the dam (Harding 2004; DWAF, 2007; Thamaga and Dube, 2018).

2.3 Mapping invasive species using remote sensing

The use of remote sensing as a tool in mapping water hyacinth is steadily increasing globally, due to the advancements of remote sensing technologies (Cavalli *et al*., 2009; Thamaga and

Dube, 2018). There is a vast body of work in developed countries, such as North America and Australia, utilising remote sensing in mapping water hyacinth (Underwood, 2006; Schmidt and Witte, 2010). Although, in Africa, especially sub-Saharan Africa, little work has been done by researchers to monitor and map water hyacinth invasions utilising remote sensing technologies (Thamaga and Dube, 2018). Majority of the studies in Africa are concentrated on Lake Victoria and Zimbabwean Lakes (Lake Chivero and Lake Manyame) (Dube *et al*., 2017; Thamaga and Dube, 2018).

The efficient management of water hyacinth invasions requires the latest information on its spatial coverage along with its temporal distribution (Patel 2012). Remote sensing techniques provide effective and economic methods that have the ability to produce accurate and timely information for mapping vegetation species (Adam *et al*., 2017). Other factors that have contributed to the increased utilisation of remote sensing methods include its extensive land coverage and accessibility of inaccessible or remote areas (Hoshino *et al*., 2012; Patel, 2012).

2.3.1 Mapping invasive species using multispectral data

Multispectral sensors (MSS), Landsat and Satellite Pour l'Observation de la Terre (SPOT) imagery, have often been preferred for the monitoring of aquatic weed dispersal and often achieve high accuracies (Shekede *et al*., 2008; Dube, *et al*., 2014; Dube *et al*., 2017; Kganyago *et al*., 2018). Landsat and SPOT data are readily available, have medium spatial resolutions, high temporal resolution and are freely obtainable (Dube *et al*., 2017; Kganyago *et al*., 2018). These are characteristics which have driven the utilisation of these sensors. However, the spectral resolutions, as well as the spatial resolutions, are at times limitations of MSS data use, as they are often not adequate (fine to coarse spatial extents and narrow spectral range) for effective vegetation mapping and identification (Adam *et al*., 2017).

Shekede *et al* (2008) utilised the supervised classification technique to map the distribution of water hyacinth in Lake Chivero, Zimbabwe, using Landsat imagery. The authors were able to map the extent of areas in Lake Chivero covered by water hyacinth for the years 1976, 1989 and 2000. Shekede *et al* (2008) observed a decline in the distribution of water hyacinth in the classified images from 42%, to 36% and finally 22% for the 1976, 1989 and 2000 images, respectively. In a more recent study, Dube *et al* (2017) tested the detection and discriminatory potential of Landsat-8 OLI in mapping water hyacinth. The authors were able to map water hyacinth at high accuracies ranging between 84 % and 100%. Likewise, Ongore *et al* (2018) utilised Landsat 7 ETM, Landsat-8 OLI and Sentinel-2 MSI imagery to map and assess the distribution of the invasive water hyacinth in the Kenyan portions of Lake Victoria, utilising both supervised and unsupervised classification techniques. The integration of the imagery from various sensors enabled the authors to detect the fluctuations in the spatiotemporal distribution of water hyacinth for a five year period (Ongore *et al*., 2018).

2.3.2 Mapping invasive species using hyperspectral data

Hyperspectral data has been proven by several authors to have very high accuracies in classifying aquatic weeds (Hansen *et al*., 2006; Anser *et al*., 2008). Hyperspectral data have high spatial resolutions, <1 m – 5 m, and high spectral resolutions, spectral bands range from hundreds to thousands and go beyond the infrared region of the spectrum (Foody, 2002). Nevertheless, the costly acquisition, availability, high dimensionality of the acquired information, tedious pre-processing, and the requirement for specialised equipment's and programmes, have limited the use of hyperspectral data (Anser *et al*., 2008; Palmer *et al*., 2014).

Hestir *et al* (2008) mapped water hyacinth in the California Delta using decision tree classification and airborne hyperspectral imagery. The HyMap data had a spatial resolution of 3 m and was used to cover a regional area of 2139 km^2. The classification from the binary trees yielded a producer's accuracy of 61.9 % and user's accuracy of 51.4 %. Further classification of the hyacinth based on phenology, yielded producer's accuracies of 86.5% and 44.9% for healthy water hyacinth and flowering water hyacinth respectively (Hestir, 2008). These are conflicting results; the low accuracies can be attributed to the presence of mixed pixels (Thamaga and Dube, 2018). Underwood *et al* (2005) had obtained better accuracy results when compared to Hestir *et al* (2008). Underwood *et al* (2005) used spectral mixture analysis in the classification of HyMap imagery to map water hyacinth and Brazilian waterweed in the Sacramento-San Joaquin Delta, USA. The resultant overall accuracies of water hyacinth mapped from five sites within the Delta and the entire Delta were 73% and 65% respectively.

2.3.3 Mapping invasive species using new generation multispectral data

According to Adam *et al*. (2017), the last decade has seen the emergence of new generation imagery characterised by high spatial and spectral resolutions. Landsat-8 OLI, RapidEye, Sentinel-2, and WorldView-2 are examples of new-generation sensors, with spatial resolutions of 30 m, 5 m, 10-60 m, and 1.5-2 m, respectively (Adam *et al*., 2017). These resolutions ensure crisper images with more details on land cover mapping.

John and Kavya (2014) employed fine spatial resolution WorldView-2 imagery combined with various band combinations, based on spectral properties of vegetation reflectance obtained from fieldwork, in order to perform unsupervised classification of aquatic weeds. This method resulted in the perfect classification of the weeds, 100%, with a band combination of red-edge, green, coastal blue and red-edge. The subsequent classification with the band combination of NIR-1, green, coastal blue and NIR-1 obtained a considerably good average of 82.35 %.

Dube *et al* (2017) also conducted two studies utilising the new generation sensor Landsat-8 OLI. The first study was conducted in Lake Manyame and the second undertaken in Lake Chivero both situated in Zimbabwe. In the Lake Manyame study, the authors used Discriminant Analysis (DA) and Partial Least Squares Discriminant Analysis (PLS-DA) in classifying the Landsat-8 OLI image. The classification yielded an overall accuracy of 95% for water hyacinth mapped in the dry season and 91 % for hyacinth mapped during the wet season. The second study, conducted in Lake Chivero, utilised a Discriminant Analysis (DA) for the analysis of the image. The variance test resulted in an overall classification of 92 % of the water hyacinth.

2.4 Control measures of water hyacinth

According to Villamagna and Murphy (2010), water hyacinth control is an absolute essential. Implementing control measures minimises the ecological and economic impacts of water hyacinth invasion (Culliney, 2005). Nevertheless, the expenses associated with the control of water hyacinth invasion are high (Culliney, 2005). These include costs of revenue lost, costs of environmental and infrastructure damage, as well as weed control cost (Culliney, 2005). Annual cost estimations of water hyacinth control in South Africa are $12 billion (van Wilgen *et al.*, 2001). This is significantly lower than the cost of water hyacinth control in India, the United States, and Brazil, valued at $39 billion, $34 billion, and $17 billion respectively (Culliney, 2005). The control of water hyacinth can be performed by the implementation of any one of three control methods, namely, biological control, chemical control and physical control (Wittenberg and Cock, 2001; Villamagna and Murphy, 2010; GEAS, 2013).

2.4.1 Biological Control

Biological control (bio-control) is regarded as the most cost-effective and environmentally friendly method of control for water hyacinth invasion (Wittenberg and Cock, 2001). Biological control of water hyacinth is a completely organic approach involving the introduction of water hyacinth consumers into infested areas (De Groote *et al*., 2003; Villamagna and Murphy, 2010; GEAS, 2013). Thus, bio-control is perceived as a sustainable approach for controlling water hyacinth over a long period of time (Hill, 2003). Biological control is not aimed at the eradication of the water hyacinth but it is an effort to mitigate its abundance and bring it down to a stage where it's not problematic (GEAS, 2013).

Biological control of water hyacinth in RSA was firstly initiated in 1973 and implemented in 1974 with the release of *Neochetina eichhorniae* (Hustache) (Cilliers, 1991). Thereafter, several other biocontrol agents have been introduced in RSA (Hill and Olckers, 2001; Hill, 2002; Besaans, 2011). There are currently six established biocontrol agents in RSA, five arthropods and one pathogen (Besaans, 2001). The arthropod biocontrol agents include two weevil species, *Neochetina eichhorniae*, *Neochetina bruchi*; a moth, *Niphograpta albiguttalis* (Warren); the mirid, *Eccritotarsus catarinensis* (Carvalho); and the galumnid mite, *Orthogalumna terebrantis* (Wallwork) (Coetzee *et al*., 2011). *Cercospora piaropi* (Tharp) is the only fungal pathogen currently established as a biocontrol agent in South Africa (Coetzee *et al*., 2011).

The performance of biocontrol agents in alleviating water hyacinth distribution is susceptible to climatic conditions and eutrophication levels of impoundments (Byrne, *et al*., 2011). Biocontrol agents are adversely affected by cold winters and frost, and high nutrient loadings in water (Hill, 2003; Byrne *et al*., 2011). Thus environmental factors contribute to the success rate of biological controls.

Culliney (2005), averaged the global success of biological control methods to be 33% based on the outcomes of biocontrol programmes. However, the success of biological control for individual countries indicated significantly high success rates varying between 50% and 83% (Culliney, 2005). New Zealand has achieved the highest success rate for their biocontrol programmes, 83%, followed by Mauritius, South Africa and Australia with success rates of 80%, 61%, and 50% respectively (Culliney, 2005).

2.4.2 Chemical Control

Patel (2012) states that the chemical control of water hyacinth is a conventional approach in the global effort to mitigate the distribution of the weed. The utilisation of chemical control dates as far back as the 1970s (Ashton *et al*., 1979; Besaans, 2011). Chemical control involves the diffusion of chemical herbicides: Paraquat, Diquat, Glyphosate, Amitrole and 2.4-Dacid, over water hyacinth (Harding 2004; Villamagna and Murphy, 2010; Patel, 2012).

Chemical control is often implemented in conjunction with the physical control of water hyacinth in large water bodies (eThekwini Municipality, 2013; Hill and Coetzee, 2017). Thus not plenty literature is available on its success as an individual method of control globally.

Herbicides are administered either utilising handheld sprays, high-pressure sprays or aerial spraying (Villamagna and Murphy, 2010; eThekwini Municipality, 2013). Ashton *et al* (1979) successfully cleared water hyacinth invasion in the Hartbeespoort Dam with the aerial application of *terbutryn* herbicide. *Terbutryn* was sprayed on three different occasions, between October 1977 and January 1978, eradicating close to 1200 ha of water hyacinth (Ashton *et al*., 1979).

The use of herbicides for the control of water hyacinth provides immediate results (Wittenberg and Cock, 2001; Harding, 2004). Herbicidal control of the weed causes it to decay and sink into the water within days to weeks (Wittenberg and Cock, 2001; Harding, 2004; eThekwini Municipality, 2013). However, this results in the need for follow-up administration of herbicides to prevent the reinvasion of water hyacinth from; germinating seeds, and increased nutrient loadings as a result of the decaying weeds, and scattered plants (Ashton *et al*., 1979; Hill, 2003; Culliney, 2005).

Unfortunately, long term use of herbicides is not feasible, the chemical make-up of the herbicides can cause environmental problems and risks to human health if not correctly applied (Wittenberg and Cock, 2001; Culliney, 2005; GEAS, 2013). In addition, herbicides can only be administrated by skilled personnel (Culliney, 2005;). Further drawbacks of utilising herbicides as a method of weed control include their high costs and the ability of weed species to evolve resistance to compounds (Culliney, 2005).

2.4.3 Physical control

Physical control, often referred to as mechanical or manual control of water hyacinth, extracts water hyacinth from waters using machinery or manually (Villamagna and Murphy, 2010; Patel, 2012; GEAS, 2013). Physical control includes harvesting, bulldozing, hand-pulling, raking, and draining of water hyacinth (Hill, 2003; Villamagna and Murphy, 2010; Patel, 2012).

Physical control of water hyacinth is invariably the first control method implemented by most countries (Hill, 2003). This is due to the socio-economic benefits related to the use of physical control measures (Villamagna and Murphy, 2010; Hill and Coetzee, 2017). Physical control methods of the invasive macrophyte promote the alleviation of poverty through job creation, as it does not require expert technical proficiency (Villamagna and Murphy, 2010; eThekweni Municipality, 2013; Hill and Coetzee, 2017). Physical control is void of herbicide use and as a result does not contaminate waters (Villamagna and Murphy, 2010; eThekweni Municipality, 2013). Additionally, the control of water hyacinth utilising physical control approaches extracts plants from waters, avoiding the creation of decaying organic matter in them (Wittenberg and Cock, 2001; eThekweni Municipality, 2013).

Perna and Burrows (2005) utilised various machinery to harvest water hyacinth from lagoons in Australia. The authors undertook the water hyacinth clearing expedition to test the relation between the macrophyte and dissolved oxygen levels in lagoon waters. The extraction of water hyacinth from the lagoons, using weed harvesters and a large rake on a land-based excavator, was a success as it increased the dissolved oxygen levels in the lagoons (Perna and Burrows, 2005). Similarly, physical control interventions in Spain have successfully been employed to harvest water hyacinth from the Guadiana River Basin (Téllez *et al*., 2008). However, Téllez *et al* (2008) further emphasis that although successful, the physical control of water hyacinth in Spain is unable to completely eradicate populations of the weed. The Tanzanian government has invested $20 000, annually, towards the physical control of water hyacinth (Mallya *et al*., 2001). This has ensured the complete eradication of water hyacinth on more than 60 landing beaches in Lake Victoria (Mallya *et al*., 2001).

Physical control methods often prove to be very costly and laborious (Hill, 2003; Culliney, 2005; Patel, 2012). This is because it requires expensive machinery such as weed harvesters, crusher boats, and destruction boats as well as recurring harvesting of the weed (Villamagna and Murphy, 2010; Patel, 2012; GEAS, 2013). Physical control of the weed is, however, not suitable for use in large areas or for large mats of water hyacinth; as the long term acquisition of power machinery tends to be expensive and the reintroduction of the macrophyte during extraction cannot be countered (Hill, 2003; Culliney, 2005; Patel, 2012).

2.5 Monitoring water hyacinth control

The control methods utilised for water hyacinth reduction and eradication should be monitored. Monitoring the efforts of the control mechanisms would provide information on their success and downfalls, in their employment as tools for the control of water hyacinth dispersion. Remote sensing and field-based methods can both be used to monitor water hyacinth control.

The use of remote sensing for monitoring water hyacinth control has several advantages (Dube *et al*., 2017). The key advantage of this approach for monitoring water hyacinth control is its real-time availability of data (Dube *et al*., 2017; Murray *et al*., 2018). This is essential for monitoring the control of water hyacinth as water flow and wind alter the positions of water hyacinth, even during efforts to control its extent. Additionally, the synoptic view offered by remotely sensed data can monitor control efforts in large water bodies efficiently and swiftly (Dube *et al*., 2017). Remote sensing data acquisition costs are relatively low, thus making it an economically feasible monitoring approach of observing water hyacinth control strategies (Dube *et al*., 2017; Murray *et al*., 2018). The repetitive coverage of areas allows for the availability of data to utilise in monitoring water hyacinth control over long periods (Dube *et al*., 2017; Murray *et al*., 2018).

Conversely, field-based methods of monitoring water hyacinth lack the sophisticated technological abilities of remote sensing methods (Murray *et al*., 2018). Field-based methodologies for monitoring water hyacinth control are generally constrained as far as spatial inclusion, costs, revisit periods and enormous workload (Palmer *et al*., 2014). Field-based approaches are limited to monitoring water hyacinth control in small water areas (Dube *et al*., 2017; Murray *et al*., 2018). Monitoring the control of this invasive weed in medium to large water bodies utilising field-based methods is costly (Murray *et al*., 2018). Field-based methods for water hyacinth control require the utilisation of boats and aircraft which are often charged by the hour, to monitor water hyacinth efficiently (Patel, 2012; Murray *et al*., 2018). Field visits, for the purpose of monitoring water hyacinth control, are performed under the direct exposure of environmental factors. Thus monitoring of water hyacinth control is not feasible during days of extreme environmental conditions (Murray *et al*., 2018). Furthermore, these techniques are inclined to biases, as the exactness, accuracy, and affectability of the outcomes in the control of water hyacinth are exceptionally subject to the analyst (Godínez-Alvarez *et al*., 2009).

The main focus of this research was to investigate the ability of new generation satellite sensors, Sentinel-2 MSI and Landsat-8 OLI, in detecting and mapping the spatial distribution of water hyacinth. There is a need to increase the use of RS which offers improved estimates in predicting, detecting, monitoring and mapping the spatial and temporal distribution of water hyacinth. Thus the application of RS will further promote efficient dam management in South Africa. Remote sensing of water hyacinth will aid water managers in the development of effective strategies for the successful control of the weed in both large and small water bodies, under different environmental conditions.

Therefore, the outcome of this study will contribute to an understanding of the role RS can play in increasing the efficiency of traditional control measures (biological, chemical and physical) of the invasive species.

CHAPTER THREE

MAPPING THE CURRENT DISTRIBUTION OF *EICHHORNIA CRASSIPES* (WATER HYACINTH) INVASION IN THE HARTBEESPOORT DAM.

3.1 Introduction

Water hyacinth is an invasive macrophyte, infesting South African inland waters (De Groote *et al.*, 2003; Hill and Coetzee, 2017). Water hyacinth is an evergreen, free-floating, vascular macrophyte (Nguyen *et al*., 2015; Thamaga and Dube, 2018). The morphology of mature water hyacinth consists of leaves that are joined to glossy, thick and ovate stalks, roots, rhizomes, stolons, inflorescences and fruit clusters (Villamagna and Murphy, 2010; Patel, 2012; Nguyen *et al*., 2015; Thamaga and Dube, 2018). Unlike many submerged and emergent macrophytes, water hyacinth is not limited to shallow waters because of its feathery roots, which are free floating near the surface of the water (Villamagna and Murphy, 2010; Patel, 2012; Güereña *et al*., 2015; Nguyen *et al*., 2015).

Water hyacinth grows optimally under warm conditions between temperatures of 25°C to 28°C, in phosphorus and nitrogen enriched waters with a pH level between 6 to 8 (Wilson *et al*., 2005). Water hyacinth rapidly colonises still or slow moving water, resulting in dense, interlocked mats (Villamagna and Murphy, 2010; Nguyen *et al*., 2015; Güereña *et al*., 2015; Thamaga and Dube, 2018). Water hyacinth has the potential to double in population between 1 to 3 weeks (Parsons *et al*., 2001). This is attributed to its rapid reproductive rates (water hyacinth reproduces both sexually and asexually) and complex root structure (DiTomaso and Healy 2003; Patel, 2012). The growth rate of water hyacinth differs substantially in static and flowing waters (Howard and Harley, 1998). In static water, the growth of water hyacinth is propagated by the inflow of nutrient-rich water from run-off, while in moving waters the nutrients are constantly moving and continuously being carried to water hyacinth (Howard and Harley, 1998).

The Karoo is the only region in South Africa where water hyacinth is absent (Henderson, 2001). The invasive weed can be found in the subtropical eastern parts, winter rainfall western parts, as well as in the temperate and cool Highveld plateaus of South Africa (Henderson, 2001; Hill and Olckers, 2001). The introduction of water hyacinth into South

African waterbodies is not certainly known as there is no clear record pertaining to it (Villamagna and Murphy, 2010). Though, Stent (1913) proposes that water hyacinth was introduced to South African waters as an ornamental plant in 1908.

The water hyacinth invasions in South Africa have had negative economic, ecological, and social impacts (Hill and Coetzee, 2017). The economic losses attributed to the invasion of water hyacinth are great and surpass those by any other class of horticultural pest (Culliney, 2005). The economic costs, inclusive of water hyacinth control costs and lost revenue, are estimated to be $12 billion (van Wilgen *et al*., 2001; Villamagna and Murphy, 2010). The thick interlocked mats of water hyacinth which lay on the surface of infested water bodies have caused several ecological problems in the country (van Wilgen *et al*., 2001; Hill, 2003). The degradation of water quality decreased dissolved oxygen levels, reduction in phytoplankton abundance, and zooplankton distributions have been identified in South Africa, as is the case in other spheres of the world (Hill, 2003). Other ecological effects of water hyacinth include the loss and suppression of local aquatic biodiversity and increased eutrophication rates in water (Hill, 2003; eThekweni, 2013). Social impacts of water hyacinth infestation include the reduction in water recreational activities (swimming, fishing, and boating) (Harding, 2004; Venter, 2004; eThekweni Municipality, 2013).

The South African government identified a need for the effective management and monitoring systems of water hyacinth (Hill and Coetzee, 2017). This need prompted the establishment of the *Working for Water* programme by the Department of Environmental Affairs in 1995 (van Wilgen, 2001; Hill and Coetzee, 2017). The *Working for Water* programme is under the administration of the Departments Natural Resources Management Programmes (Hill and Coetzee, 2017). *Working for Water* is mandated to protect water resources in addition to ensuring the security of water supply by ensuring the control of invasive alien species (van Wilgen, 2001; Hill and Coetzee, 2017). This programme controls invasive alien species by physically removing them (Hill and Coetzee, 2017). Thus, since inception, the programme has generated numerous jobs and contributed to the alleviation of poverty in the country (Hill and Coetzee, 2017). The government spent over $100 million within the first 5 years of *Working for Water* programme (van Wilgen, 2001). Nonetheless, efforts by the *Working for Water* programme have been ineffective for water weeds as compared to their terrestrial counterparts (Hill and Coetzee, 2017).

Spatial data can be utilised as a tool for managing water hyacinth dynamics (Byrne *et al*., 2011). Several authors have proven the feasibility of utilising fine spatial resolution imagery in detecting, mapping and monitoring the growth of aquatic weeds (Masocha and Skidmore, 2011; Cheruiyot *et al*., 2014; Zhang *et al*., 2017). Remote Sensing is ideal for monitoring invasive infestations as it offers low cost, high temporal resolution and fine to medium resolution data (Jensen, 2000; Foody, 2002).

RS data can be used to advise water managers on the spread of invasive aquatic species (Dube *et al*., 2017). There are limitations of these studies in mapping water hyacinth, given the fact that the dynamic and the movement of water hyacinth requires high temporal resolution remote sensing data. However, most of the high temporal data are very broad in terms of spatial data. Thus multi-sensor remote sensing can help in this aspect. The objective of this research is to test the use of both Sentinel-2 MSI and Landsat-8 OLI in detecting and mapping water hyacinth.

3.2 Materials and Methods

3.2.1 Study Area

The Hartbeespoort Dam is situated in Hartbeespoort town in the North West Province (Figure 5). The town is located west of Rustenburg, north of Johannesburg and east of Pretoria. The construction of the dam commenced in the early 1900s and was completed in 1925 (Venter, 2004). The dam was constructed to serve as an impoundment for irrigation water and to supply potable water to surrounding communities (Harding, 2004; Venter, 2004). The Hartbeespoort Dam is situated within the Crocodile River catchment; the dam flows north into the Crocodile River (DWAF, 2007). The Magalies River and Crocodile River are the dam’s major tributaries, from the west and south, respectively (Venter, 2004).

Hartbeespoort Dam covers approximately 18.83 km^2 with a maximum depth of 45.1 m (Harding, 2004; Venter, 2004). The dam is one of seven dams in South Africa that are hypertrophic (DWAF, 2007). The Hartbeespoort Dam is now not only a natural resource, but a major tourist prime-spot utilised for recreational activities (Harding, 2004; Venter, 2004). The areas around the edges of the dam consist of agricultural land, recreational facilities, industrial land, privately owned businesses and residential areas (Harding, 2004; Venter, 2004).

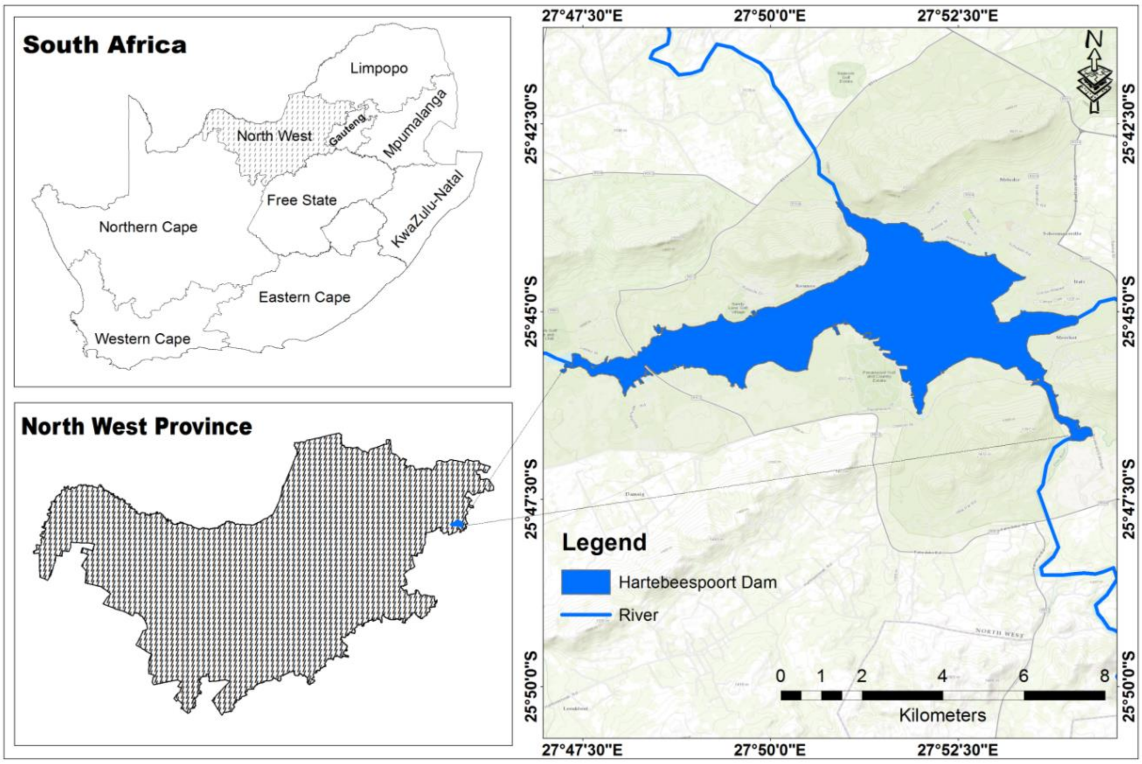


Figure 5: Map of Hartbeespoort dam in relation to the country and North West province.

3.2.2 Remote Sensing Data Acquisition

Remotely sensed imagery was acquired from two satellite sensors; Landsat 8 OLI and Sentinel-2 MSI, to map the current distribution of water hyacinth in the Hartbeespoort Dam. Images from varying sensors were acquired for the purpose of comparing the ability of the sensors in mapping and detecting water hyacinth from other land use land cover classes (LULCC) in the area. Single scene Landsat-8 OLI and Sentinel-2 MSI images encompassing the study area were downloaded at no cost from the United States Geological Survey (USGS) Earth Explorer portal, http://earthexplorerusgs.gov/ and European Space Agency (ESA) Copernicus Open Access Hub, http://scihub.copernicus.eu, respectively. The Landsat-8 OLI image with a fine spatial resolution of 30 m was captured on the 26th October 2018, while the Sentinel-2 MSI with different spatial resolutions was captured on the 27th October 2018. The difference between the two images is no greater than 24 hours. The 24-hour weather record in the Winburg station shows no extreme weather conditions were recorded on the 27th October 2018. The averaged wind speed and wind direction of the day, at 20 m above ground, were 5.19 m/s and 115 ° true north (southeast), respectively. The weather records were obtained from the Wind Atlas of South Africa (WASA) download portal hosted by the Council for Scientific and Industrial Research (CSIR).

Both images were captured under cloud-free conditions during the dry season. The dates of the image acquisition were selected based on the availability of images from both sensors, considering a minimal acquisition difference of no more than three days. Landsat-8 OLI is a multi-spectral imaging sensor. The Landsat 8 mission was a collaboration between the National Aeronautics and Space Administration (NASA) and USGS. The satellite was launched in 2013, in order to provide data continuity to previous Landsat missions by ensuring continued data acquisition and availability of Landsat products. Similar to its predecessors (Landsat 4, 5 and 7), Landsat 8 has a revisit period of 16 days. Furthermore, Landsat 8 OLI has a swath width of 185 km^2, nine spectral bands, eight of which have a medium spectral resolution of 30 m and a 15 m panchromatic band (Table 1). The improvements of Landsat-8 sensor specifications provide crisper images, which aid in the accurate classification of the images.

On the other hand, Sentinel-2 MSI, similar to Landsat-8 OLI, is a multi-spectral imaging mission. Sentinel-2 MSI is a high spatial resolution sensor, commissioned by ESA Copernicus with a 290 km^2 swath width. The mission consists of twin satellites which provide systematic coverage, with a 5-day revisit frequency, as a pair, and 10 days individually. The high revisit period makes Sentinel-2 imagery applicable to mapping water hyacinth distribution. Water hyacinth distribution is continually changing. Thus periods in between mapping water hyacinth distribution should be minimal to accurately show its distribution over time. The movement of water hyacinth is affected by the directions and speed of water and wind flows. Thirteen spectral bands ranging between the spectral regions of 430 nm and 2323 nm are employed to measure reflected solar radiances by the Sentinel-2 MSI (Drusch *et al*., 2012). Four of the thirteen spectral bands have a fine spatial resolution of 10 m, while six have a moderated spatial resolution of 20 m and the remaining three possess a coarse resolution of 60 m (Table 1).

3.2.3 Image Pre-processing

Prior to any analysis, each image had to be pre-processed to minimise the extent of atmospheric effects and obtain true reflectance values of objects, as well as enhance the geometric properties of the images (Lu *et al*., 2004; Lillesand *et al*., 2015). Lu *et al* (2004) state that atmospherically corrected, radiometrically enhanced and geometrically accurate images are a prerequisite for the suitable and accurate analysis of all images.

3.2.3.1 Landsat-8 OLI pre-processing

Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) was employed for the radiometric calibration of the Landsat-8 OLI image to top-of-atmosphere (TOA) radiance values. The image was thereafter additionally atmospherically corrected utilising the same model, FLAASH, embedded in ENVI 5.4 software (Shalby and Tateishi, 2007). The atmospherically corrected image was thereafter loaded into ArcMap to be clipped to the study area size.

3.2.3.2 Sentinel-2 MSI pre-processing

The ESA SNAP software was used for the atmospheric correction and geo-referencing of the Sentinel-2 MSI image, utilising the Sen2Cor plugin embedded in the software. Sen2Cor minimised all the atmospheric additives which were present on the image, then resampled the image to a spatial resolution of 10 m to capture the small distribution of water hyacinth. This resulted in the atmospherically corrected image having only ten spectral bands (Bands: 2, 3, 4, 5, 6, 7, 8, 8A, 11 and 12) of the original thirteen.

The image was then converted to ENVI format, which resulted in ten separate bands. The Sentinel-2 MSI image was subsequently displayed in ENVI classic 5.4 software where the image bands were stacked in chronological order into a single image. Finally, the image was converted to ArcMap raster format to allow for further analysis and the clipping to the extent of the study area.

Table 1: Spectral, spatial and radiometric resolutions of Landsat-8 OLI and Sentinel-2 MSI and

Sensor	**Sentinel-2 (MSI)**		**Landsat-8 (OLI)**	
Band	**Pixel size (m)**	**Wavelength range (nm)**	**Pixel size (m)**	**Wavelength range (nm)**
1	60	430-457	30	433-453
2	10	448-546	30	450-515
3	10	538-583	30	525-600
4	10	646-684	30	630-680
5	20	694-713	30	845-885
6	20	731-749	30	1560-1660
7	20	769-797	30	2100-2300
8	10	763-908	15	500-680
8A	20	848-881	-	
9	60	932-958	30	1360-1390
10	60	1336-1411	-	
11	20	1542-1685	-	
12	20	2081-2323	-	
Swath width		290 km		185 km
Orbit altitude		786 km		705 km
Revisit time	10 days (S2A)/ 5 days (S2A/B)			16 days

3.2.4 Ground Reference Data

Land use and land cover classes present in the study area were defined using both the Sentinel-2 MSI and Landsat-8 OLI images and expert-based approach. Five LULCC were identified on the images. The identified LULCC are as follows; Water hyacinth, Bare Land, Built-Up, Vegetation and Water (Table 2). Ground reference samples, of no less than 300, were obtained for each of the LULCC by randomly creating ground reference points across the various LULCC on both images. Obtaining ground reference points from images is a meticulous process. The ground reference points have to be within a single pixel which is pure. This is to ensure that there is no confusion in the spectral properties of the different LULCC. A great number of samples were required for each LULCC on each of the two images to ensure high classification accuracy (Mesev, 2010). Samples are acquired for the retrieval of the unique spectral signature characteristics of the different LULC classes.

The ground reference samples were then randomly split into 70% training data and 30% test data using the R programming language in the R statistic interface (Table 3). The training dataset was used to classify the image and the test dataset to validate the accuracy of the classification. Land cover and land use classes which were identified in the study, along with their attributes of the features each class entails are shown in (Table 2).

Table 2: Land use and land cover classification schema

LULCC	Code	Attributes
Water Hyacinth	WH	Only water hyacinth
Bare Land	BL	Exposed rock and land without any vegetation.
Built-Up	BU	Residential, industrial (factories) and commercial structures.
Vegetation	V	Forests, agricultural crops, grasses, and trees.
Water	W	Dams, rivers, streams, and reservoirs.

Table 3: Landsat-8 OLI and Sentinel-2 MSI training and test reference data.

LULCC	Training data	Test data	Total
Water Hyacinth	226	97	323
Bare Land	931	399	1330
Built-Up	954	409	1363
Vegetation	527	226	753
Water	245	105	350

3.2.5.1 Random Forest Classifier

Random forest machine learning algorithm is a non-parametric supervised classifier that was developed by Breiman (2001). According to Adam *et al.* (2017), RF was created to increase the precision of classification and regression trees (CART). Breiman (2001) achieved this by introducing the bagging operation (bootstrap operation), where several decision trees are combined and each tree contributes a vote towards allocating a class to a pixel and, ultimately towards the overall classification of the image (Breiman, 2001; Adam *et al*., 2017). Several classification trees (*ntree*) are grown on the bootstrap samples of the input data. Every single classification tree develops on a bootstrap sample, which amounts to two-thirds of the input data, referred to as "in-bag" data (Breiman, 2001). The remaining one-third of the input data that are excluded in the bootstrap sample is known as the "out-of-bag' OOB samples. OOB samples are employed to measure the role of each variable in the final classification model as well as in approximating the misclassification error of the model (Breiman, 2001; Adam *et al*., 2017). Thereafter the ensemble randomly splits the trees into many nodes utilising random subsets of the predictive variables (*mtry*). The default *mtry* value is a product of the square root of the total number of variables unless otherwise specified by the user (Breiman, 2001). Trees are fully grown without being pruned to ensure that the nodes reach purity (Breiman, 2001). *Ntree* and *mtry* are the only parameters required by the RF algorithm. This makes the RF algorithm easy to utilise as only two parameters need optimisation (Breiman, 2001).

The random forest classifier additionally provides various measurements of variable importance as part of the classification process (Breiman, 2001; Thabeng *et al*., 2019). The mean decrease in accuracy is one such measurement of variable importance and it indicates the responsibility of each band in the classification process. The tuning of *mtry* and *ntree* parameters was done using a *randomForest* library of R statistical packages v3.4.1 for this study. A grid search approach based on the OOB error estimate was used to calculate the optimum combination of *mtry* and *ntree* parameters (Breiman, 2001). The grid search values for *mtry* and *ntree* for the Sentinel-2 MSI image ranged from 1 to 10 and 500 to 10000, respectively, with a specified interval of 1000 for the *mtry* while that of the Landsat-8 OLI image ranged from 1 to 7 and 500 to 10000, respectively, with a specified interval of 1000 for the *mtry*.

3.2.6 Accuracy Assessment

Accuracy assessment utilises the test data, randomly obtained from the 70:30 split of the ground reference data (Table3). The test data was used to assess the accuracy of classification in both images obtained from the RF classifier. Confusion matrices were then generated to compute the overall accuracy, producer's accuracy, and user's accuracy, by comparing the reference imagery with the class assigned by the classifier (Adam *et al*., 2017).

Overall accuracy is the ratio, represented as a percentage, between the total number of the validation data samples and the number of accurately classified test data samples, while producer's accuracy represents the number of accurately classified test samples per LULCC. User's accuracy expresses the possibility that of test data samples belonging to a specific LULCC as well as the performance of the classifier in accurately assigning a test sample to such a class.

3.3 Results

3.3.1 Random forest Optimisation

Optimising the parameters is essential for determining the best parameter pair to train the RF algorithm for the classification of the five LULCC identified in the study area. The optimisation of the RF parameters, *mtry* and *ntree,* produced OOB error rates of 6.18% and 4.82% for the Landsat-8 OLI data and Sentinel-2 MSI data, respectively. The 6.18% error rate was produced from the *mtry* and *ntry* combination of 4 and 500 (Figure 6a). Conversely, the 4.82% error resulted from *mtry* and *ntree* combinations of 3 and 500 (Figure 6b). The highest OOB error yielded by the Landsat-8 OLI data was ~7% from the *mtry* value of 7 and *ntree* combination values ranging from 500-10000. Whereas, the highest OOB error of ~6 % for the Sentinel data is a product of the *mtry* value of 10 and *ntree* value ranging from 1000 to 3000 and 4000 to 10000.

The contribution of all the bands in the classification is indicated by a variable importance measurement. The bands with the highest mean decrease in accuracy are those of utmost importance during the classification process. NIR, red and coastal bands were allocated as the important bands for the Landsat-8 OLI image (Figure 7). The utility of each band in mapping LULCC was further evaluated on the Landsat-8 OLI image and the coastal (0.433 – 0.453 μm), red (0.630 – 0.680 μm) and shortwave infrared (SWIR) (1.36 – 1.39 μm) bands emerged as the three most important for the classification of water hyacinth on the Landsat-8 OLI image (Figure 8).

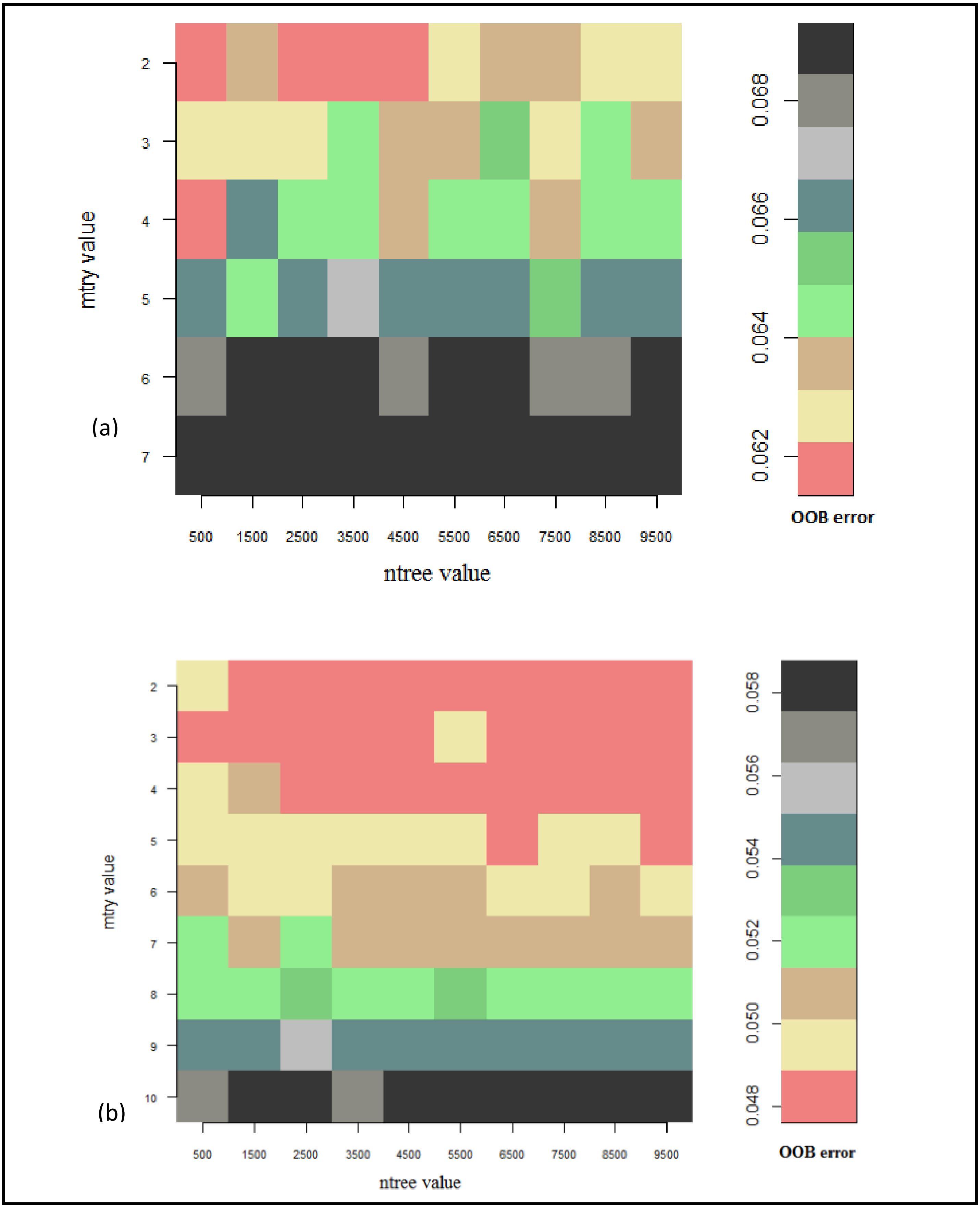


Figure 6: Random Forest optimisation of parameters (*mtry* and *ntree*) (a) Sentinel-2 MSI optimisation parameters (b) Landsat-8 OLI optimisation parameters

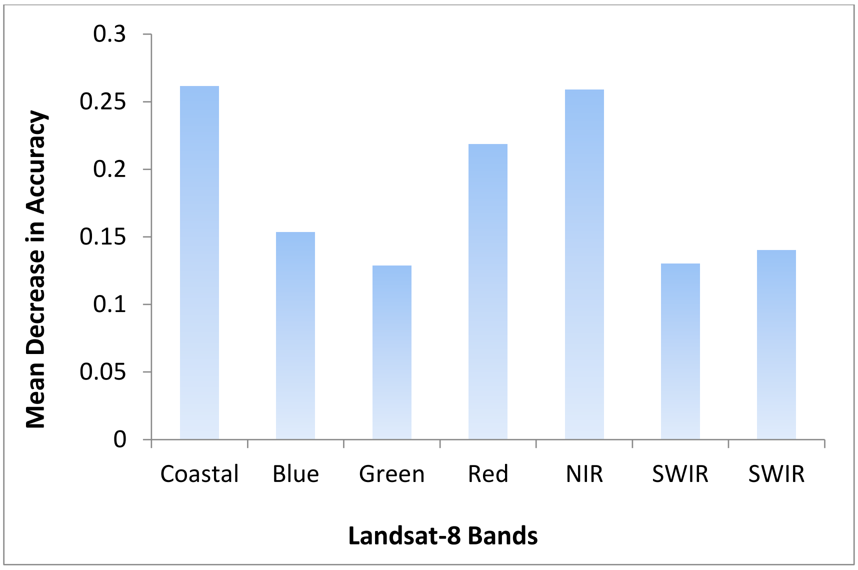


Figure 7: Measuring the importance of the Landsat-8 OLI bands in classification process using Mean Decrease in accuracy score.

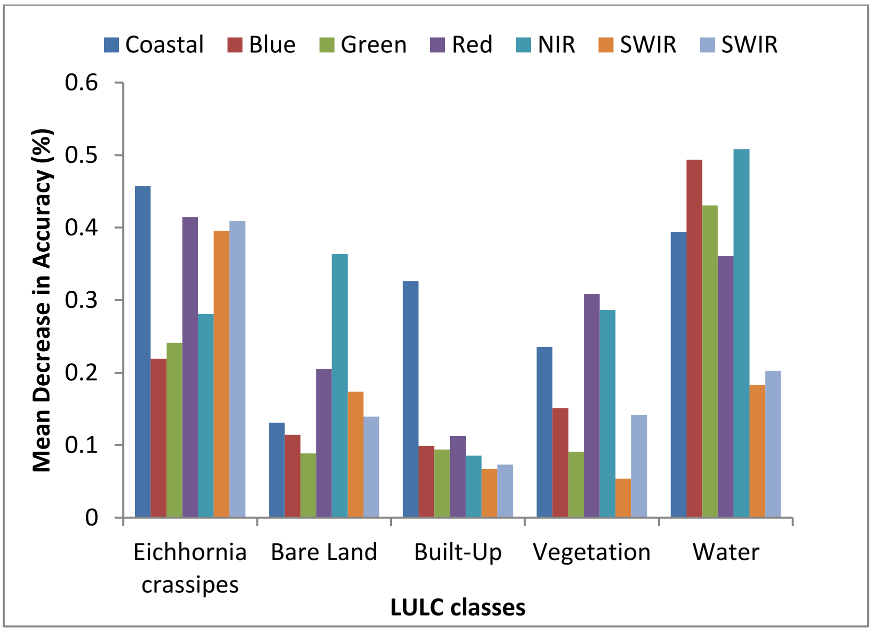


Figure 8: The relationship between each individual LULCC and the importance of the Landsat-8 OLI bands. The highest mean decrease in accuracy shows the most important band.

Likewise, the mean decrease in accuracy measurement was performed for the Sentinel-2 MSI image. It identified the blue, red, the third vegetation red edge and NIR bands as the important bands for the classification of the Sentinel-2 MSI image (Figure 9). Furthermore, the LULCC specific measure of the mean decrease in accuracy of the Sentinel-2 MSI image identified the red (0.646 - 0.684 µm), SWIR (2.08 - 2.32 µm) and the first two vegetation red edge bands (0.646 – 0,713 µm) as those of importance for the classification of water hyacinth utilising the Sentinel-2 MSI image (Figure 10).

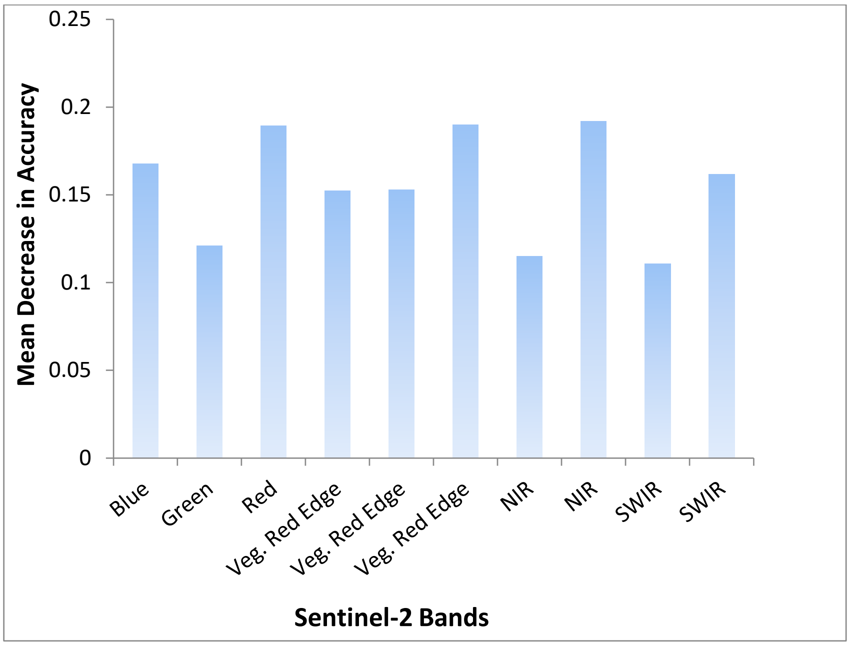


Figure 9: Measuring the importance of the Sentinel-2 bands in classification process using Mean Decrease in accuracy score.

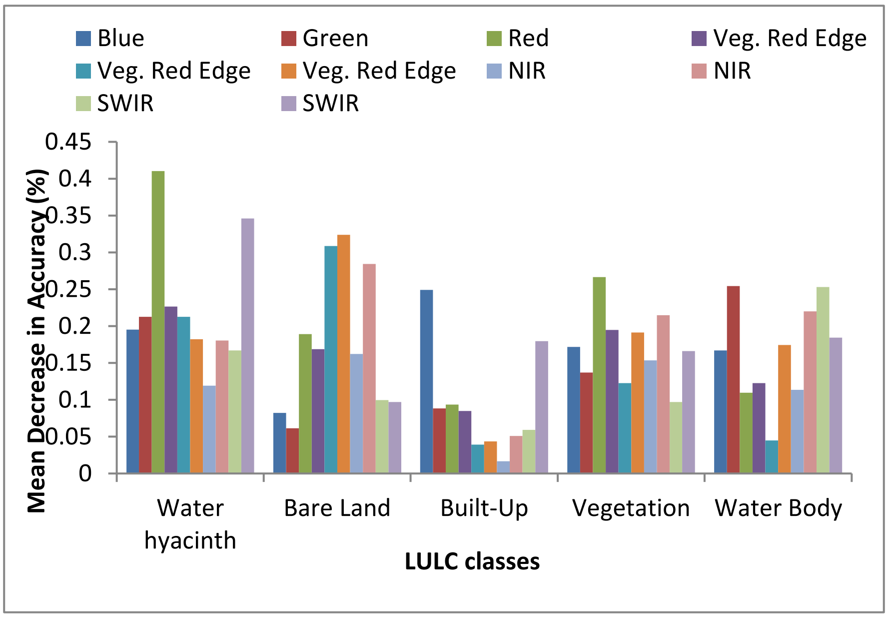


Figure 10: The relationship between each individual LULCC and the importance of the Sentinel-2 MSI bands. The highest mean decrease in accuracy shows the most important band.

3.3.2 Image classification

The classification of the Landsat-8 OLI image as well as that of the Sentinel-2 MSI image, using the RF classifier, was performed to discriminate water hyacinth from other LULCC in the Hartbeespoort area. The RF classifier efficaciously delineated water hyacinth and the other LULCC on both images (Figure 11 and Figure 12). Water hyacinth covers only a minute percentage of the study area, accounting for only 0.2% area coverage of the study area on both classified images (Figure 13 and Table 4). The extent of vegetation cover differed significantly for the two images. Vegetation covered 17% of the Landsat-8 OLI image, but its extent was more widespread on the Sentinel image, covering 42.62%. Similarly, the distribution of bare land did not coincide on the images. Bare land cover was estimated to be 66.13% for the Landsat-8 OLI image, while it was significantly lower at 40.51% for the Sentinel-2 MSI image. The estimation of spatial coverage of the remaining LULCC, water and built-up, was fairly close, such that water amounted for ~0.65% on both images. While the built-up LULCC accounted for 13.2 % on the Landsat-8 OLI image and 17% on the Sentinel-2 MSI image.

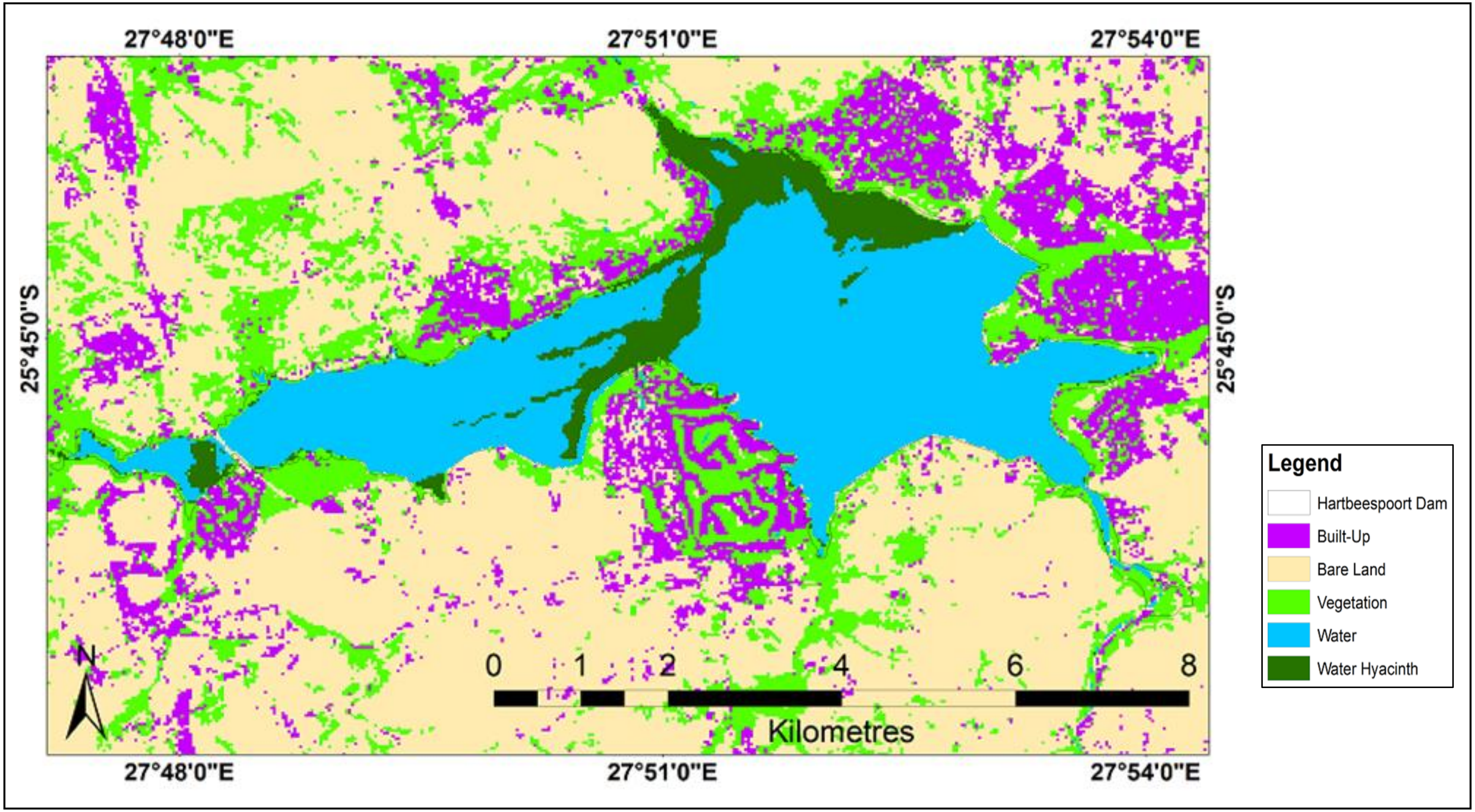


Figure 11: LULCC map of the Landsat-8 OLI data using the RF classifier.

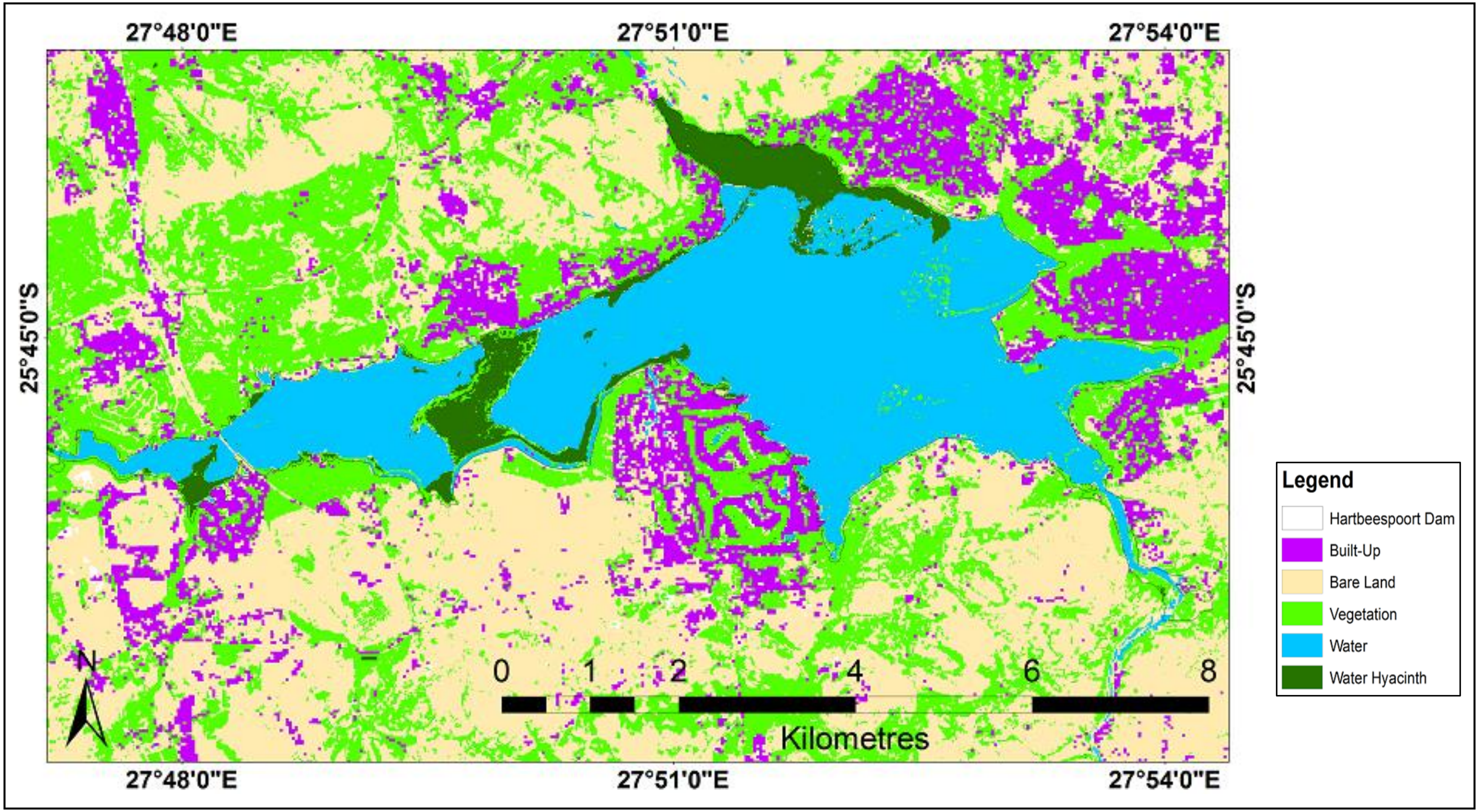


Figure 12: LULCC map of the Sentinel-2 MSI data using the RF classifier.

3.3.3 Accuracy assessment

The performance of the RF classifier was verified utilising the test data, which is 30% of the ground reference data for each image.

3.3.3.1 Landsat-8 OLI accuracy assessment

The RF classifier achieved an overall accuracy of 89.88% for the classification of the Landsat-8 OLI image (Table 5). The user's accuracies were all considerably high, ranging within the proximity of 90 % for all the LULCC, while the producer's accuracies ranged between 80.41% (water hyacinth) and 98.9% (water) with a *Kappa* coefficient value of 0.8134 (Table 5). The *Kappa* coefficient value indicates that the classifier performed 81.34% better than a chance classification would have performed. The user's accuracy for the water hyacinth class, 91.76%, is a resultant of only 7 pixels from the other LULCC being erroneously misclassified as water hyacinth. The producer's accuracy was greatly lower than the user's accuracy at 80.41%. This is due to 19 of the 97 water hyacinth pixels being classified as other LULCC in the study area.

3.3.3.2 Sentinel-2 MSI accuracy assessment

The overall accuracy of 93.13% was obtained for the classification of the Sentinel-2 MSI image (Table 6). The user's accuracies, too were similarly high, for the image varying between 87.93% (built-up) and 100% (water). Likewise, the producer's accuracies yielded considerably high results, with 89% (built-up) being the lowest producer's accuracy and 100% (water) the highest producer's accuracy. A user's accuracy of 95.70% was obtained for the water hyacinth class, due to four pixels being erroneously classified as water hyacinth, while the producer's accuracy was 91.75%, due to eight water hyacinth pixels being misclassified as vegetation. A *Kappa* coefficient value of 0.7751 was calculated from the imagery.

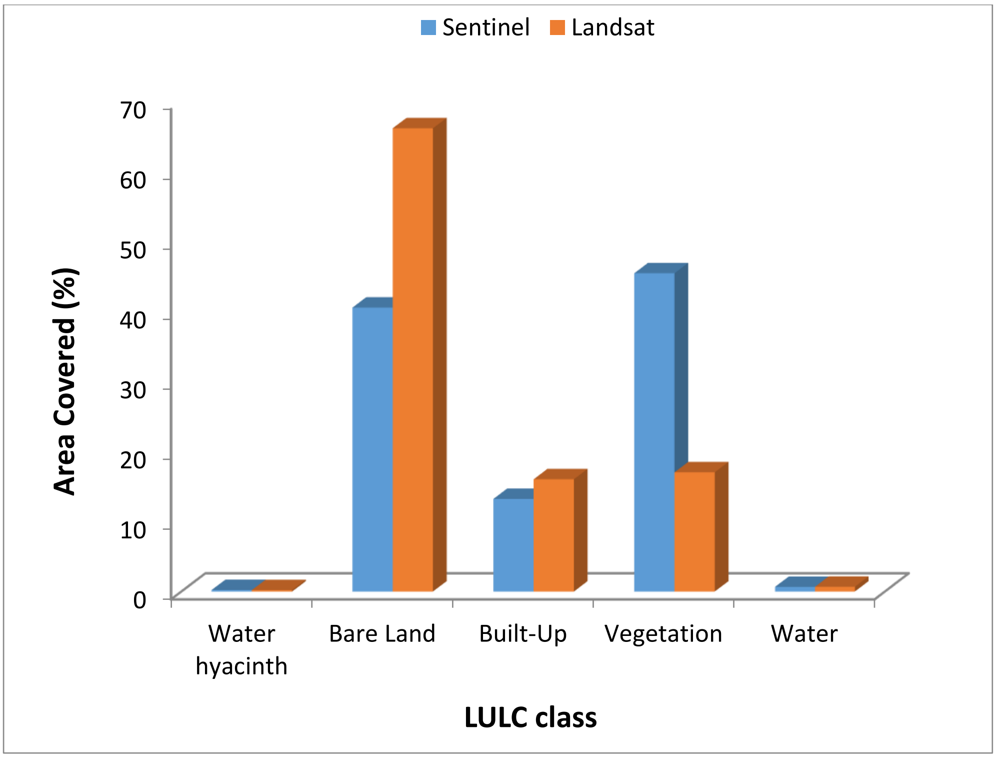


Figure 13: LULCC area cover in percentage.

Table 4: Area cover of LULCC in hectares and percentage for the Sentinel-2 MSI image and Landsat-8 OLI image.

	Landsat-8 OLI		Sentinel-2 MSI	
	ha	**%**	**ha**	**%**
Water hyacinth	468	0.2	492	0.21
Bare Land	154788	66.13	94820	40.51
Built-Up	37451	13.2	30897	16
Vegetation	39791	20.8	106312	42.62
Water Body	1568	0.67	1545	0.66

Table 5: Landsat-8 OLI confusion matrix.

	Water hyacinth	Bare land	Built-Up	Vegetation	Water	Sum	User's accuracy
Water hyacinth	**78**	0	0	7	0	85	**91.76**
Bare land	0	**360**	41	0	2	403	**89.33**
Built-Up	0	36	**365**	34	0	435	**83.91**
Vegetation	18	3	3	**397**	0	421	**94.30**
Water	1	0	0	0	**180**	181	**99.45**
Sum	97	399	409	438	182	1525	
Producer's accuracy	**80.41%**	**90.23%**	**89%**	**91%**	**98.90%**		
Overall accuracy	**89.88**						
Kappa	**0.8134**						

Table 6: Sentinel-2 MSI confusion matrix

	Water hyacinth	Bare Land	Built-Up	Vegetation	Water	Sum	User's accuracy
Water hyacinth	**89**	0	0	4	0	93	**95.70**
Bare land	0	**371**	48	0	0	419	**88.54**
Built-Up	0	25	**357**	24	0	406	**87.93**
Vegetation	8	3	4	**410**	0	425	**96.47**
Water	0	0	0	0	**182**	182	**100**
Sum	97	399	409	438	182	1525	
Producer's accuracy	**91.75%**	**92.98%**	**87%**	**94%**	**100%**		
Overall accuracy	**93.13**						
Kappa	**0.7751**						

3.4 Discussion

Water hyacinth is a major freshwater invader in South Africa and requires consistent monitoring for its effective management (De Groote *et al.*, 2003). The availability of data from new generation sensors, offering high-resolution data, provides a possibility for the mapping and monitoring of water hyacinth on regular bases. The main objective of this study was to investigate the performance of new generation multispectral sensors, Sentinel-2 MSI and Landsat-8 OLI, in the detection and mapping of water hyacinth and other LULCC in Hartbeespoort, located in the North West Province, RSA. This objective was probed through the employment of the RF algorithm for the classification of both the Sentinel-2 MSI and Landsat-8 OLI images.

The considerably high overall, users, and producers classification accuracies obtained in this study, for both images, demonstrated the capabilities of the sensors in distinguishing water hyacinth from other LULCC. The overall classification accuracy was significantly high for both images, 93.13 % (Sentinel-2 MSI) and 89.88 % (Landsat-8 OLI). These results may also have been favoured by low species diversity in the aquatic environment of the study area (Ongore, 2019). Furthermore, the reflective properties of water hyacinth differ from those of algal blooms and other aquatic plants; that is, water hyacinth reflects longer wavelengths than algal blooms, thus it is easily distinguishable from algae, attributing to the high overall accuracies achieved (Ongore, 2019).

The producers' accuracies for the water hyacinth class differed significantly between the images. The Sentinel-2 MSI image achieved a high producer's accuracy of 91.75 %, while that of the Landsat-8 OLI was relatively lower, at a moderate 80.41 %. This indicates that Sentinel-2 has a greater ability to delineate water hyacinth from other LULCC, namely vegetation when being compared to Landsat-8 OLI. The LULCC map produced from the

Sentinel-2 MSI imagery was able to detect and map water hyacinth as well as other aquatic vegetation present in the Hartbeespoort Dam (Figure 12). Sentinel-2 MSI's ability to delimit the invasive water hyacinth from other macrophytes can be attributed to its high spatial resolution and the inclusion of the red-edge band in its spectral library. The vegetation red edge band possesses great vegetation mapping capabilities, enabling the better classification of the Sentinel-2 MSI (Drusch, 2012; Ramoelo *et al*., 2015).

The classification of the two images clearly indicates the distribution of water hyacinth in the dam. The invasive macrophyte only accounts for 0.2%, a negatable contribution, of land cover on the classifications of the Sentinel-2 MSI and Landsat-8 OLI images. However, by placing emphasis on the Hartbeespoort Dam, the water hyacinth cover amounts to 29.85% and 31.84% of the dam on the Landsat-8 OLI and Sentinel-2 MSI imageries, respectively. The spatial extent of water hyacinth in the Hartbeespoort Dam is mainly augmented by anthropogenic influences. These include the daily discharge, approximately 600 million litres of untreated wastewater into the dam's catchment, nutrient-rich stormwater runoff, and pollution of upstream rivers through the informal utilisation of their waters (DWAF, 2007). These activities promote high levels of nutrients (N and P) which result in uncontrolled growth of water hyacinth (Bicudo, 2007; Téllez *et al*., 2008; Villamagna and Murphy, 2010; Patel, 2012).

There is a significant difference in the estimation of bare land and vegetation by the two images. Bare land cover was estimated to be 66.13% and 40.51% by the classifier for the Landsat-8 OLI and Sentinel-2 MSI images, respectively. This should not be the case as the images were acquired within a day of each other. The variations in the images can, however, be due to images having varying spatial, spectral and radiometric resolutions (Lillesand *et al*., 2015). Due to the differences in spatial resolution, the size of the smallest earth object captured by the sensors differed (Lillesand *et al*., 2015). This results in the recorded reflectance of objects (LULCC) being different for the sensors. Overestimation of pixel composition by the Landsat-8 OLI sensor resulted in an increased number of pixels being classified as bare land. Sentinel-2 MSI, recorded a high area cover of vegetation (45.42 %), while Landsat-8 OLI only showed 17 % vegetation cover. The 10 m spatial resolution of Sentinel-2 MSI is able to detect greater detail than that of Landsat-8 OLI, which is only 30 m. Thus small vegetation areas, up to 10 km^2, may have not been captured by the Landsat-8 OLI sensor, leading to the overestimation of pixel composition.

The use of Sentinel-2, for particularly mapping water hyacinth distribution is relatively lesser than that of Landsat-8 OLI. This lack of empirical data on the use of Sentinel-2 is due to the fact that Sentinel-2 MSI has only recently just been launched (Mutanga *et al*., 2012; Ramoelo *et al*., 2015; Dube *et al*., 2017; Thamaga and Dube, 2018). However, several authors have achieved plausible results in the delineation of other vegetation species using Sentinel-2 MSI data (Dube *et al*., 2017; Shoko and Mutanga, 2017). The authors attributed the success of their results to Sentinel-2's high spatial resolution of 10 m and the inclusion of the vegetation red edge bands. Landsat-8 OLI has improved mapping capabilities, it has better spectral, spatial, temporal and radiometric characteristics in contrast to its predecessors (Shekede *et al*., 2008; Dube *et al*., 2017; Thamaga and Dube, 2018). Radiometric improvements of Landsat-8 OLI equipped the sensor with spectral bands that can discriminate water hyacinth from other aquatic plant species in their vicinity (Thamaga and Dube, 2018). Dube *et al* (2017) achieved a significantly high overall accuracy of 95 %, mapping water hyacinth using Landsat-8 data. The authors utilised discriminate analysis, as well as partial least squares, discriminate analysis for the classification of the image.

Fine to medium spatial resolution imagery, such as those employed in this study, are freely obtainable, have the potential to map and monitor water hyacinth and can provide up-to-date information on its invasion. The utilisation of images from various sensors (Sentinel-2 MSI and Landsat-8 OLI) ensured the mapping of water hyacinth for two successive days. Up-to-date information about the distribution of water hyacinth on inland water bodies is crucial as it would aid water managers in understanding the dynamics involved in the movement, distribution pattern as well as the growth rate of the hyacinth. Water managers should utilise imagery from different sensors to map and monitor the ever-changing distribution patterns of water hyacinth, as was done in this study. The imagery acquired on two consecutive day's demonstrated the need for water hyacinth to be mapped on a continuous basis as it is not a stationary plant. The free-floating nature of the plant allows it to continuously change position as a result of water flow, wind direction and human interference. Weather records from WASA indicated that there were no extreme weather occurrences on the 26th and 27th October 2018. The wind data indicated that the dominant wind direction for the 27th of October was southeast at an averaged speed of 5.19 m/s. This coincides with the drastic change in the position of the water hyacinth from the 26th October to the 27th October 2018. The movement of the water weed can be subtle or noticeable, depending on water and wind movements as they are major influencers of its spatial distribution. Thus periods in between mapping water hyacinth distribution should be minimal to accurately demonstrate its distribution over time. Satellite sensors have fixed temporal frequencies, thus mapping water hyacinth should be done utilising sensors that have revisit periods that overlap with one another. This would ensure that the water hyacinth distribution is monitored more regularly and its changing distribution patterns documented. This would enable better management of the plant.

3.5 Conclusion

This study aimed to examine the ability of Sentinel-2 MSI and Landsat-8 imagery in mapping the spatial distribution of water hyacinth in the Hartbeespoort Dam. The following conclusions were drawn from this work:

- Both sensors, Sentinel-2 MSI and Landsat-8 OLI, can be utilised in the accurate monitoring and mapping of water hyacinth.
- The spatial distribution of water hyacinth was satisfactorily detected and mapped at high accuracies (89.88% and 93.13% overall accuracies) using the Landsat-8 OLI visible and NIR bands and Sentinel-2 MSI visible, vegetation red-edge and NIR bands, respectively.
- Sentinel-2 MSI slightly surpassed Landsat-8 OLI in mapping the water hyacinth. This is attributed to the fact that Sentinel-2 MSI has a greater spatial resolution (10 m) compared to that of Landsat-8 OLI (30 m).
- Due to a greater spatial resolution of 10 m, Sentinel-2 MSI was also able to detect and differentiate water hyacinth from other aquatic vegetation in the dam, which the coarser 30 m spatial resolution of Landsat-8 OLI was unable to do.

The introduction of free and readily available satellite sensors, with a wide swath-width (large coverage), high temporal, spatial, spectral and radiometric resolutions is important in promoting the advancement and utilisation of remote sensing technologies for the management of water hyacinth. New generation multispectral sensors, Sentinel-2 MSI and Landsat-8 OLI, with medium spatial resolutions, are a significant source of timely data. Their data can be acquired and used for mapping and monitoring the spatial distribution, and propagation rates of water hyacinth bypassing the environmental and atmospheric conditions that limit conventional field-based monitoring approaches.

CHAPTER FOUR

EVALUATING THE SUCCESS OF THE PHYSICAL CONTROL OF *Eichhornia crassipes* IN THE HARTBEESPOORT DAM of SOUTH AFRICA: A REMOTE SENSING APPROACH.

4.1 Introduction

Water hyacinth has infiltrated the waters of tropic and sub-tropic regions globally (Téllez *et al*., 2008; Patel, 2012). Environmental and climate changes due to economic development and the growing numbers of the human population will enable the proliferation of water hyacinth to higher latitudes (Patel 2012). The presence of water hyacinth in water is perceived as a negative globally, including in its native Brazilian waters (Bicudo *et al*., 2007; Patel, 2012; Thamaga and Dube, 2018). The negative impacts of water hyacinth are experienced economically, ecologically and socially (Culliney, 2005; Villamagna and Murphy, 2010; Hill and Coetzee, 2017). The control and eradication of water hyacinth have proven to be a difficult undertaking once it's established (Villamagna and Murphy, 2010; Hill and Coetzee, 2017). The control of the submerged macrophyte is extremely challenging due to the weeds ability to rapidly and vastly spread, and the high costs associated with the control (Villamagna and Murphy, 2010; GEAS, 2013;).

Water hyacinth causes substantial annual economic losses (Villamagna and Murphy, 2010; Patel, 2012; GEAS 2013). These losses are a combination of control costs, lost revenue and infrastructure repair costs (Culliney, 2005). Billions of dollars are spent by countries worldwide in an attempt to control the spread of water hyacinth, with the highest goal being to completely eradicate it (van Wilgen *et al*., 2001; Culliney, 2005). van Wilgen *et al* (2001) estimated that annual control costs of water hyacinth, alone, are more than $700 million in South Africa. This figure increases considerably to $12 billion when coupled with losses and damages to infrastructure (van Wilgen *et al*., 2001). Water hyacinth has vast ecological impacts (Patel, 2012; Villamagna and Murphy, 2012). Water hyacinth changes natural habitats by reducing biodiversity, decreasing dissolved oxygen levels, decreasing water quality, altering ecological and hydrological processes, changing soil chemistry, simplifying food webs and increasing eutrophication (Culliney, 2005; Patel, 2012; Thamaga and Dube, 2018). Biodiversity loss from water hyacinth invasion is a result of the weed suppressing the growth of indigenous plants, by out-competing and smothering them due to its rapid growth (Villamagna and Murphy, 2010; Patel, 2012; GEAS, 2013). Water hyacinth decreases dissolved oxygen levels in water by decreasing oxygen production by algae and preventing the transfer of oxygen from the air to the water surface, as a result of the large water hyacinth mats formed on the water (Villamagna and Murphy, 2010). The social impacts of water hyacinth are due to the weed blocking waterways and their apparent encroachment of waters (Patel, 2012). This causes a reduction in agriculture, recreation and aquaculture as the water becomes inaccessible (Patel, 2012).

Water hyacinth, although its presence in environments is perceived as a negative, has some positive impacts (Villamagna and Murphy, 2010; Patel, 2010). The speculated areas of water hyacinth use are vast and plenty (Patel, 2012). Water hyacinth can be utilised for wastewater treatment, electricity generation, animal fodder, medicines, agriculture, as a substrate for bioethanol and biogas production, and industrial use (Patel, 2012). However, the negative impacts of water hyacinth in environments have driven initiatives for the control of water hyacinth by governments and environmentalists globally.

Controlling water hyacinth infestations can be performed biologically, chemically or physically, or by combining either of the two control approaches (Villamagna and Murphy, 2010; Patel, 2012). Bio-control of water hyacinth has been the most preferred control method throughout the world (Williams *et al*., 2007). It owes its utilisation to being the most environmentally friendly, non-labour intensive and cost-effective method in controlling water hyacinth (Culliney, 2005; Patel, 2012). Biological control entails introducing water hyacinths' natural enemies, pathogens and allelopathic plant extracts into infested environments (Patel, 2012). The effects of this method are only visible after a long time, thus it is often employed as a long-term measure of control (Hill and Olckers, 2007). Though, Williams *et al* (2007) observed the rapid reduction of the water hyacinth in Lake Victoria following the implementations of bio-control measures.

Chemical control is the least favoured method of water hyacinth control as its repeated use is harmful to the environment and costly (Villamagna and Murphy, 2010; Patel, 2012; Hill and Coetzee, 2017). It uses herbicides which are harmful to the environment, when used excessively or are incorrectly applied (Villamagna and Murphy, 2010; Patel, 2012). Although it has been an effective method of control of the weed worldwide, its use is limited

(Villamagna and Murphy, 2010; Patel, 2012;). This is because it has adverse environmental impacts, including the degradation of water quality and the endangerment of aquatic life (Patel, 2012).

Physical control, on the other hand, often follows biological control efforts (Villamagna and Murphy, 2010). Physical control of the weed can be done manually, but~~,~~ at times requires the use of machinery and is highly laborious (Patel, 2012). These factors make it the most expensive approach for controlling water hyacinth (Villamagna and Murphy, 2010; Patel, 2012). This method involves harvesting the weed (manually or mechanically) and draining water bodies (Villamagna and Murphy, 2010; Patel, 2012). Physical control of water hyacinth is an effective method as its results can immediately be observed (Villamagna and Murphy, 2010; Patel, 2012). However, water hyacinth infestations soon return after physical removal utilising machinery, due to the shredded water hyacinth regenerating in other areas (Culliney, 2005; Villamagna and Murphy, 2010; Patel, 2012).

All three of these control methods have previously been utilised in the control of water hyacinth in the Hartbeespoort Dam, at times conjointly (van Wilgen, 2001). Although, the physical extraction of the weed has intensively been used for invasion control in South Africa since 1995 and has surpassed the use of the other control methods (van Wilgen, 2001). The main tributary of the Crocodile River, a river which flows directly into the Hartbeespoort Dam, is the Jukskei River which flows from the Gauteng Province, carrying in its flow waste from three Metropolitan areas; Johannesburg, Ekurhuleni and Tshwane (DWAF, 2007; Waaigras, 2015). All the waste that is carried along with the flow of the Jukskei is ultimately deposited into the Hartbeespoort Dam (DWAF, 2007; Waaigras, 2015). The waste consists of litter, sediments, and sewage, all of which are detrimental to the aquatic ecosystem in the dam (DWAF, 2007; Waaigras, 2015). Sewage spills, from waste treatment plants upstream, deposit nutrient-rich faecal matter into the dam (Waaigras, 2015). The faecal deposits are rich in N and P. These nutrients promote the eutrophication in the dam as they encourage the growth of water hyacinth and algal blooms.

The Water Act of 1998 stipulates the establishment of Resource Management Plans for the various catchment zones in South-Africa and the formation of a Resource Management Agency, combining public and private stakeholders (Fanie, 2016). This legislative stipulation was the basis for the formation of the Hartbeespoort Resource Management Plan (Fanie, 2016). The year 1995 saw the inception of the *Working for Water* programme; the programme deals with the physical removal of invasive and alien plant species and has created thousands of jobs since its formation (van Wilgen, 2001; Hill and Coetzee, 2017). Monies amounting to $100 million were spent on the physical control of invasive plants by the *Working for Water* programme in a period of 5 years (van Wilgen, 2001). In 2005, the Minister of Water and Sanitation, Buyelwa Patience Sonjica, launched the Hartbeespoort Dam Remediation Programme (HDRP) (Fanie, 2016). HDRP, colloquially known as the *Harties Metsi A Me* programme, which directly translates to, "My Water", is a biological remedial programme for the dam which was operational for a little more than a decade (Fanie, 2016). The programme was aimed at addressing the eutrophication and improving water quality in the dam in two distinct phases (DWAF, 2007). The first phase involved the mechanical removal of water hyacinth by the *Working for Water* programme while the second phase entailed the treatment and removal of bulk phosphate (DWAF, 2007). Water hyacinth distribution is highly influenced by temperatures and nutrient growth (DWAF, 2007). Harding (2004) found that the proliferation of water hyacinth is increased during the summer months when water temperatures are high, stormwater run-off is increased and solar radiation is optimal.

With the advent of remotely sensed data, research into the changes of land cover can be commissioned at low cost, in less time, and with better accuracy (Forkuo and Frimpong, 2012; Thamaga and Dube, 2018). Remote sensing is ideal for monitoring water hyacinth change in distribution and spatial extent. Remote sensing has varying spatial resolutions, fixed revisit periods, the ability to access areas which are not easily accessible and spectral abilities beyond the visible region (Palmer *et al*., 2014). Satellite remote sensing has been widely used as an effective and efficient means to monitor land cover patterns at a large geographic extent across the world due to the synoptic view it offers (Thamaga and Dube, 2018).

4.2 Materials and Methods

4.2.1 Study Area

The Hartbeespoort Dam is situated in Hartbeespoort town in the North West Province. The town is located west of Rustenburg, north of Johannesburg and east of Pretoria (Figure 14). The Hartbeespoort area is arid to semi-arid (DWS, 2016). The climate in the area has generally been recognised as a dry type (DWS, 2016). Hartbeespoort and its surrounding towns are typically warm and it receives most of its rainfall during the summer months (between December and March). This is not always the case in the area due to orographic precipitation, microclimate as a result of the dam, in addition to regional thunderstorms (DWS, 2016). Hence the rainfall in the area is unpredictable and unreliable, often fluctuating widely around the annual mean. The area receives an annual rainfall of 500 mm to 680 mm (Harding, 2004; Venter, 2004)

The construction of the dam commenced in the early 1900s and was completed in 1925 (Harding, 2004; Venter, 2004). The dam was constructed to serve as an impoundment for irrigation water and to supply potable water to surrounding communities (Harding, 2004; Venter, 2004). The Hartbeespoort Dam is situated within the Crocodile River catchment, being fed by the Crocodile River from the south and additionally flowing north into the Crocodile River (Harding, 2004).

Hartbeespoort Dam covers approximately 18.83 km^2 with a maximum depth of 45.1 m (Venter, 2004). The dam is now not only a natural resource but a major tourist attraction utilised for recreational activities (Harding, 2004; Venter, 2004). The areas around the edges of the dam consist of agricultural land, recreational facilities, industrial land, privately owned businesses and residential areas (Harding, 2004; Venter, 2004).

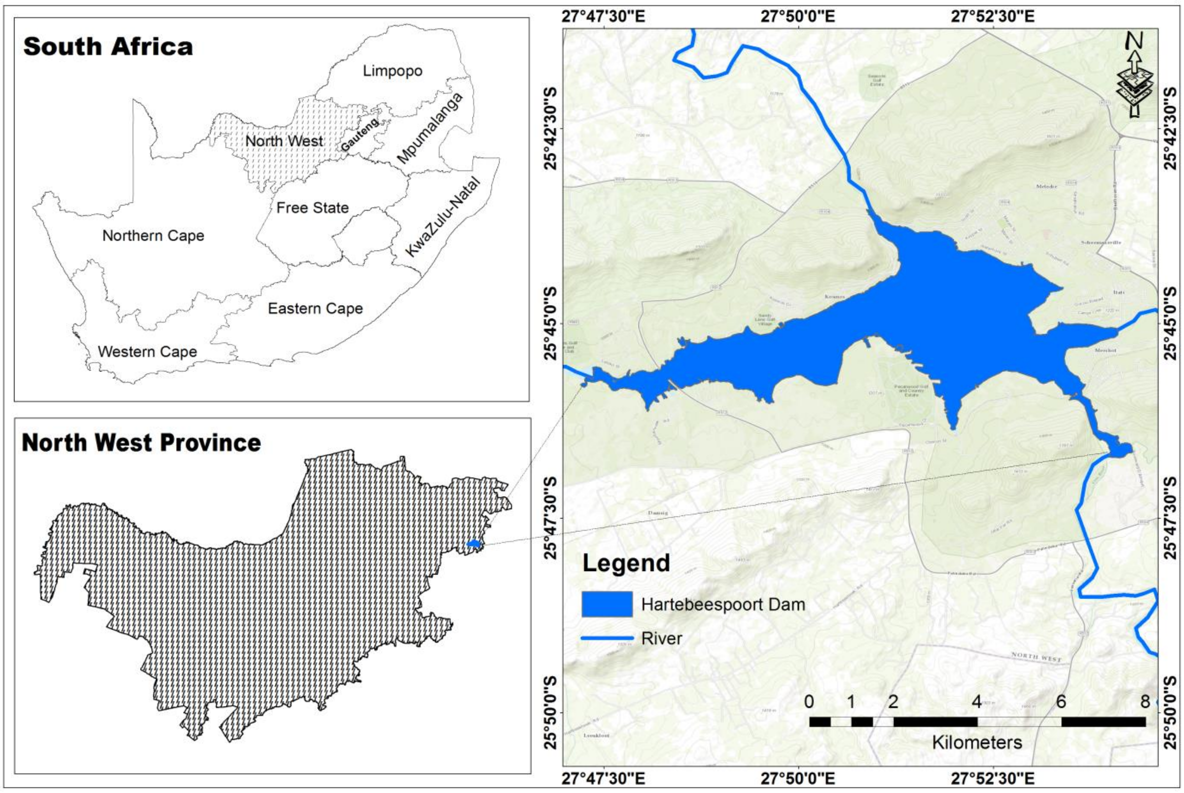


Figure 14: Map of Hartbeespoort dam in relation to the country and North West province.

4.2.2 Remote Sensing Data Acquisition

The availability of archived remotely sensed data provides a platform for the spatiotemporal analysis of aquatic weed infestations (Dube *et al*., 2014; Shekedede *et al*., 2008; Thamaga and Dube, 2018). This study made use of four Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery obtained freely from the USGS Earth Explorer portal, http://earthexplorerusgs.gov/. Images pairs of two months, with 0% cloud cover, were acquired for the years 2007 and 2009 (Table 7). The first images were purposely selected to correspond with the commencement of active removal of water hyacinth in Hartbeespoort Dam, 5 January 2007 and 31 March 2009. The latter were downloaded to represent water hyacinth infestation post-physical control initiatives, 18 September 2007 and 26 November 2009.

The Landsat 7 ETM+ satellite was launched by NASA in 1999. Thus Landsat 7 ETM+, along with data from previous Landsat missions, has archived, real-time and historical images which are available and accessible free of charge (Dube *et al*., 2014). The availability of historical images provides great prospects for spatiotemporal mapping and monitoring of aquatic weeds (Dube *et al*., 2014; Shekede *et al*., 2008; Thamaga and Dube, 2018). Landsat 7 ETM+ is an along track (whisk broom) scanner with a medium spatial resolution sensor of 30m (Chastain *et al*., 2019). The sensor has eight multispectral bands and sensing capabilities between wavelengths of 0.45 – 12.50 µm (Table 8). The sensor's revisit period is 16 days and it also has a relatively vast swath width of 185 km. These specifications are more suited for mapping water hyacinth in large areas, which are preferably isolated from other aquatic vegetation. This is because this sensor does not have the spectral capabilities to separate water hyacinth from other vegetation and is rather coarse for utilisation to monitor water hyacinth in small water bodies (Thamaga and Dube, 2018). Furthermore, the availability of historical data for Landsat missions makes it suitable to observe historical trends in the distribution of water hyacinth.

Table 7: Landsat 7 ETM+ image acquisition information for monitoring the physical control of water hyacinth in the dam.

Year	Acquisition date	Path	Row
2007	05 January 2007	170	78
	18 September 2007	170	78
2009	31 March 2009	170	78
	26 November 2009	170	78

Table 8: Landsat7 ETM+ sensor specifications.

Landsat ETM+ 7 Bands	Wavelength (μm)	Resolution (m)
Band 1 - Blue	0.45 - 0.52	30
Band 2 - Green	0.52 - 0.60	30
Band 3 - Red	0.63 - 0.69	30
Band 4 - Near Infrared	0.77 - 0.90	30
Band 5 - Short-wave Infrared	1.55 - 1.75	30
Band 6 - Thermal Infrared	10.40 - 12.50	60
Band 7 - Short-wave Infrared	2.09 - 2.35	30
Band 8 - Panchromatic	0.52 - 0.90	15

4.2.3 Image Pre-processing

Landsat 7 ETM+ images recorded after 2003 have scan line errors due to the sensor's scan-line corrector malfunctioning (Markham *et al*., 2004; Thamaga and Dube, 2018; Chastain *et al*., 2019). This resulted in the loss of 22 % of the data captured in a normal ETM+ scene (Thamaga and Dube, 2018). Prior to the images being pre-processed, the scan line errors (present on all four images) had to be repaired. The scan line errors were rectified utilising the "landsatGapFill" tool of the ENVI 5.4 toolbox.

Thereafter the images were pre-processed to atmospherically correct surface reflectance values and minimise atmospheric additives such as noise and haze (Lu *et al*., 2004). The pre-processing of the images was executed using the FLAASH model. The images were atmospherically corrected using FLAASH subsequent to being radiometrically calibrated to top-of-atmosphere (TOA) radiance values (Shalby and Tateishi, 2007; Chastain *et al*., 2019).

All images were acquired from a single sensor and therefore had the same geometric extent. Image-to-image coregistration of the images was thus not necessary. The images were additionally subset utilising a shapefile of the study area, ensuring that they have the same size (area cover) and overlaid precisely.

4.2.4 Ground Reference Data

Ground reference data for the LULCC in the study area were obtained using the Landsat 7 ETM+ true images. The true colour images are obtained from a 3, 2, 1 RGB band combination. The LULCC in the study area were discriminable and five LULCC selected. These included; Water hyacinth, Bare land, Built-Up, Vegetation and Water (Table 9).

Reference samples, of no less than 200 points, were obtained for each of the LULCC by creating ground reference points (shapefiles) of the LULCC on all the images (Table 11). Reference data had to be obtained from each image as the distribution of water hyacinth and the other LULCC classes is expected to have changed over the period of the study. Reference samples are acquired for the extraction of spectral signature characteristics of the different LULC classes. Thus the reference points had to be precisely placed in pure pixels to avoid spectral and pixel confusion during the classification process. A large number of samples were required for each LULCC on each of the images to ensure high classification accuracy (Mesev, 2010). The reference samples were delineated utilising ArcGIS software.

The delineated reference samples of each image were subsequently randomly split into 70% training data and 30% validation data using an R programming language in the R statistic interface (Table 10). The training data sets were used to classify the images and the validation dataset to test the accuracy of the classification.

Table 9: Land use and land cover classification schema

LULCC	Code	Attributes
Water Hyacinth	WH	*Eichhornia crassipes* (water hyacinth) only.
Bare Land	BL	Exposed rock and land without any vegetation.
Built-Up	BU	Residential, industrial (factories) and commercial structures.
Vegetation	V	Forests, agricultural crops, grasses, and trees.
Water	W	Dams, rivers, streams, and reservoirs.

Table 10: Landsat7 ETM+ training and test dataset specification for the 05-Jan-07, 18-Sep-07, 31-Mar-09 and 26-Nov-09 Landsat 7 ETM+ images.

	05-Jan-07		18-Sep-07		31-Mar-09		26-Nov-09	
LULCC	Training	Test	Training	Test	Training	Test	Training	Test
Water Hyacinth	140	60	357	153	280	120	350	150
Bare Land	210	90	289	124	245	105	385	165
Built-Up	294	126	189	81	210	90	196	84
Vegetation	280	120	301	129	251	110	247	106
Water	280	120	189	81	231	99	259	111

4.2.5 Image Classification

Image classification is a method in which pixels with similar digital numbers (DN) are grouped together to form a single class (Lillesand *et al*., 2015). The spectral properties of the resulting groups distinguish the LULCC from each other (Lillesand *et al*., 2015). This study employed the RF algorithm for the classification of all the images into the identified LULCC available in the study area (Table 9). The classes were grouped (classified) according to the spectral signatures developed from 70 % of the ground reference data. The classification of the images was performed using the *randomForest* classification package in R statistical software 3.1.3 and ENVI 5.4 software respectively.

4.2.5.1 Random Forest Classifier

Random forest machine learning algorithm is a non-parametric supervised classifier that was developed by Breiman (2001). According to Adam *et al.* (2017), RF was developed to increase the CART accuracy Breiman (2001) achieved this by introducing the bagging operation (bootstrap operation), where numerous decision trees are combined and all contribute a vote towards the allocation of a class to pixel and, ultimately the overall classification of the image (Breiman, 2001; Adam *et al*., 2017). Several classification trees (*ntree*) develop from the bootstrap samples of the input data; the bootstrap amounts for 2/3of the input data which is commonly known as "in-bag" data (Breiman, 2001). The remaining 1/3 of the original data is referred to as the out-of-bag (OOB) samples. The OOB samples are employed to measure the role of every single variable in the final classification model as well as in approximating the misclassification error (Breiman, 2001; Adam *et al*., 2017). Thereafter random subsets of the predictive variable (*mtry*) are used to randomly split the trees. The default *mtry* value is a product of the square root of the total number of variables unless otherwise specified by the user (Breiman, 2001). The trees are allowed to grow to their fullest extent without being trimmed or clipped to ensure that the nodes reach purity (Breiman, 2001). *Ntree* and *mtry* are the only parameters required by the RF algorithm. This makes the RF algorithm easy to utilise as only two parameters need optimisation (Breiman, 2001).

The random forest classifier additionally provides various measurements of variable importance as part of the classification process (Breiman, 2001). The mean decrease in accuracy is one such measurement of variable importance and it indicates the role of every band in the classification process.

In this study, the optimisation of *mtry* and *ntree* parameters was done using a *randomForest* library of R statistical packages v3.4.1. A grid search approach based on the OOB error estimate was used to find the optimum combination of *mtry* and *ntree* parameters (Breiman, 2001; Thabeng *et al*., 2019).

4.2.5.2 Accuracy Assessment

Accuracy assessment examines the performance of classification technique in the allocation of pixels to LULCC based spectral signatures, which were defined by the training dataset. The test data (30% of the ground reference data) was utilised to test the performance of classification by the RF algorithm. Confusion matrices were then generated to compute the overall accuracy, producer's accuracy, and user's accuracy, by comparing the reference imagery with the class assigned by the classifier (Adam *et al*., 2017).

Overall accuracy is the ratio, represented as a percentage, between the number of the total sum of the test data and the number of the accurately classified test data, while producer's accuracy depicts the number of accurately classified test samples per LULC. User's accuracy expresses the possibility of a test sample belonging to a particular LULCC and that the classification technique correctly assigned it to such a class.

4.2.6 Change detection

Change detection analyses are often applied on multi-temporal datasets to define the extent, nature, rate of land cover change, and spatial pattern over space and time (Forkuo and Frimpong, 2012). Singh (1986) defined change detection as the process of identifying changes in the state of an object or phenomenon by observing images at different times. There are several statistical and mathematical algorithms available to estimate change using remote sensing data (Singh, 1986). The change detection algorithms include but are not limited to vegetation index rationing, principal component analysis (PCA), image differencing and post-classification comparison (Singh, 1989).

The change detection statics in ENVI 5.4 utilise the post-classification comparison algorithm to estimate the change in an area (Hegazy and Kaloop, 2015). Thus the change detection statistics were utilised in this study. The change detection statistics require the input of two images, an initial state image, and a final stage image. The two images are utilised to compute the change statistics based on a class for class comparison of the LULCC which were classified. That is, the post-classification comparison identifies classes where pixels in the final state image have changed from the initial state image. The change detection statistics were produced between the image pairs for 2007 (05 January and 18 January) and 2009 (31 March and 26 November) respectively.

4.3 Results

4.3.1 Random forest Optimisation

The tuning of the RF parameters was done using the 10- fold cross-validation method. RF parameters are trained to determine the best parameter pair for the classification of the images (Figure 15). The variables had to be optimised for each of the Landsat7 ETM+ images. The OOB errors of the images, in chronological order from the image acquired on the 5th January 2007 onwards, were 1.25%, 0.75%, 3.14%, and 0.42%, respectively (Figure 15). The image captured on the 26th November 2009, achieved the lowest OOB error, 0.42%, obtained from a *mtry* and *ntree* combinations of 6 and 3500. The OOB errors of 1.25% and 0.75% were achieved for the 2007 images, as a result of *mtry* and *ntree* parameter combinations of 2 and 500 and 2 and 2000, respectively. The 2009 march image had a low error of 3.14% from parameter combinations of 2 and 3500.

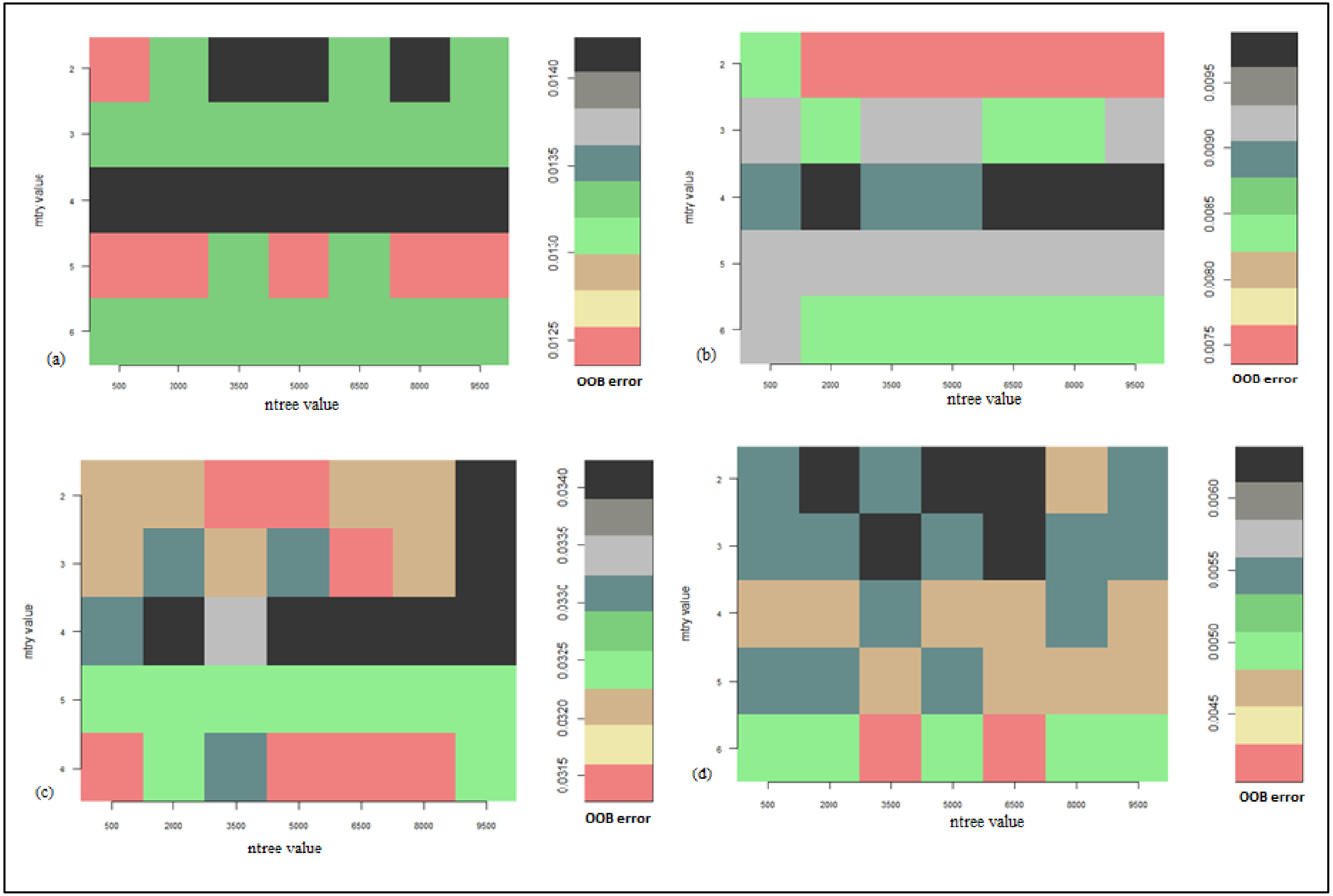


Figure 15: Random Forest optimisation of parameters (*mtry* and *ntree*) for the Landsat7 ETM+ imagery (a) 5 January 2007 image optimisation (b) 18 September 2007 image optimisation (c) 31 March 2009 image optimisation (d) 26 November 2009 image optimisation.

The mean decrease in accuracy illustrated the importance of each band in mapping the LULCC of the study area. The bands with the highest mean decrease in accuracy for each of the Landsat7 ETM+ imagery are indicative of the most important bands for the classification of the images. The mean decrease in accuracy showed that the bands of importance differed for each of the images, even though the images were acquired by the same sensor (Figure 16). The important bands for the 2007 January image are the visible bands (0.45-0.69µm) and the NIR band (0.77 - 0.90µm). Notably, NIR (0.77 - 0.90µm) had the highest mean decrease in accuracy for the September 2007 data, while the red (0.63 - 0.69µm) and blue (0.45 - 0.52µm) bands of the visible region of the spectrum had the highest decrease in mean accuracy for the March 2009 image. Finally, the mean decrease in accuracy illustrated that NIR (0.77 - 0.90 µm) is an important variable in the classification of the November 2009 image.

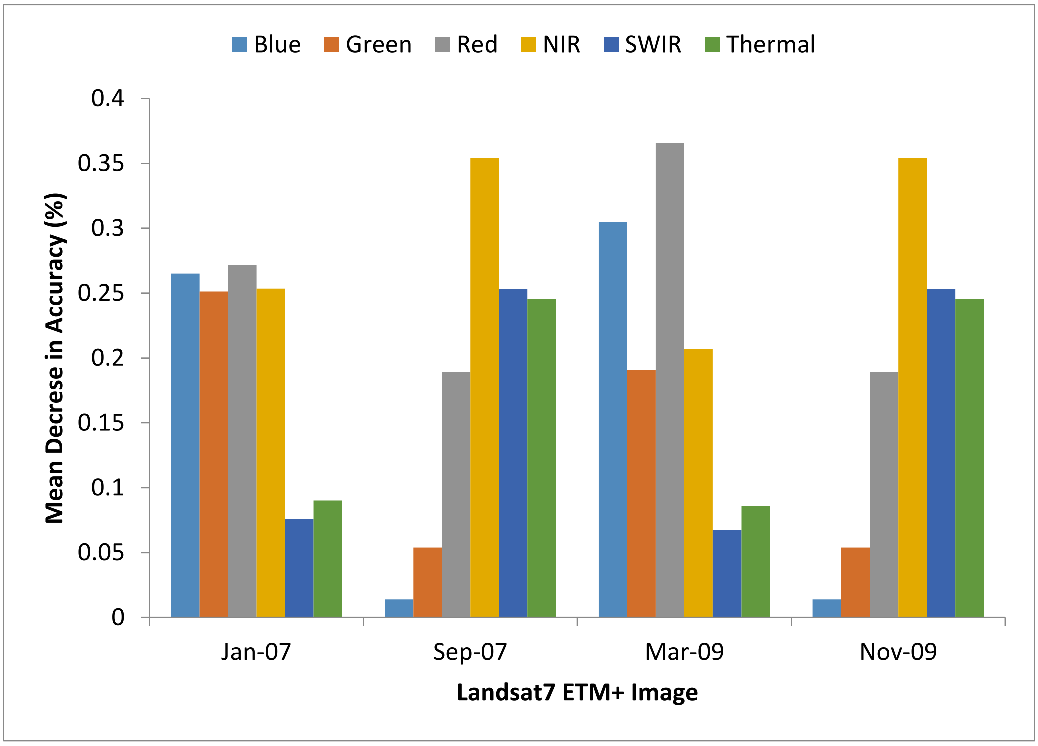


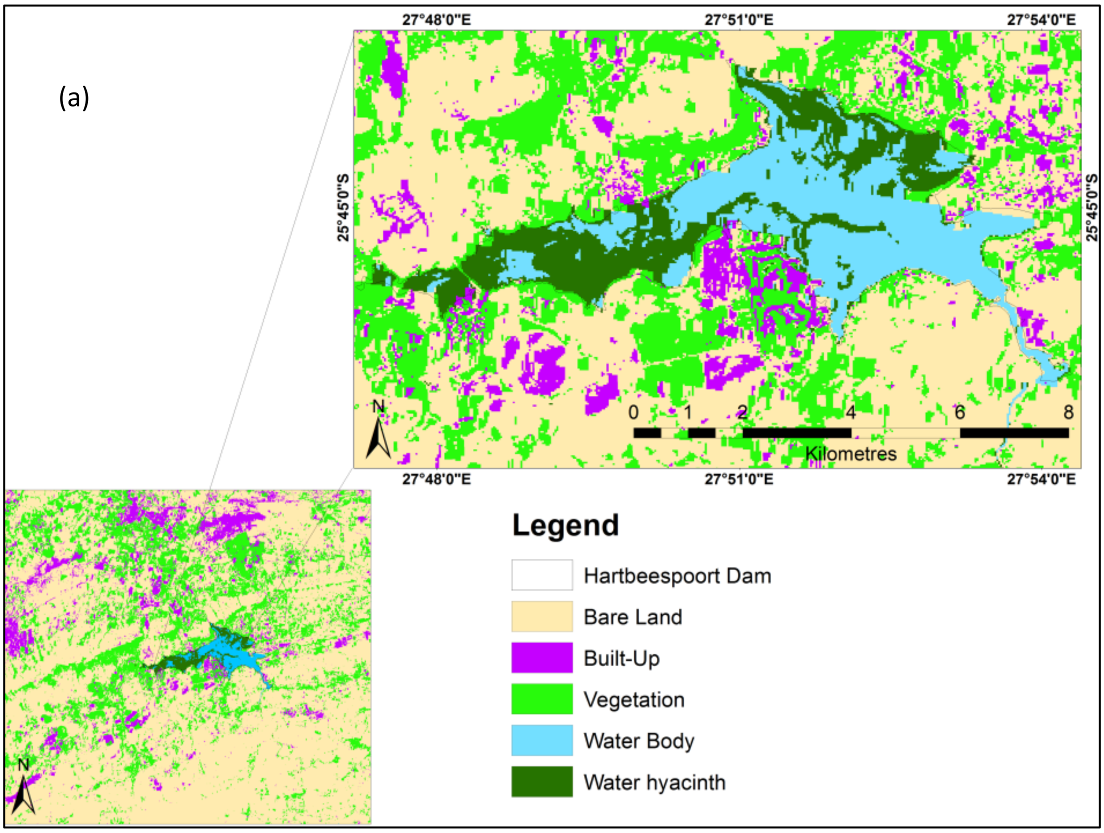
Figure 16: Measuring the importance of the Landsat7 ETM+ bands in classification process using Mean Decrease in Accuracy score for the four Landsat7 ETM+ images.

4.3.2 Image classification

Image classification was performed to show the change in the distribution and proliferation of water hyacinth, during the periods of active physical control of water hyacinth and post the implementation of physical control efforts (Figure 17 and Figure 18). The delineation of the LULCC displayed the variations in the extent, abundance, and pattern of water hyacinth between the 2007 (Figure 17) and 2009 (Figure 18) image pair, respectively. Water hyacinth covered more than ¾ of the dam in January 2007, covering 78.57% of the dam. This value declined in the subsequent September 2007 image, to 46.02%. This was a total loss of 32.55% of the initial water hyacinth in an eight-month period. In 2009, water hyacinth initially covered close to half of the dam (48.18%) in March and declined by ~20% in November to 28.20%.

The LULCC map of January 2007 indicates that 858 hectares of the 234 066 hectares of land were covered by water hyacinth. It further illustrated that bare land was the most abundant land cover class, accounting for 175 940 hectares of the entire study area, followed by vegetation covering 45685 hectares. On 18th September 2007, the extent of water hyacinth had decreased by 0.11%, to account for only 613 hectares of the entire study area. This was a reduction of 245 hectares. Bare land was still the most dominate LULCC, covering an increased area of 85.97% of the study area. This increase in bare land resulted in a decrease of vegetation cover by 13.36%, which amounted to 32 216 hectares (Table 11). In March 2009, water hyacinth covered 0.29% of the entire area. As a result of the physical removal of the invasive weed, the value decreased by 0.10%, changing from a distribution of 688 to 465 hectares. Contrary to the 2007 images, the distribution of vegetation increased while that of bare land decreased from March to November 2009 (Table 11).

The LULCC maps generated from the images captured during the active physical control of the water hyacinth have a higher area cover of water hyacinth, as compared to those captured months later when the removal of hyacinth had ceased. In all the images the bare land was the most dominant LULCC, followed by vegetation, with built-up showing a steady increase throughout the period of the study and water levels fluctuating.



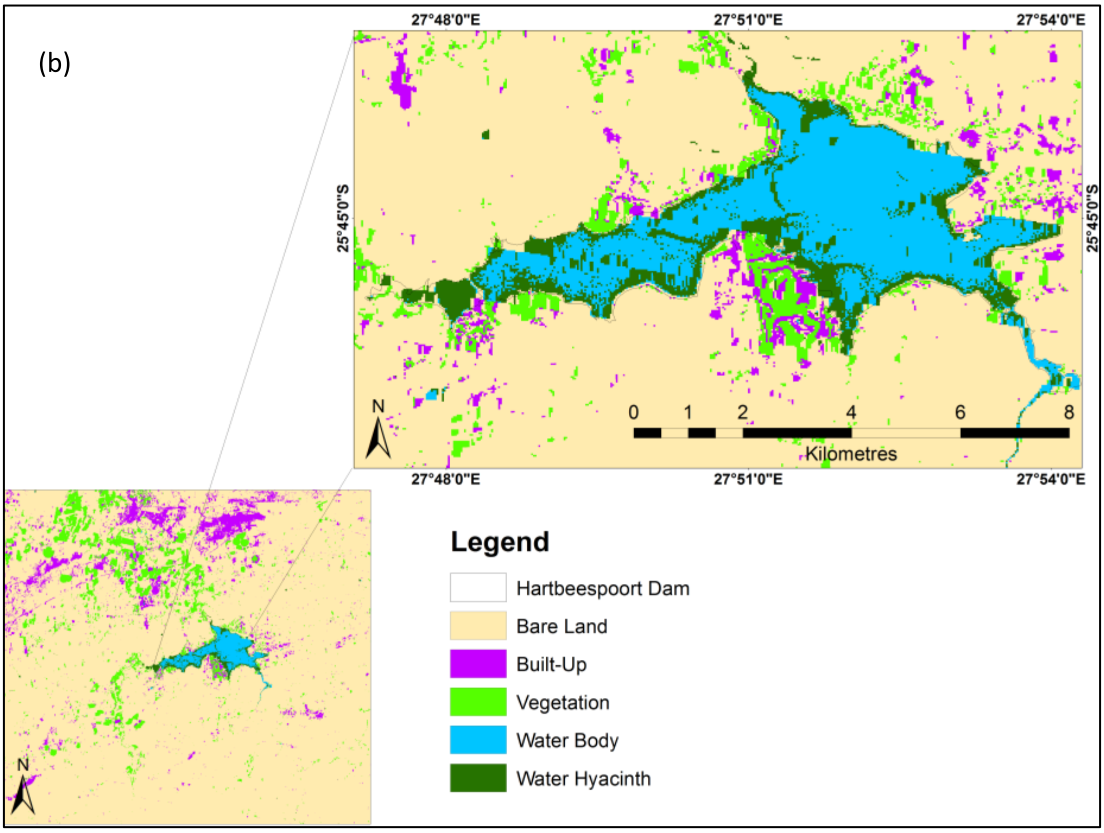
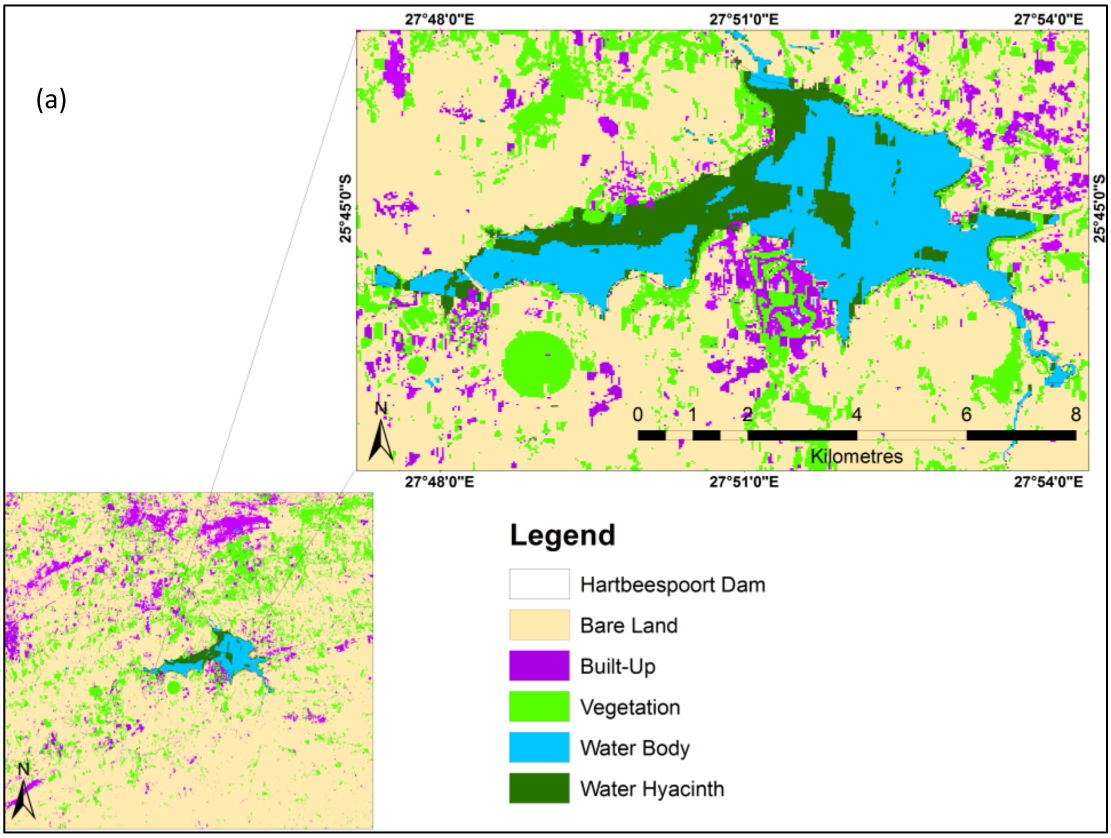


Figure 17: Classification of Landsat7 ETM+ imagery using the RF classifier for 2007 (a) 5 January 2007 (b) 18 September 2007.



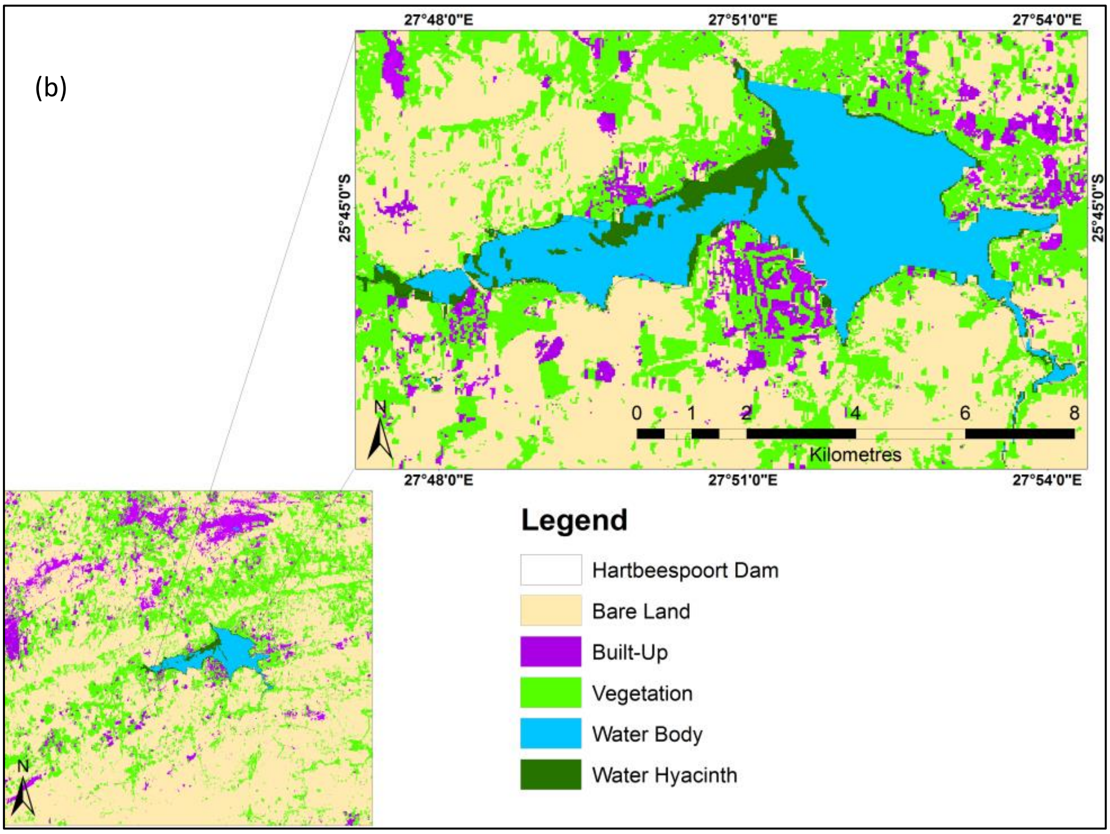


Figure 18: Classification of Landsat7 ETM+ imagery using the RF classifier for 2009 (a) 31 March 2009 (b) 26 November 2009.

4.3.3 Accuracy assessment

The performance of the RF classifier was verified utilising the test data, which is 30% of the ground reference data, respectively for each image (Table 12). The overall accuracies obtained from the classification of the images are relatively high, with values ranging from 83.42 to 90 %. Water hyacinth had moderate to high producer's accuracies, with the lowest value of 75% is that of the classification of the September 2007 image, whereas the classification of the March 2009 image yielded the highest accuracy of 96.67. The water hyacinth amounted to < 1% cover of the study area while bare land was consistent in being the most abundantly distributed LULCC throughout the duration of the study (Figure 19). While, water hyacinth prevalence in the study area fluctuated, as a result of the physical removal of the weed and its subsequent reoccurrence post-physical removal. Water had very high accuracies overall, ranging between 93.64 and 100%, this indicates that the water class did not share its spectral signature with any other class.

The Kappa Coefficient values for the study sites showed a higher rating ranging from 0.78 to 0.88. According to Landis and Koch (1977) a Kappa Coefficient value of between 0.61 – 0.80 is "substantial" and that of between 0.81 – 1.00 is "almost perfect".

Table 11: LULCC area cover in hectares and percentages.

	2007				2009			
	Before		After		Before		After	
LULC	%	ha	%	ha	%	ha	%	ha
Water hyacinth	0.36	858	0.25	613	0.29	688	0.19	465
Bare Land	72.95	175940	85.97	207348	75.23	181434	67.08	161796
Built-Up	4.35	10492	4.69	11305	5.29	12758	5.53	13331
Vegetation	18.94	45684	5.58	13468	15.66	37758	23.56	56825
Water	0.45	1092	0.55	1332	0.59	1428	0.68	1649

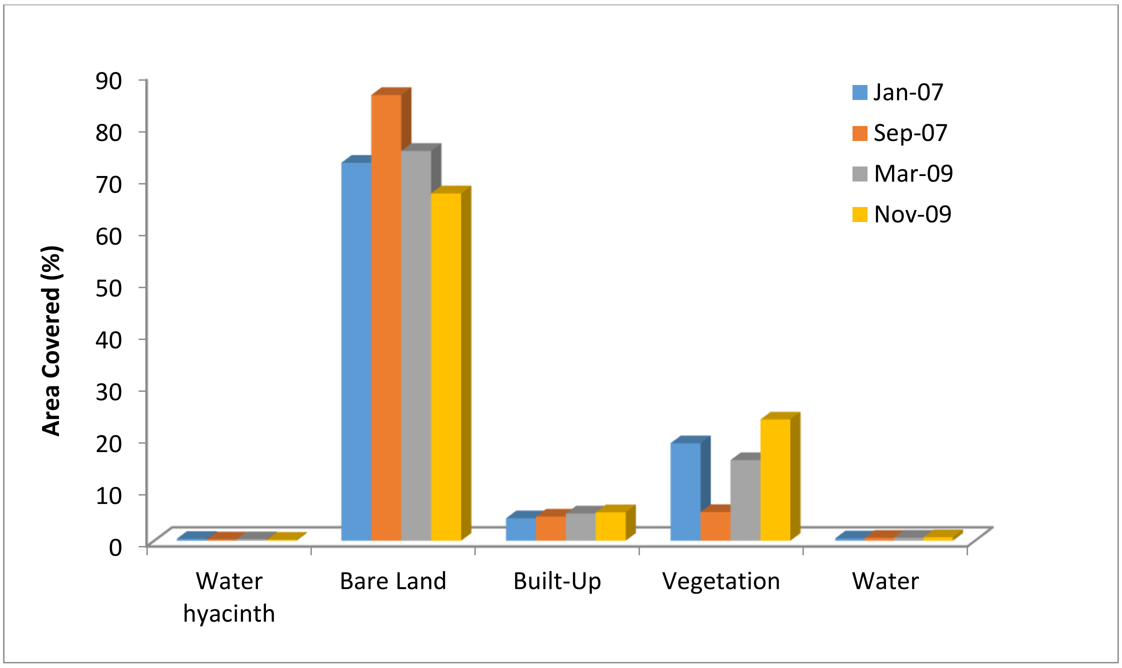


Figure 19: Area cover of LULCC in percentage.

Table 12: Confusion matrices of the Landsat 7 ETM+ images used in the study.

Month/ year	Overall accuracy	Kappa Coefficient	Accuracy type	Water hyacinth	Bare Land	Built-Up	Vegetation	Water
Jan-07	83.42	0.7895	Producer's	84.97	78.86	72.62	82.58	100
			User's	84.96	75.19	75.31	84.50	100
Sep-07	84.88	0.8083	Producer's	75	73.33	83.33	85	100
			User's	75	70.97	84	88.70	97.56
Mar-09	90.16	0.8813	Producer's	96.67	86.96	83.93	87.64	96.19
			User's	95.60	86.02	87.04	85.71	96.19
Nov-09	88.80	0.8624	Producer's	94.67	86.67	79.12	82.08	99.04
			User's	94.04	86.14	85.71	82.86	93.64

4.3.4 Change Detection

In the evaluation of the physical control measures of water hyacinth in the Hartbeespoort Dam, change detection statistics, between the two periods, were produced from the classified image pairs. The change was assessed by computing the differences in pixels between the Landsat 7 ETM+ image pairs. Therefore, for the images acquired in 2007, the pixel difference was obtained from subtracting the aggregated LULCC map pixel composition of 05 January 2007 from those of the 18 September 2007 LULCC map (Table 13). In the same manner, the 2009 change detection statistics resulted from subtracting the 31 March 2009 LULCC pixels from those present in the 26 November 2009 LULCC map (Table 14). The physical removal of water hyacinth as a measure of control resulted in the change in the spatial distribution of the hyacinth in the Hartbeespoort Dam. This change, quantified as percentages in the change matrices, can be used to infer on the success of the physical control of the water hyacinth in 2007 and 2009. The change in the distribution of water hyacinth and other LULCC is represented by the class changes.

Table 13: 2007 change detection statistics between the 5th January and 18th September.

2007 Change Detection Statistics (%)						
Month	January (Initial State)					
	LULC	**Water hyacinth**	**Bare Land**	**Built-Up**	**Vegetation**	**Water**
September (Final State)	Water hyacinth	**26.35**	0.05	0.04	0.07	22.94
	Bare Land	15.53	**91.78**	62.72	81.21	3.6
	Built-Up	1.05	4.84	**33.61**	2.78	0.66
	Vegetation	3.61	3.3	3.61	**15.89**	0.76
	Water	53.46	0.03	0.02	0.05	**72.04**
	Class Total	100	100	100	100	100
	Class Changes	72.6	8.22	66.35	84.11	27.96
	Image Difference	-28.55	16.7	27.03	-70.52	21.94

A decrease in the cover extent of a LULCC is expressed as a negative image difference, whereas an increase in the spatial extent of a LULCC is expressed by positive image difference values. The total change in the distribution (area cover) of a LULCC is indicated in the class change. The change is calculated when a LULCC is transformed from one class to another LULCC. The fields that are in bold in the change detection matrices of 2007 (Table 13) and 2009 (Table 14) image pairs represent the percentage of each LULCC that was not altered between the initial and final stages of mapping. The water hyacinth distribution was reduced by 28.55% in 2007; this percentage represented 72.6% of the total class change of water hyacinth. Similarly, vegetation cover too was drastically reduced, with an image difference of -70.52%. These reductions in vegetation and water hyacinth extent led to an increase in other LULCC. A notable change of -11.22% of water hyacinth dissemination was recorded for 2009. Alike, the area cover of bare land receded by 12.86%. Contrary to the aforementioned, built-up, vegetation and water LULCC experienced gains of 10.50%, 15.43 and 22.37%, respectively.

Table 14: 2009 change detection statistics between the 31st March 2009 and 26th November 2009.

2009 Change Detection Statistics (%)						
Month	**March (Initial State)**					
	LULC	**Water hyacinth**	**Bare Land**	**Built-Up**	**Vegetation**	**Water**
November (Final State)	Water hyacinth	**27.295**	0.068	0.059	0.081	4.878
	Bare Land	9.731	**76.463**	33.716	49.207	0.958
	Built-Up	0.785	3.313	**53.274**	1.739	3.044
	Vegetation	6.997	20.123	12.89	**48.925**	8.136
	Water	55.192	0.032	0.061	0.048	**82.985**
	Class Total	100	100	100	100	100
	Class Changes	72.71	23.54	46.73	51.08	17.02
	Image Difference	-11.219	-12.856	10.497	15.434	22.37

4.4 Discussion

Physical control methods were the initial control methods utilised in the Hartbeespoort Dam for combating water hyacinth invasions (Ashton *et al*., 1979). Water hyacinth present in the Dam was solely managed by physical removal of the plant up till 1977 (Ashton *et al*., 1979). The year 1977 saw the sudden increase of water hyacinth in the Hartbeespoort Dam, consuming 60% of the dam (Ashton *et al*., 1979). This commanded the implementation of integrated control methods for the management of the weed. The assimilation of physical control methods along with biological control and/or chemical control was employed to prevent the spread of the water weed (Ashton *et al*., 1979). This was done in an attempt to prevent future invasions of such great magnitudes (Ashton *et al*., 1979).

The introduction of biological control and chemical control were unable to deter the use of physical control methods; physical control of water hyacinth remains the most utilised control method in the dam until today. Physical control alone is unable to be implemented over the vast area of the dam (Ashton *et al*., 1979). However, government interventions such as the *Working for Water* programme have ensured that physical control methods remain the most dominant control approach in the Hartbeespoort Dam (van Wilgen *et al*., 2001; Fanie, 2016; Hill and Coetzee, 2017). Initiatives such as *Working for Water* and *Harties Metsi A Me* were specifically established for the physical control of invasive species nationwide (Hill and Coetzee, 2017). The aforementioned, are government programmes created for the empowerment of the youth and previously disadvantaged groups of South Africans through the conservation of biodiversity and protection of indigenous vegetation species by eradicating foreign and invasive species (Fanie, 2016; Hill and Coetzee, 2017;). These initiatives offer employment to the youth, unskilled and previously disadvantaged minorities, in so doing fighting to alleviate poverty and promoting the socio-economic standards of the country (Hill and Coetzee, 2017). The physical extraction of water hyacinth further has the potential to be economically beneficial (Patel, 2012). The weed can be used for: the production of biogas, treatment of wastewater, generation of electricity, purification of water, animal fodder, and as a fertiliser (Lidsey and Hirt, 1999; Patel, 2012)

The successes of physical control measures of water hyacinth in the Hartbeespoort Dam for the periods of 2007 and 2009 were assessed through change detection analysis and the mapping of water hyacinth for the two years, respectively. The resultant LULCC classification maps of the Landsat 7 imagery were satisfactory; the overall accuracies ranged between 83% and 90%, which are reasonably high. This was successfully done using the random forest algorithm for the classification of the Landsat 7 ETM+ images.

According to Harding (2004), the extreme rapid re-invasion of water hyacinth, in the early 2000s, into the Hartbeespoort Dam began with the presence of a barge along the perimeter of the dam. This saw the instigation of the *Harties Metsi A Me* programme (employing *Working for Water* agents) (Harding, 2004). The first pilot studies, focused on a small area of the dam, were done in 2005 and yielded pleasing results (Fanie, 2016). Thereafter the full programme was launched in 2007 to control water hyacinth invasions in the Dam (Fanie, 2016). This resulted in the decline of water hyacinth, as is proven by this study (Figure 17 and Table 13). Two years into the continued control of water hyacinth, 2009, the joint efforts of the *Harties Metsi A Me* and *Working for Water* programmes reduced the water hyacinth concentration by 12% (Table 14). Water hyacinth control by the *Working for Water* programme was unable to completely rid the Hartbeespoort Dam of the invasive species. The physical control of the weed is limited in terms of spatial coverage. Thus, its utilisation for the control of the water weed in large areas with extensive water hyacinth mats is not suitable (Culliney, 2005; Patel, 2012). Even though *Working for Water* is mandated for the removal of water hyacinth, their physical control methods are ineffective against the weed (Hill and Coetzee, 2017). The physical control of the submerged weed invariably leads to fragmentation of the weed mat and subsequent dispersal and increased infestation of the weed (Hill and Coetzee, 2017). Hence, the efforts of *Working for water* are more suited for the control of terrestrial invasive species.

Change analysis done on the two pairs of Landsat7 ETM+ images indicate notable changes of the water hyacinth. The reduction in the spread of water hyacinth on the later images indicates that the physical removal of the hyacinth offers a temporary solution by reducing water hyacinth spread during removal. Nevertheless, physically controlling the spread of the macrophyte in the dam is a futile effort, as it is unable to entirely eradicate the weed. Furthermore, the pulling of the weed from the waters causes an increased movement of the water, which in turn propagated the dispersion of the weed (Patel, 2012). This results in the water hyacinth infestation of previously clear areas, promoting the potential of the re-infestation of cleared areas.

4.5 Conclusion

This study aimed to assess the success of physical control measures that have previously been used to mitigate the spread and reduce the abundance of water hyacinth, by using multitemporal remote sensing data. Change detection analysis, utilising historical Landsat-7 ETM+ data, were used to assess the successes of physical control measures employed against the weed for the periods of 2007 and 2009 in the Hartbeespoort Dam. The following conclusions were drawn from this work:

- Water hyacinth distribution for the years 2007 and 2009 were able to be detected and mapped with significantly high overall accuracies (83.42%, 84.88%, 90.16%, and 88.80%) utilising the Landsat 7 ETM+ historical data.
- Control and management of water hyacinth are challenging and require great economical (financial) resources, as the long term acquisition of power machinery and employment of manpower tends to be expensive.
- The reintroduction of the macrophyte after its extraction is inevitable, as physical control measures are unable to completely eradicate the weed (in large water bodies) and they further promote the movement of water hyacinth to previously uninvaded waters.
- Physical control has to be undertaken as a long-term, continuous approach in order for it to have lasting visible results on the mitigation of water hyacinth.

The physical control methods employed against water hyacinth in South Africa, under the *Working for Water* programme, have to some extent been successful. This is measured by the significant reduction in the percentage cover of the weeds, visible immediately and in the months subsequent to the physical control of the weed. The *Working for Water* programme should be long-term and continuous, with minimal intervals, to assure increased control of the weed. However, unless the primary driver of disturbance, eutrophication by nitrates and phosphates, in aquatic ecosystems is addressed, the physical control of the water hyacinth will be monotonous and minuscule, with continued reinvasion and invasions by new species.

CHAPTER 5

OVERALL CONCLUSION

The tuning of the RF parameters, *mtry,* and *ntree*, is a prerequisite for the RF classifier as it detects the optimal *mtry* and *ntree* combinations to be utilised for the classification of images. Water hyacinths are among the most invasive aquatic plant species in South Africa as they are vastly spread over inland water bodies. The distribution of water hyacinth is significantly influenced by human negligence. Therefore, it should be monitored on a continuous basis as its proliferation can lead to negative impacts on the environment and livelihoods of communities situated in close proximity to water hyacinth infested waters. The morphology of water hyacinth makes it unique, as its free-floating roots allow for the daily change in its distribution. Thus the change in the distribution can be a result of several individual factors or a combination of factors, including: water flow, wind direction, wind speed, hence predicting the change in the distribution of water hyacinth can prove challenging.

The objectives of this study were reached as water hyacinth distribution in the Hartbeespoort Dam was successfully mapped using random forest classifier. Furthermore, by employing change detection as a tool, this study was able to infer on the success rates of physical control of water hyacinth in the Hartbeespoort Dam for 2007 and 2009.

The spatial extent of water hyacinth varied drastically due to the influence of water movement and wind constituents, within a 24 hour period. Influences by these natural factors combined with the high rates of eutrophication in the dam are constantly extending the distribution of water hyacinth. The study showed the capability of both Sentinel-2 MSI and Landsat-8 OLI in detecting and mapping water hyacinth. Nevertheless, Sentinel-2 MSI data surpassed that of Landsat-8 OLI, by yielding greater overall and producers accuracies. Furthermore, the LULCC classification of the Sentinel-2 image was able to differentiate and delineate algal blooms present in the dam along with the water hyacinth. The high 10 m spatial resolution of the Sentinel imagery allowed for increased detail and detection of land cover and land use areas. Contrary, even with increased radiometric and spectral properties, Landsat-8 OLI was unable to detect the algal blooms amongst the water hyacinth due to its spatial resolution of 30 m. Pixel composition was thus agglomerated and the pixel assigned to the LULCC with the majority spatial extent, therefore algal blooms present in the dam were not detected by the Landsat-8 OLI sensor.

The RF classifier further demonstrated that the most important RGB band combination for mapping water hyacinth using Sentinel-2 MSI is inclusive of red, SWIR-2 and vegetation red-edge 1. While the RGB band combination for Landsat data is coastal, red and SWIR. The classification of the images was in most aspects similar, except for the vegetation class, which indicated a major difference in the land cover of the area. The difference in the extent of vegetation cover can be attributed to mixed pixels in the Landsat data, as it has a coarser spatial resolution compared to Sentinel-2 data.

The physical removal of the water hyacinth by the *Working for Water* programme under the *Harties Metsi A Me biological* remedial programme significantly influenced water hyacinth distribution in the Hartbeespoort Dam. Physical removal of the weed yields immediate results and the distribution of water hyacinth is greatly visibly reduced in months following the harvesting of the weed. However, the programmes have not been able to fully eradicate the invasive species as the dam is too large for the efficient application of this control method. Physical control is most effective for small areas and is feasibly inappropriate for large areas. Additionally, the physical control of the submerged weed makes the efforts redundant as the weed fragments and disperses, resulting in an increased infestation of the weed. The physical removal of the plant should be combined with other control methods and carried out regularly to ensure that the dissemination of the weed does not spread or otherwise increases. The continued physical control of water hyacinth through the *Working for water* programme is beneficial for the socio-economic status of the nation. Though their efforts against the submerged weed are arguable, their continuation is inevitable as it contributes towards the betterment of the country’s ecological, social and economic security.

Water managers need an easy and reliable approach to map and monitor water hyacinth distribution and growth. Remote Sensing methodologies, such as those employed in this study, are reliable (demonstrated by the overall high classification accuracy’s of the images) and relatively easy to perform. Unlike conventional monitoring approaches, remote sensing offers a larger area cover, access to inaccessible areas and is not limited by costs. Thus greater emphasises should be placed on the utilisation of remote sensing for monitoring water hyacinth. This would increase the efficiency of control methods, as they would be applied to the most affected areas, in turn decreasing costs associated with the control of the weed.

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