Mapping the distribution and abundance of common reeds *Phragmites australis* in the Nylsvley Wetland, South Africa using SPOT and Landsat imagery

By

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ABSTRACT

Extensive research on the biology and ecology of *Phragmites australis* has been done since the 1960s. This has been carried out to manage and monitor the distribution of *P. australis*. *Phragmites australis* is one of the most invasive plants in wetlands that thrive successfully as compared to the native species. *Phragmites australis* alters hydrology and wildlife habitat, increases fire potential, and shades native species. In this study, the distribution and abundance of *P. australis* was mapped and analysed. To understand the distribution and abundance of the common reed *P. australis* invasions, research in a spatial context at several scales is required. In this study, Landsat 4-5 Thematic Mapper (TM), Landsat 8 Operational Land Imager (OLI), and SPOT 6 were used to map the distribution of *P. australis* in Nylsvley Wetland. Five sampling sites were selected in Nylsvley Wetland and reference data was collected to aid the classification process. Nylsvley Wetland is considered one of the largest floodplain systems in South Africa, with the Nyl River flowing through the central and North eastern parts of the Nylsvley Nature Reserve. The surface area of *P. australis* will be estimated using Garmin® Etrex 62 Global Positioning System (GPS) within the selected sites. Images from year 2011, 2013, 2015 and 2017 for SPOT and Landsat were selected for further *P. australis* classification. Supervised classification was used to classify the satellite images into different classes. From the classification images it was observed that *P. australis* covers a small area of the study site relative to other identified land cover types and were mostly distributed along the river system. However, SPOT images showed an increasimg trend in *P. australis* cover which was not evident on Landsat images. Accuracy assessment was performed to compare the performance of SPOT and Landsat. The results showed that average overall accuracy was 71.50% and 61.62% for SPOT and Landsat, respectively. Correlation between the classified image is shown by the overall kappa coefficient average of 0.5648 and 0.37 for SPOT and Landsat, respectively.

Keywords: *Phragmites australis*, Remote sensing, Landsat, SPOT, Supervised Classification, Accuracy assessment

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DECLARATION

I declare that the thesis hereby submitted to the University of Venda, for the degree of Masters in Environmental Science has not been submitted previously by me for a degree at this or any other university; that it is my own work in design and in execution, and that all material contained herein has been duly acknowledged.

______________________________ 15/03/2021_____________

Cyncinatia Malapane Date

DEDICATION

This study is dedicated to my daughter Quinn Khano Mbulaheni, brothers Surprise, Emmanuel and Kabelo, and nephews Shepard, Blessing and Lehlogonolo who gave me extra strength throughout the degree programme.

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CHAPTER ONE: GENERAL INTRODUCTION

1.1. Background

Non-native *P. australis,*also known as common reed is a tall cane-like grass that can form dense monotypic stands in different habitats, including wetlands (Wilcox and Petrie, 1999). *Phragmites australis* reproduces both sexually and asexually, and their seeds can be spread by wind and animals, or intentionally introduced by humans (Pellegrin and Hauber, 1999). Most commonly, however, *P. australis* spreads by horizontal above-ground stolons and underground rhizomes, and once established in an area, they are difficult to eradicate or control (Hudon et al., 2005).

Phragmites australis is an aggressive invasive plant species that colonises and outcompetes native vegetation. With their competitive ability, they tend to displace the native vegetation around them (Bolton and Brooks, 2010). According to Mal and Narine (2004), *P. australis* grows mostly in wetland areas that have been disturbed such as degraded salt and freshwater marshes and swamps, along streams, lakes, ponds, and roadside ditches. *P. australis* dominates the surrounding plants and animals, altering their habitats. As a result, *P. australis* also alters the accessibility of humans to water resources thus having major economic effects, including decreasing the value of properties due to use impairment (Hazelton, 2018).

In general, invasive plant species affect the native population and the ecosystem invaded both directly and indirectly. Invasive species can directly affect native species by decreasing the germination of seeds and survival through litter deposition, reducing available water resources (D'Antonio and Vitousek, 1992). The invasive species can affect ecosystems indirectly by changing soil biogeochemistry, geomorphology, and hydrology of the area that they invade (Mack and Antonio, 1998).

Studies on *P. australis* have been carried out to manage and monitor their distribution. Various methods such as grazing and burning are utilised by resource managers to eradicate and control *P. australis* (Hazelton et al., 2014). In some areas *P. australis* can be identified as one of the invasive plants that poses a risk to global wetlands (Ontario Ministry of Natural Resources, 2011). According to Blossey (2003), identifying the differences in morphological characters can help wetland managers to make educated choices on obtrusive *P. australis* control. The spread of *P. australis* is of concern to ecosystem managers, and it is important to come up with managing techniques to limit its spread.

This study aims to map the distribution and abundance of the common reed *P. australis* within the Nylsvley Wetland using both the SPOT series of CNES (Space Agency of France) (South Africa National Space Agency) and Landsat dataset. Establishing the trends of *P. australis* distribution can assist in coming up with control measures. Monitoring the distribution and pattern of *P. australis* over time depends on the sustainable supervision of the wetlands (Adam et al., 2010). Preliminary recognition and accurate data about the dispersal of species are important to foresee, evaluate, control, and alleviate their negative effects on the current ecosystem wellbeing (Callaway et al., 2000).

Remote sensing techniques have been widely applied in mapping, classifying, and monitoring invasive species, with wetland vegetation mapping being one of the most performed by researchers and scientists for several decades. Satellites images have been used for mapping wetland vegetation since the early 1970s (Holmgren et al., 1998). With the development of information technology, remote sensing became more productive and economical in recent years. Currently remote sensing is widely used as an effective tool to provide spatial and temporal information about vegetation and non-native species in wetlands. Remote sensing techniques offer information that is relatively accurate and up to date (Adam et al., 2010). This information assists in sustainable, effective monitoring and management of wetland vegetation. Remote sensing is less expensive and more time efficient than actual field surveys. However, together these two methods bring out the best results.

In this study, mapping tools are used to identify the location and extent of *P. australis*. However, mapping *P. australis* in freshwater is challenging due to changing water levels and density of vegetation (Bruce et al., 2007). To understand the distribution and abundance of *P. australis* invasions requires an analysis of the spatial context. SPOT and Landsat Enhanced Thematic Mapper (ETM+) data were compared in this study, to assess their accuracies in mapping the distribution and abundance of *P. australis* in the Nylsvley Wetland. The comparison is based on the satellite sensors' ability to accurately identify areas with *P. australis* and separate these from other vegetation types. Landsat provides the wider view and low cost needed for practical applications but has shown less ability for distinguishing species than SPOT data (Pengra et al., 2007). Multispectral imagery analysis techniques have proven to be adequate for distinguishing *P. australis* from local wetland vegetation. However, this regularly requires extra data such as multi-temporal imagery (Ghioca-Robrecht et al., 2008).

1.2. Problem statement

Invasive plant species can lower the ability of native species to thrive. Of concern is the introduction of *P. australis* in wetlands (Mal and Narine, 2004). Rapid expansion of *P.*

australis is of concern because it displaces the native vegetation and decreases the overall biodiversity. *Phragmites australis* grows up to 5.5 m tall restricting shoreline views (Avers et al., 2007). It grows at a fast rate and its dead material forms a large concentration of dry plant material, causing an increase in the rate of wildfires that can threaten commercial and residential properties.

1.3. Research aims

1.3.1. Main aim

To map the distribution and abundance of *P. australis* in the Nylsvley Wetland using both SPOT and Landsat imagery.

1.3.2. Specific aims

- To determine the distribution and abundance of *P. australis* in Nylsvley comparing both SPOT and Landsat satellite data.
- To assess the changes in spatial distribution of *P. australis* in Nylsvley over time using SPOT and Landsat satellite data

1.4. Hypothesis

The distribution and abundance of *P. australis* will change with time.

- *Phragmites australis* is more widely distributed and abundant in more recent years relative to previous years.

1.5. Justification and significance of the study

The invasion of *P. australis* has negative impacts on the surrounding wetlands wildlife such as other macrophytes leading to an imbalanced ecosystem. *Phragmites australis* are very aggressive and displace wildlife living in and nearby the wetland. Analysing the spread of *P. australis* motivates the need to better understand the abundance of *P. australis* globally, as well as to better understand the structures of establishment for the purposes of future management planning. This study will provide beneficial data for those who seek to manage *P. australis* in wetland plant communities. The goal of this study is to provide information about the distribution and abundance of *P. australis* by comparing two datasets (SPOT and Landsat). These would contribute towards the formulation of more effective methods to control and manage common reeds.

The study will further provide information about their distribution, which is currently inadequate (Saltstonstall, 2002). This will allow the prediction of future trends on distribution and abundance of *P. australis* through the analysis of past and current information. Analysing the trends on the distribution of *P. australis* helps identify some of the most important implications of complex interactions between social and environmental processes hence, the research will guide interested parties to carry out necessary actions in managing the invasion of *P. australis*. The study will also provide well-documented data about the area (square meters) that is occupied by *P. australis* within the Nylsvley Wetland and the data can be used by the Nylsvley Nature Reserve to develop effective management strategies to control *P. australis.*

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

Wetlands are amongst the most valuable and productive natural ecosystems covering about 6% of the Earth's surface (Castañeda and Herro, 2008). They provide essential services such as groundwater recharge and providing storage for floodwaters. Wetland vegetation acts as a barrier to erosion. They also provide habitats for wildlife and act as both carbon and nutrients sinks. They act as pollution control by filtering and reducing sediments in the water column.

Despite their importance, recent studies have shown that approximately 50% of the wetlands in the world have been lost (Davidson, 2014). Human activities play a major role in modifying wetlands, and more than half of the world's wetlands have been transformed or degraded in the past 150 years (Gardner et al., 2015). Currently, the rate of conversion of wetlands is greater than that of any other aquatic or terrestrial ecosystem (Kandus et al., 2011). According to Schummer et al. (2012), a constant increase in the human population will put more pressure on the remaining wetlands.

Apart from human pressure, non-native species are considered a serious threat to wetland vegetation communities (Lantz, 2012). They compete successfully for resources and slowly replace the native plants around the wetland. *Phragmites australis* is one of the non-native species that colonise wetlands and displace native species. According to Short et al. (2017) once established in an area, it is difficult to control or eradicate. It has high competitive ability which allows it to modify the nutrient cycle and change the hydrological regimes in wetlands.

Remote sensing has been used successfully in identifying change in wetland vegetation for years. Current trends in assessing wetlands vegetation changes using satellite images show many applications of change detection methods. However, very few applications have focused on *P. australis* changes in wetlands (Ndzeidze, 2008).One disadvantage of Landsat over SPOT is the poor spatial resolution which can lead to confusion between *P. australis* and other types of vegetation, especially if their spectral properties are similar (Laba et al., 2008). High-spatial-resolution satellite imagery provides the ability to detect very small patches of *P. australis*. Mapping the distribution and abundance of *P. australis* assists in implementing effective control measures and management techniques.

2.2. Ecology of *Phragmites australis*

Phragmites australis tolerates a wide range of environmental conditions, from fine to sandy topsoil, fresh to saline water, and a wide range of pH (ISSG, 2011). However, it mostly favours the wetland-upland interface (Avers et al., 2014). According to USDA, NRCS (2016) *P. australis* has a 75% chance to occur in wetlands. Fofonoff et al. (2015) also stated that *P. australis is* tolerant to a wide range of temperatures, but not highly frost resistant (Haslam, 1972). It is most often found in wetland areas that are disturbed by *inter alia* altered hydrology, sedimentation, and nutrients load.

The life expectancy of *P. australis* is approximately 4–5 years, but with clonal growth stands they have been known to survive over thousands of years (Haslam, 1972). They reproduce both sexually and asexually (Fofonoff et al., 2015). Cross-pollination with other plants is probably most common in *P. australis*, but self-pollination may occur (Gucker, 2008). Their seeds can, however, also be transported by birds, water via waterways, or by flooding (Haslam, 1972).

2.3. Distribution and abundance of *Phragmites australis*

Although it is suggested that *P. australis* are native to Australia, it is believed that they originate from the Middle East (Swearingen and Saltonstall, 2010). They are currently globally distributed and considered native to Europe. Among all flowering plants, *P. australis* are one of the most widely distributed, with a very extensive native range throughout the world. *Phragmites australis* have been colonizing North America for over 3,000 years (Niering and Warren, 1980), and have shown a great deal of expansion along the Atlantic Coast during the past century (Meyerson et al., 2000).

Phragmites australis are now regarded as one of the aggressive invaders and have recently expanded throughout the world (Rice et al., 2000). According to Weber (2003), *P. australis* are native in Europe and have been introduced to all other areas including Africa. According to Powell (2007), *Phragmites australis* distribution is highly dependent on the functioning of the wetland ecosystems. The variation of the distribution of *P. australis* is influenced by environmental conditions such as the availability of water in the wetland (Amelie et al., 2014).

Phragmites australis can be found occasionally along ponds and marshes from the Atlantic to the Pacific coasts of Canada, but other studies indicate that its range has increased from local clustering of populations to a more widespread distribution (Gervais et al., 1993). According to Tucker (1990), *P. australis* grows in every continent except Antarctica. Although *P. australis* are not common in other areas, presently they are distributed throughout the globe.

The major system of *P. australis* is freshwater but it may also be found in both brackish and salty wetlands. However, system dynamics differ between wetter and dryer sites (Güsewell and Klötzli, 2000).

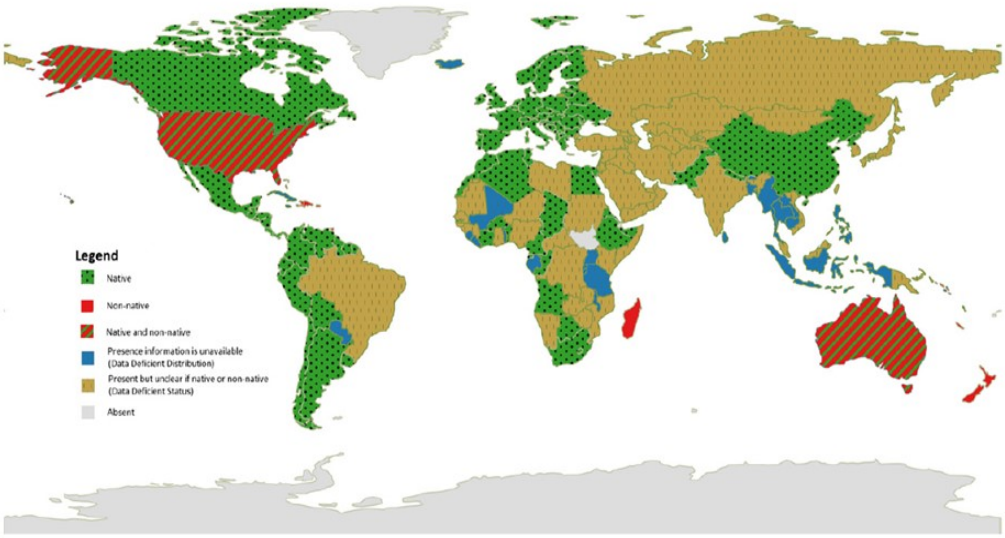

Figure 2.1 Global distribution of *Phragmites australis* (adapted from Güsewell and Klötzli, 2000).

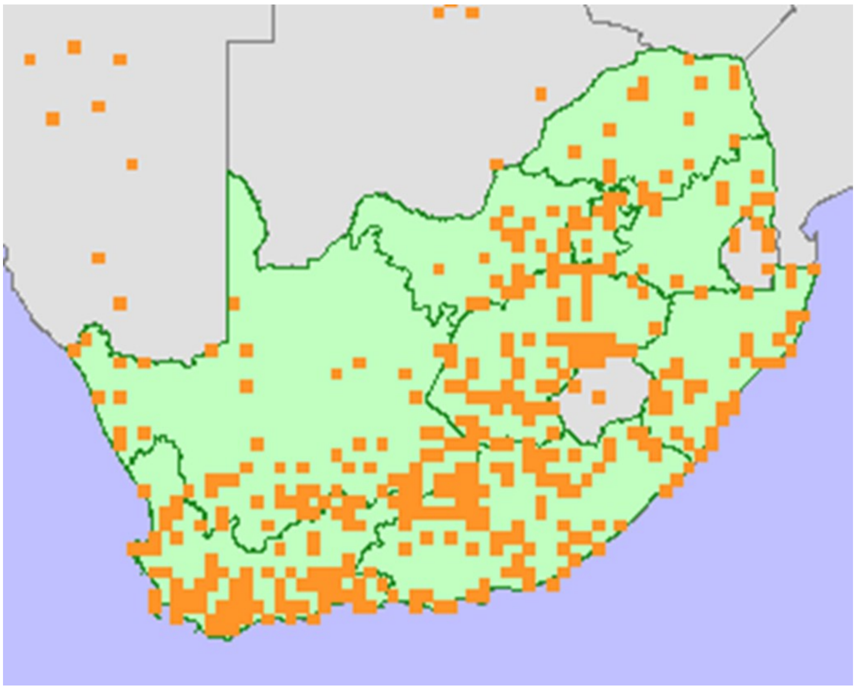

Figure 2.2 Spatial Distribution of *Phragmites australis* in South Africa (adapted from Fish and Victor 2006)

Phragmites australis are widely distributed in South African provinces as shown in Figure 2.2. They are sparsely distributed in the North-eastern part of South Africa (Limpopo) compared to the western part of South Africa (Western Cape) whereit is densely distributed. In the interior part of the country (Free State) the plant is also densely distributed. *Phragmites australis* seem to be dispersing extensively in the Limpopo province (Fish and Victor, 2006).

2.4. Historic overview of remote sensing

Remote sensing is the science, art, or technology of acquiring information about the earth's objects and the surrounding environment with the use of sensors located at a distant location from the features of interest (Meijerink, 1996). Remote sensing started as early as 1859 when Gaspard Tournachon took an oblique photograph of a small village near Paris from a balloon, marking the beginning of the era of earth observation and remote sensing (Aggarwal, 2004).

His example was soon followed by people all over the world. In the United States, aerial photography from balloons played an important role in revealing the defense positions in Virginia during the civil war (Colwell, 1983). Other scientific and technical developments in the United States accelerated the development of photography and lenses; and applied airborne earth observation and remote sensing in this war.

The next period of fast development took place in Europe. Aeroplanes were used on a large scale for photo reconnaissance during World War I (Macdonald, 1984). Aircraft proved to be more reliable and more stable platforms for earth observation than balloons. The use of aerial photos by civilians commenced during the period between World War I and II (Brown, 1999). Application fields of airborne photos at that time included geology, forestry, agriculture, and cartography. This coincided with improvements in the development of cameras, films and interpretation equipment (Paine and Kiser, 2012)

The most necessary developments of aerial images and image interpretation was used almost at some stage in World War II. It was during this interval that the development of near-infrared photography, thermal sensing and radar commenced. Only near-infrared photography and thermal-infrared proved very valuable to separate real vegetation from its surrounding. The first successful airborne imaging radar proved to be valuable for night-time bombing. Because of that, the system was called by the military ‘plan position indicator’ and was developed in Great Britain in 1941 (Witmer, 2015). After the wars into the 1950’s, remote sensing systems continued to evolve from the structures developed for the war effort (Aggarwal, 2004). Colour Infrared (CIR) Photography was found to be of importance in plant science. In 1956, Colwell conducted experiments on the use of CIR for the classification and identification of vegetation types, in addition to the detection of diseased, damaged or stressed vegetation. It was also in the 1950s that significant progress in radar technology occurred (Aggarwal, 2004). Since the first launch of the satellites in the 1970s, remote sensing has been continuously growing as a science and in every field of study. Remote sensing techniques have yielded promising results across the globe (Adam et al., 2010).

2.5. Remote sensing of *Phragmites australis*

Assessing land cover change of wetlands provides the foundation for a better understanding of the relationships and interactions between man-made and natural phenomena of the wetlands (Liu et al., 2004). Increased understanding is necessary for improved resource management (Jensen, 2005). Remote sensing has been successfully used in assessing land cover change around and within wetlands for years. Remote sensing techniques are less costly and less time-consuming for large geographic areas as compared to actual field mapping (Kaplan and Avdan, 2017). Therefore, it provides a unique opportunity to characterize the spatiotemporal distribution of wetland changes and to collect important information on wetlands that is too difficult to obtain using field-based methods (Dixon and Candade, 2008). Detecting changes in wetlands using satellite images has greatly facilitated qualitative and quantitative spatial and temporal analysis of change (Ndzeidze, 2008).

To understand the distribution and abundance of *P. australis* invasions, research in a spatial context at several scales is required. According to Mathre (2011), global studies using image processing analysis of *P. australis* have been conducted all over the world. Previously, studies have been conducted to determine areas with *P. australis* using Landsat data. According to Liira et al. (2010), satellite images with medium resolution can be used successfully to monitor macrophyte vegetation in wetlands. Satellites such as SPOT-5 were used successfully to determine the location of *P. australis* (Laba et al., 2008). SPOT and

Landsat data have been individually used to map the distribution of *P. australis* but have rarely been used together.

The area covered by Landsat is wider, lower cost and necessary for practical applications (Bruce et al., 2007). Laba et al. (2010) states that Landsat (TM)'s resolution is, however, not enough to determine invasive species that cover a small area and does not allow the identification of an invasive impact until the species has reached dominance. Davranche et al. (2010) argue for the benefits of SPOT5 imagery, whereas, Ghioca-Robrecht et al. (2008) recognise the benefits of different satellite images.

Studies indicate that the Maximum likelihood image classification is successfully used in classifying patches of *P. australis* (Knudby and Nordlund, 2011). This method uses training sites, areas of pixels with known class type to train the computer to recognize the different classes. The choice of appropriate training samples depends upon the analyst's knowledge of the actual features portrayed in the image (Forgette and Shuey, 1997). The downside of the maximum likelihood classification method is that classes of interest may not correspond to spectrally unique or homogeneous classes.

The other disadvantage is that training data acquisition is time-consuming and expensive. According to Laba et al. (2010) "several supervised classifications methods were trialed, and the Maximum Likelihood Classifier achieved the highest separation between classes" and yield the best result. One of remote sensing limitations is often the case of mixed pixel problem, where one pixel may contain multiple land cover types, which reduces accuracy in image assessment and increases bias of small land cover types (Powell et al., 2007).

2.6. Remote sensing techniques for image classification

The process of identifying land cover change in wetlands includes image classification which allows for the differentiation of various land cover in wetlands. Image classification is the task of extracting classes of information in an image by identifying a group of homogenous pixels representing features of interest (Natural Resource Canada, 2016). In this procedure, the analyst attempts to classify each pixel into a class or theme by using the spectral information provided in each pixel.

The classification procedure relies upon the detection of spectral responses of various feature classes (Meijerink, 1996). Such classification techniques include unsupervised classification, supervised classification, and hybrid classifications. However visual interpretation was one of the techniques often used in the past to differentiate various land cover in satellite images (Green et al., 1994).

2.6.1 Visual interpretation

In the past satellite imagery used visual interpretation to identify land covers including *P. australis* (Nayak and Sahai, 1985). More recent studies have been conducted on water turbidity, seasonal water fluctuations and vegetation status of Harike wetland in Punjab, India. These used visual analysis of false color composite images (Chopra et al., 2001). According to Johnston and Barson (1993), visual interpretation of hard-copy images is useful for an overview and reconnaissance mapping of wetlands, especially for those who lack remote sensing knowledge.

2.6.2. Unsupervised classification or clustering

Unsupervised classification, or clustering, groups together pixels with similar spectral values. Clusters information are given class labels. Spectral classes are chosen by the computer without the analyst's intervention where the selection process is based only on deferential information in the data (Natural Resources Canada, 2016). Various computers are equipped with special programs called clustering algorithms, which are used to determine the natural groupings in image data.

Unsupervised classification is less time consuming, the training phase is eliminated, and the classes are distinct units. However, the clusters may not correspond to desired information classes. Studies have revealed that the unsupervised method is the most used method and the most successful when many clusters are used (Ramsey and Laine, 1997). However, the number of clusters sought by the computer is predetermined by the analyst. Hence, unsupervised classification process is not completely without human supervision. Studies conducted in California's Central Valley used 230 clusters per Landsat TM scene for identifying wetlands land covers (Kempka et al., 1992).

2.6.3 Supervised classification

This method uses training sites, which are areas of pixels with known class type, to train the computer to recognize the different classes (Hepper et al., 1990). The choice of appropriate training samples depends upon the analyst's knowledge of the actual features portrayed in the image. Therefore, the image analyst is responsible for directing the classification of various feature classes in a multispectral image (Foody and Mathur, 2004). Supervised classification approaches are mostly preferred over unsupervised because the cover class labels of interest are chosen *a priori* (Demir et al., 2012).

A supervised classification relies solely on the statistical characteristics of the pixel's brightness values in different bands to spectrally recognize similar areas for each class. Modern computer-based image processing software is equipped with a special program to recognize the spectrally similar areas in an image (Siddiqui, 2016). The downside of this method is that classes of interest may not correspond to spectrally unique or homogeneous classes. Furthermore, training data acquisition is time consuming and expensive (Sen et al., 2020).

Supervised classification has different techniques, such as minimum distance to means, parallelepiped and maximum likelihood classification. Minimum distance to means classifiers calculate the centroid of the training data classes and assign pixels that are unknown to the class with the nearest centroid (Nair and Bindhu, 2016). This technique has been used to map land use changes of wetlands (Forgette and Shuey, 1997). Parallelepiped uses the various spectral values in the training data to define a region in data space. Pixels that fall into the similar data space are classified into that class. This method was used with Landsat TM images in the Florida Everglades (Hines et al., 1993).

Maximum likelihood classification uses the means and variances of the training data to estimate the probability that a pixel is a member of a class. The pixel is then placed in the class with the highest probability of membership. This method generally gives more promising results than minimum distance to means or parallelepiped classifiers because the covariance of the data is considered. Hence, the maximum likelihood classification is the commonly used supervised classification method to map changes in wetlands (Macleod and Congalton, 1998).

2.6.4. Principal component analysis

Another approach for unsupervised classification is to use principal component analysis (PCA) to reduce the number of bands, and then apply clustering to the first few principal components. Principal Component Analysis (PCA) is a method that uses mathematical techniques to reduce the dimensionality of a data set (Jackson, 1983). According to Sebastia et al. (2013), it refers to a mathematical transformation involving the correlation of multispectral data from one band to the other. It is based on the logic that the level of a pixel in one band can to some degree be predicted from the level of that pixel in another band. PCA can be used as a technique for identifying wetland change (Muchoney and Haack, 1994).

The principal aim of this operation is to reduce the information contained in multi-spectral bands into few new images (Gupta et al., 2013). The principal component images describe data more efficiently than the original bands. The technique is more appropriate in situations where little background information about the area of interest is available (Gupta et al., 2013). This approach was used together with ancillary data on wetlands to separate wetlands from other land uses (Ozesmi, 2002). Merged data transformation technique was used to assess wetland change on the Kafue Flats in Zambia. The aim was to evaluate the potentials and disadvantages of using PCA for wetland change on this heterogeneous land cover scene.

2.6.5 Hybrid classifications

This method uses a mixture of both supervised and unsupervised classification techniques. One hybrid technique is to input statistics that is descriptive from a clustering algorithm into a maximum likelihood classifier (Hasmadi et al., 2009). In hybrid classification approach, unsupervised classification is done on only a part of the study area. Thereafter the clusters are assigned information classes, clusters statistics are created and input into a maximum likelihood classifier so that the entire study area can be classified (Ernenwein, 2009).

This method was used in the study conducted in Canadian artic and subarctic wetlands by Pope et al. (1994). Hybrid classification was also used in north central Georgia to identify woos stork habitat using late spring Landsat TM data (Ozesmi et al., 2002). This method combines the advantages of both supervised and unsupervised approaches. They can be valuable for wetland studies because of the complex variability of spectral responses of wetland vegetation.

2.7. Impacts of *Phragmites australis* on the wetland environment

2.7.1. Ecological impacts

Invasive species can lower the ability of plant diversity to thrive and decrease the quality of wildlife habitats within wetland and other sensitive environments (Laba et al., 2008). Invasive species occupy a large amount of space, which causes the displacement of native species. The problem of invasive species faced by wetlands in South Africa is significant; approximately 10 million ha has been invaded to some extent (Dean et al., 2000). These have a significant impact on the native species and trophic structure. The introduction of *P. australis* in wetlands is of particular concern (Mal and Narine, 2004).

Phragmites australis pose a threat to the wetlands environment by forming thick impenetrable stands that compete successfully with native vegetation (Minchinton et al., 2006). Their competitive ability allows them to spread throughout wetland ecosystems. *Phragmites australis* are one of the greatest threats to the wetland ecosystem worldwide and their impacts are increasingly becoming a harmful component (Mack et al., 2000).

Phragmites australis establish themselves more rapidly in adjacent areas, especially areas that are disturbed. Factors that contribute to *P. australis* invasions include disturbance of soil (Ailstock et al., 2001), pollution, alteration of the natural hydrological regime, increased sedimentation (Marks et al. 1994), and increases in nutrient concentrations (Hansson and Fredriksson, 2004). According to Windham and Meyerson (2003), *P. australis* changes wetland hydrology, sedimentation, nitrogen retention, and decrease dissolved oxygen, resulting in habitat alteration (Rooth et al., 2003). Due to their high productivity and transpiration, they tend to absorb high amounts of water compared to native plants (Marks et al., 1993).

2.7.2. Economic impacts of Phragmites australis

Phragmites australis can absorb a high amount of water due to their deep roots, these prevent drainage leading to reduced crop production (Bonanno, 2011). They can block sight lines at intersections creating driving hazards. In conservation areas, overgrowth of *P. australis* has resulted in reduced property values, recreational opportunities, and reduced aesthetic enjoyment. Their dense stands prevent access and penetration can be difficult because of abrasions from the sharp-edged vegetation. Reduction of native fish and wildlife populations result in reduced recreational value for birdwatchers, walkers, naturalists, boaters, and hunters (Tewksbury et al., 2002). Such use impairment and restricted shoreline view also reduce property values (Avers et al., 2010). In addition to economic impacts, the introduction of *P. australis* poses a risk to human life and property. The Michigan Department of Transportation (MDOT) considers *P. australis* to be a safety hazard, as its height and dense growth may block signs and view of access roads, drives and curves (Sturtevant, 2019).

2.8. Contribution of *Phragmites australis* to biodiversity

Phragmites australis have a high ability in nutrient uptake and because of this, it improves water quality by filtration (Jiang et al., 2007). They have, therefore, been used as vegetative filters for wastewater treatment (Adler et al., 2008). *Phragmites australis* have dense stands and extensive root systems that prevent and minimise the effects of water erosion (Hawke and Jośe, 1996). In other countries such as Europe, *P. australis* are used commercially for livestock fodder, cellulose production, and thatching (Swearingen and Saltonstall, 2010). Despite its status as the global's "worst" invasive plant species, in Canada, *P. australis* are still considered ornamental in some garden and landscape designs (MNR 2010).

Phragmites australis produces various potentially interesting pharmacological compounds (Kiviat 2010). However, to our knowledge, there is currently no research that focuses on that area. *Phragmites australis* were used for medicinal purposes to treat diarrhea and gastrointestinal problems and it is also used traditionally in native American tribes (University of Michigan, 2016). In other tribes*, P. australis* was used as a material for building and to make products such as mats and buckets (University of Michigan, 2016). The seeds of *P. australis* were eaten in the absence of other food (University of Michigan, 2016). As much as it is a problem to most countries *P. australis* provide habitats and food for smaller organisms such as reptiles and insects (Kiviat, 2010). In South Arica, *P. australis* is used extensively for hut building, fencing, craftwork, and thatching (Rooyen et al., 2004).

2.9. Management of *P. australis*

Phragmites australis are powerful invaders that take over the area in which they are introduced, and once they colonise, they are not easy toeliminate. There are several methods so far used to control the overgrowth of *P. Australis* viz, ecological and non-ecological. These methods can be used either individually or in combination. According to Avers et al. (2014), effective control is likely to require multiple treatments using a combination of methods. However, some studies suggest that these methods are fully effective when used alone (Marks et al., 1994). Reinvasion by *P. australis* is likely when the management intervention is not maintained or closely monitored. The response of *P. australis* to control methods differs in different systems and will depend on the conditions that exist in that area (Güsewell and Klötzli, 2000).

2.9.1. Non-ecological management

Burning is one of the non-ecological methods used to control *P. australis*, however, it does not reduce the ability of *P. australis* to grow since rhizomes are covered by a layer of either soil or water (Marks et al., 1994). In most cases, burning is not applicable as it may stimulate the growth of young shoots, due to an increase in light exposure, especially in spring. In wetlands that are near urban areas and have high conservation status, burning is not an appropriate management method. Another downside of burning is that it reduces vegetation cover for wildlife habitats (Mamolos et al., 2011).

Another common non-ecological method used to manage *P. australis* is the application of herbicides. Herbicides are more effective when used in combination with other methods such as burning and mechanical methods. Treatment should be done repeatedly for several years to avoid re-establishment of *P. australis* (Avers et al., 2014). Herbicides need to be carefully applied as they are not species-specific and may affect native plant species (Pagnucco et al., 2015).

2.9.2. Ecological management

Grazing and cutting have been used to reduce *P. australis* beds and density. Grazing may compress the rhizomes; however, this may not be as effective as other methods. Studies conducted by Van Deursen and Drost (1990) found that cattle consumed approximately 67–98% of aboveground *P. australis* biomass. Grazing has not been considered as a suitable management method because the *P. australis* tend to establish again and reach an equilibrium state (Vulink et al., 2000).

Another ecological method is cutting. This method manipulates the possible growth of *P. australis* (Russell and Kraaij, 2008). In general, cutting increases the density of *P. australis* (Warren et al. 2001), while it decreases shoot length and the decomposition of organic matter. Cutting can also be used together with burning to avoid accumulation of biomass. Other ecological methods include flooding, whereby water level is increased to control the growth of *P. australis*. Although *P. australis* are intolerant of persistent flooding, increasing water level alone is not effective in controlling them, hence the use of combined methods for better and lasting results.

2.10. Conclusions

Wetlands are freshwater systems that provide essential services throughout the globe. They provide habitats for thousands of species and act as carbon and nitrogen sinks. Wetlands, like any other water system, encounter challenges such as non-native species invasions, including *P. australis*. *Phragmites australis* compete successfully for resources, negatively affecting other native species. Mapping the distribution of *P. australis* assists in coming up with more effective management and monitoring tools and plans of their establishment. Remote sensing has been used successfully for the past decades to map the distribution of *P. australis*. To understand their distribution and abundance, research in a spatial context at several scales is required. Satellite images can be used successfully to monitor macrophyte vegetation in wetlands. Satellites such as SPOT-5 and Landsat are used to determine their location. SPOT and Landsat data have been individually used to map distribution of *P. australis* but rarely used together.

CHAPTER THREE: MATERIALS AND METHODS

3.1 Study area

The Nylsvley Nature Reserve (NNR) is located within the Waterberg district municipality between the latitudes of 24º35'S and 24º40'S, and longitudes of 28º35'E and 28º45'E in Limpopo Province. The Nylsvley Wetland covers a total area of 3965.3 ha (LEDET, 2013) and is situated within the Mookgophong Local Municipality. The altitude of NNR ranges between 1080 m and 1154 m above sea level, with a median altitude of 1100 m. The nature reserve is a 40 km^2 protected area, lying on the seasonally inundated floodplain of the Nyl River.

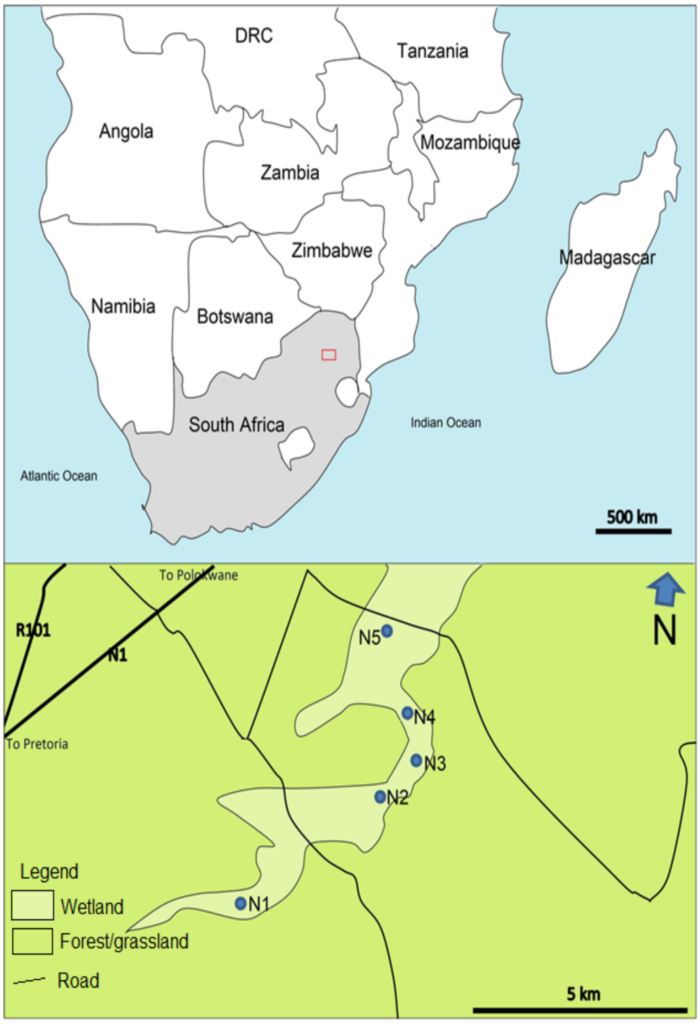

Figure 3.1 Location of the study sites within the Nylsvley Wetlands, Limpopo Province of South Africa. N1 to N5 are the sites visited for field data collection.

3.1.1. Climate

The climate of Limpopo is mostly dry and it receives most of its rainfall in summer between the months of September and March (Vermeulen et al., 2012). The local rainfall ranges between 200 and 2000 mm per annum, the provincial mean annual rainfall is 530 mm. The NNR gets an average annual rainfall of 648 mm, most of which is falling in summer. Waterberg district region receives the least amount of rainfall in July and most in November. The reserve has a monthly maximum temperature ranging from 22°C in July to 31°C in February (Scholes and Walker, 2004).

The climate of the NNR is characterized by cool dry winters and warm wet summers. About 60% of summer rainfall occasions occur as serious thunderstorms spreading across just a few kilometres in distance, while the other 40% of precipitation events are delicate downfalls traversing different spans. The mean yearly precipitation of the Waterberg region is 623 mm with a mean temperature of 19°C (Coetzee et al., 1976).

3.1.2 Topography

The NNR has a gently sloping landscape, with several rocky outcrops that spread throughout the reserve. According to LEDET (2013), there are few outcrops, namely the Stemmerskop and Maroelakop, which are located at the central interior of the reserve at an altitude of 1 132 m above sea level and in the eastern corner of the reserve at an altitude of 1 154 m above sea level, respectively. A third unnamed outcrop is located inside the western corner of the nature reserve at an altitude of 1 122 m above sea level.

3.1.3. Vegetation

The Waterberg Biosphere represents a considerable area of the savanna biome of Southern Africa. The Waterberg contains a high level of biological diversity, which includes many red data and orange listed species of conservation concern, and many endemic species. Habitats are adequately represented to ensure that the current high biodiversity is maintained. The NNR has low human density resulting in large areas of unspoiled wilderness and open spaces being a main characteristic of the Waterberg Biosphere.

Figure 3.2 The tallest trees are *Burkeaafricana*, while the lower tree layer is composed of *Terminalia sericea* and *Dichrostachyscinerea*, with the tall grass *Hyperthelia dissoluta* characteristically present on the well-drained sandy soils (Photo: T.H. Setsaas).

Sour Bushveld is characterized by Transvaal beech (*Faureasaligna*), common hookthom (*Senegalia caffra*), wild seringa (*Berkeaaficana*), silver cluster-leaf (*Terminalia sericea*) and African wattle (*Peltopehorumafricanum*) on the deep sandy areas and steep and bare rock. Other common treespeecies of the area arepaperbark false-thorn (*Albiziatanganyicensis*) and velvet bushwillow (*Combretum molle*). River-bank and freshwater habitats including wetlands are characterised by Transvaal red milkwood (*Mimusopszevheri*), tigerwood (*Clerodendrum glabrum*), and common wild fig (*Ficusthonningi*) (Madilonga, 2017)

3.1.4 Land use

Presently, an estimated 80 000 people inhabit the Waterberg Biosphere (Madilonga, 2017). The Waterberg lies in the Waterberg district of the Limpopo Province of South Africa (Netshipale et al., 2017). After cattle grazing brought a nadir of ecosystem health issues in the mid-1900s, the inhabitants gradually became aware of the advantages of restoring habitats to accommodate the original species of antelope, other bovids, black and white rhino, giraffe, hippopotami, warthogs and other important species whose numbers had declined with the advent of cattle. A steady rise in eco-tourism has increased the interest in game farming and land conservation practices to restore indigenous species to the Waterberg (Constant et al., 2015).

3.1.5. Geology

The geology of the area consists of sandstones with some shales (Blight, 2004) as shown in figure 3.3. The sandstones of the Waterberg cluster are typically found within the higher reaches of the field and are semi-permeable with high infiltration rates (Higgins et al., 1996). The Waterberg cluster additionally consists of some greywacke, mudstones, and siltstones (Roberry, 2011). The centre reaches of the field are comprised of felsites of the Rooiberg cluster. Basalts of the Karoo sequence typify the lower reaches of the Waterberg, being areas of spring water sources. The 15 m deep alluvium overlay covering most of the Nyl watercourse vale, is primarily identified as Waterberg arenaceous rock (Higgins, 1996).

The geological characteristic of this area has been hypothesized firstly as a Zebidelia fault running through the Nyl watercourse vale. The movement related to this fault is thought to have created a basin which has subsequently been filled up with sediment from the Nyl watercourse (Tooth, et al., 2002). This hypothesis has but recently challenged by McCarthey, et al.(2011), proposing that rather than tectonic forces, the deep geological phenomenon of the Nyl has been due to the obstruction of the lower reaches by coarse-grained sediment being delivered by steep tributaries. This successively has caused back ponding and thus gradient reduction within the higher reaches. Regardless, it has created an unusual hydrological formation where the watercourse flows up to 35m higher than the bedrock (McCarthey et al., 2011).

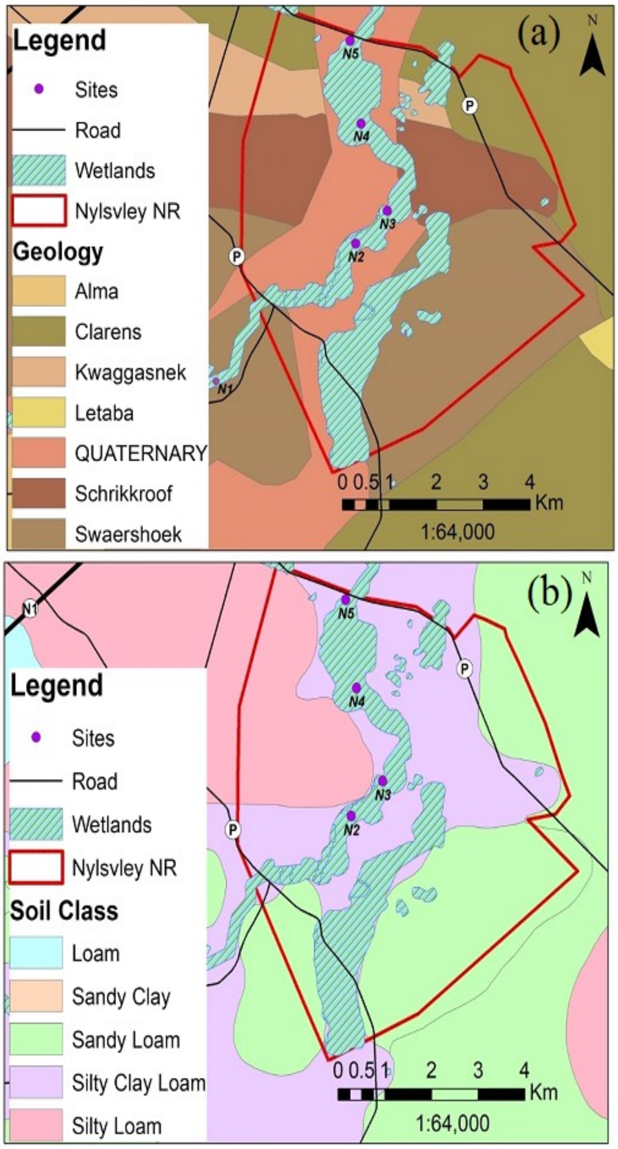

Figure 3.3 Map showing the (a) geology and (b) soil type of the Nylsvley Nature Reserve

3.1.6. Hydrology

The Nylsvley Wetland is considered one of the largest floodplains in South Africa with the Nyl River flowing through the central and North-Eastern parts of the NNR. NylsvleyWetland is a seasonal natural inland covering approximately 70 km^2 It is comprised of a seasonal river associated with a grassland floodplain. The floodplain gets most of its influx from streams and rivers draining from the south-eastern edge of the Waterberg plateau, with its primary water input coming from the Olifant spruit (contributing eighty percent of the overall annual drift). The Groot Nyl and Klein Nyl Rivers contribute minimally (LEDET, 2013).

Hydrologically the Nylsvley floodplain serves as a basin, temporarily storing floodwater and later releasing it slowly back into the Nyl River. The floodplain contributes significantly to groundwater recharge within the area with high groundwater yields in the Waterberg area occurring near the lower floodplain. The Nylsvley floodplain wetland plays a vital role in supplying water for the biodiversity of the surroundingarea (LEDET, 2013).

3.2. Research design

A quantitative methodology was undertaken to study the distribution of *P. australis* along the Nylsvley Wetland, using a shoreline survey technique. This technique allows for the evaluation of the distribution density of *P. australis*. Shoreline surveys are commonly utilised because they are available, and satisfactory for *P. australis* area mapping. Typically, *P. australis* is found on the shorelines, which facilitates data analysis and pattern evaluation.

3.3. Preliminary work

This is the first stage of the research that provides an overview of the study area. It is made up of a secondary desktop study and a reconnaissance survey.

3.3.1. Desktop study

A desktop study was carried out before field work to acquire first-hand information about the geology of the area. This was done through the access of existing data from scientific and commercial databases and available project sources. These sources are books, journals, previous reports, internet resources and topographic maps as well as geological maps.

3.3.2. Reconnaissance survey

An overview field survey of the study area was carried out before actual fieldwork. Visual observations were carried out to gather information about the topography, vegetation, soil and general characteristics of the Nylsvley Wetland. This stage aided the preparations of actual field work and selection of appropriate methods of acquiring data in the field.

3.4. Data collection

3.4.1. Sampling methods

The classification processes of remote sensing imagery requires some reference data from ground cover features to aid in identifying features within the image. To obtain these ground control points (GCPs), field work was completed on the 25th of March 2020. A total of 5 points were taken using a Garmin GPS60 unit. This was conducted mainly to help in classifying different land covers within the wetland. The surface area of *P. australis* was estimated using Garmin® Etrex 62 Global Positioning System (GPS) by calculating the area round the *P. australis* patches. The GPS points were taken at all five sites and test sites were selected to further assist in ground truthing. Ground truthing is essential to relate image data to real features and materials on the ground. The training sites selected assisted in the accuracy assessment of the supervised classification of the images. Hence, errors of omission and commission were minimized.

Figure 3.4 *P. australis* stands within study area at different field sites.

3.5. Remote sensing

3.5.1. Image selection

High spatial resolution Landsat 5 TM (Thematic Mapper), Landsat 8, and SPOT 5 and 6 were used in mapping the distribution of *P. australis*. The Landsat images were obtained from USGS and the SPOT images were requested from the South African National Space Agency (SANSA). High spatial resolution on satellite images often comes at the expense of image swath width. The large swath width and moderately high (30m) spatial resolution of Landsat TM make the sensor's imagery suitable for mapping the distribution of *P. australis* .SPOT, however, has a higher spatial resolution of 1.5 m hence, the comparison of the two. The images were enhanced to improve visual interpretation and appearance of land features. To do that, image enhancement techniques such as linear contrast stretching, and edge enhancement filters were applied.

The images were all taken in early spring for both SPOT and Landsat. The Nylsvley Wetland shapefile was overlaid on the images so that only the study area was covered and processing time was lowered significantly. Classified images used have 4 classes namely: trees, grass, bare land, and *P. australis*.

3.5.2 Image pre-processing

Pre-processing techniques, sometimes referred to as image restoration and rectification, are normally required for easy visual interpretation and understanding of imagery before the main data analysis and information extraction are conducted (Bazeille et al., 2006). These pre-processing techniques are generally intended to correct for sensor-specific radiometric and geometric errors or distortions of data (Schowengerdt, 2012).

The image was pre-processed with the aim of correcting defects inherent in remotely sensed data (i.e. radiometric and geometric distortions) and enhancing the quality of the raw data to facilitate interpretation of the data (Chang 2018). In this study, image restoration was applied to the images to compensate for image errors, noise, and geometric distortions introduced during the scanning, recording, and playback operations. This was performed through the application of geometric correction, radiometric correction (haze compensation) and noise reduction filters developed by ERDAS imagine 2014. The objective was to make the restored image resemble the scene on the terrain.

3.5.2.1 Radiometric correction

Radiometric correction is important to ensure that terrestrial variables retrieved from optical satellite sensor systems are calibrated to a common physical scale. Radiometric correction is one of several corrections performed on satellite image data prior to the retrieval of land, atmosphere, and ocean information. These pre-processing procedures are essential for ensuring high-quality information from remote sensors. Radiometric correction ensures that measurements and methods yield self-consistent and accurate geophysical and biophysical data, even though the measurements are made with a variety of different satellite sensors under different observational 20 conditions and the parameter retrieval methodologies vary. Radiometric correction was performed to remove noise and haze on the images.

3.5.2.2. Geometric correction

Geometric correction is to correct the geometric distortions, internal and external distortions. Raw digital images usually contain geometric distortions so that they cannot be used as maps. The sources of these distortions range from variations in the altitude, velocity of the sensor platform, to factors such as panoramic distortion, earth curvature, and atmospheric refraction and relief displacements. The intent of geometric correction is to compensate for the distortions introduced by these factors so that the corrected image will have the geometric integrity of a map (Lillesand and Keifer, 1994).

3.5.2.3 Image enhancement

A 3 × 3 edge sharpening filter and non-directional edge enhancement, developed by ERDAS imagine 2014, was applied to the image to sharpen linear features in the image while non-directional edge enhancement was applied to enhance the edges of linear features without considering their orientation. Contrast stretch and tonal enhancement were also applied to improve the brightness differences of the image. A contrast stretch was performed with the aim of improving the brightness differences uniformly across the dynamic range of the image.Tonal enhancement filters improve the brightness differences in the shadow, mid tone or highlight (bright) regions at the expense of the brightness differences in the other regions (Suman et al., 2014).

3.5.2.4 False colour composite images

A False Colour Composite (FCC) image is an effective means for visual interpretation of multi-spectral imagery (Aqdus et al., 2012). This is because the human eye is more sensitive to colour than greyscale brightness variations and thus colour images are easier to interpret (Lissner et al.,2012). The bands, 4 (blue), 5 (green) and 6 (red) were used to generate RGB (red-green-blue) composites associated with both high spatial and spectral information (Zhimin et al., 2002).

3.5.3. Image processing

The detection of fine-scale details in structure, texture, and pattern on very high spatial resolution image data allows identification of some macrophytes up to species level (Bryson et al., 2013; Visser et al., 2013). The individual monochromatic bands were combined using the layer stacking tool, in ERDAS imagine 2014. This was accomplished by loading bands 1, 2, 3, 4, 5, 6, 7, 8 and 9 from Landsat and band 1, 2 and 3 from SPOT into the programme and combining them using the layer stacking tool to form the required dataset: a true colour composite map. It should be noted that the acquired remotely sensed data came in a form of individual monochromatic bands (i.e. Very Near Infrared (VNIR) bands, SWIR bands). These bands, on their own, were not effective for identifying different land covers, therefore the individual bands were combined to form one dataset, which could then be used to identify different land covers of interest. The nearest neighbour resampling method was used during the layer stacking to ensure that all the pixels in the bands were reordered in an appropriate manner, and to ensure that the radiometric integrity of the data remained intact. Selected images were overlaid by the Nylsvley catchment to ensure an effective extraction to cover only the study site.

3.5.4. Image classification

Image classification is a common method of categorizing land into various use functions. This procedure assigns data cells to one of many groups of land-cover classes/features depending on the reflectance values within the area on the image. There are three main categories of classification methods: unsupervised, supervised and combined. This study only used supervised classification.

There are several classification techniques used for the identification of *P. australis* stands, including minimum distance (MINDIST), maximum likelihood (MAXLIKE), and Bayesian soft classifier (BAYCLASS). Maximum likelihood classification was chosen for the study because it is comparatively the most powerful method as well as a better method for training sites with a large sample size. It is also a relatively better method for mixed pixels (Ilic, 2012). Maximum likelihood classification is based on Bayesian probability theory, evaluating the probability of pixels belonging to a category and classifying those pixels with the highest probability to the category (Clark Labs, 2007). This is the most common supervised classification used within remote sensing studies of vegetation. Using maximum likelihood, all pixels in the image are assigned to a signature class, which was developed during signature creation. The satellite images were therefore classified according to different land covers. Four classes were created, namely *P. australis*, grasses, trees, and bare land.

3.6 Data analysis and interpretation

3.6.1 Area calculation

The total area covered by *P. australis* was calculated using the "Calculate Geometry" function in the attribute table by right-clicking on the "Sh_Area_ha" field and selecting "Calculate Geometry". "Area" was selected as the property, the same coordinate system as the data source was used, which is UTM Zone 17N, and "Hectares" was selected as the units. No projection was lost during the conversion process, as the coordinate system was retained as being UTM Zone 17N. The area calculation of the *P. australis* class for each selected year was done to compare and define the difference and distribution patterns changes of *P. australis*.

3.7 Accuracy assessment

One of the most important final steps of classification process is accuracy assessment. The aim of accuracy assessment was to quantitatively assess how effectively the pixels were sampled into the correct land cover classes. The key emphasis for accuracy assessment pixel selection was on areas that could be clearly identified in more than one satellite image. It was, therefore, carried out to compare the performance of classified images for both SPOT and Landsat data in mapping the distribution and abundance of *P. australis*.

Accuracy assessment points were created on ArCMap using classified images for both SPOT and Landsat images. Thereafter the points were converted to KML file and imported on Google Earth as shown in Figure 4.15. The purpose of using Google Earth in this case was to determine correctly classified pixels over incorrectly classified pixels of each land cover. A total of 86 points were randomly selected. According to Tammy et al. (2011), the higher the number of points selected the more reliable the results. The points were subsequently represented on attribute table to validate the classified land classes as shown in Figure 4.16.

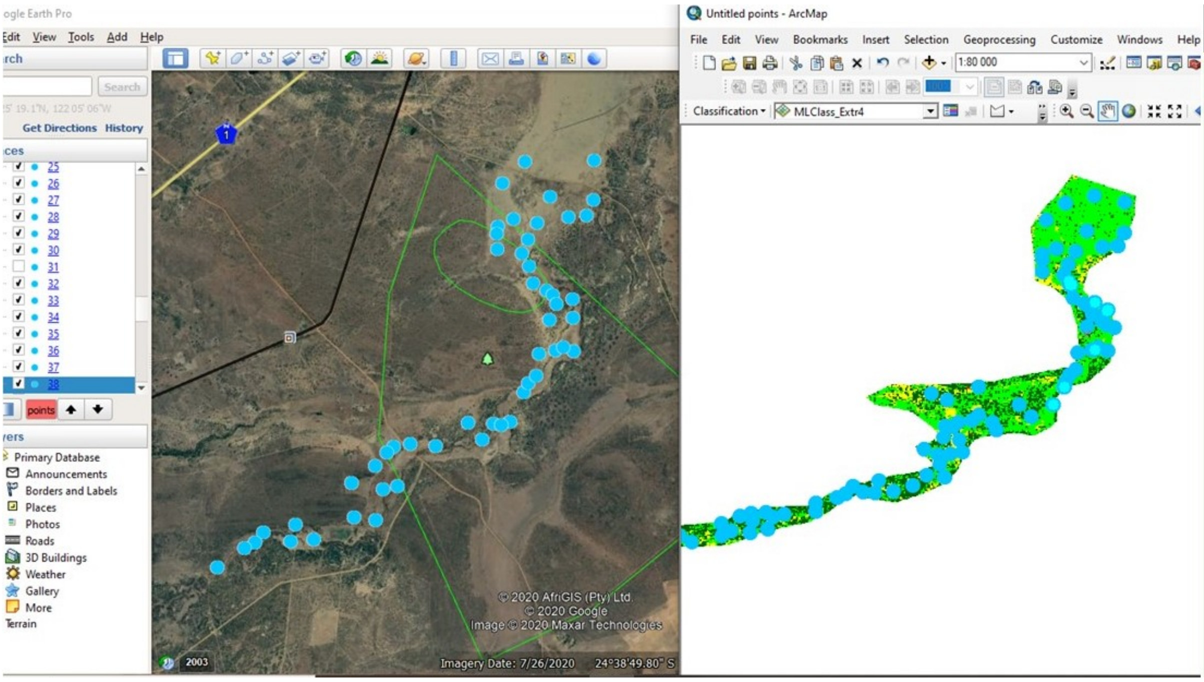

Figure 3.5 Accuracy assessment points on ArcMap

FID	Shape *	Id	user	Producer
0	Point	1	1	1
1	Point	2	1	1
2	Point	3	1	1
8	Point	9	1	28
14	Point	15	1	1
15	Point	16	1	38
33	Point	34	1	28
37	Point	38	1	38
38	Point	39	1	28
40	Point	41	1	1
41	Point	42	1	28
43	Point	44	1	1
45	Point	46	1	1
46	Point	47	1	28
48	Point	49	1	28
50	Point	51	1	1
51	Point	52	1	28
52	Point	53	1	28
54	Point	55	1	1
56	Point	57	1	1
57	Point	58	1	1
58	Point	59	1	1
61	Point	62	1	1
63	Point	64	1	1
64	Point	65	1	1
66	Point	67	1	28
69	Point	70	1	28
73	Point	74	1	1
74	Point	75	1	28
77	Point	78	1	1
78	Point	79	1	1
79	Point	80	1	38
9	Point	10	14	28
10	Point	11	14	28
21	Point	22	14	28
36	Point	37	14	28
55	Point	56	14	28
60	Point	61	14	28
65	Point	66	14	28
75	Point	76	14	28
76	Point	77	14	28
3	Point	4	28	1
4	Point	5	28	1

FID	Shape *	Id	user	Producer
5	Point	6	28	14
6	Point	7	28	14
7	Point	8	28	28
11	Point	12	28	28
12	Point	13	28	28
13	Point	14	28	14
16	Point	17	28	14
17	Point	18	28	28
20	Point	21	28	38
22	Point	23	28	28
23	Point	24	28	28
24	Point	25	28	28
25	Point	26	28	28
26	Point	27	28	28
27	Point	28	28	28
28	Point	29	28	28
29	Point	30	28	28
30	Point	31	28	28
31	Point	32	28	28
32	Point	33	28	28
34	Point	35	28	1
35	Point	36	28	28
39	Point	40	28	28
42	Point	43	28	28
44	Point	45	28	28
47	Point	48	28	1
49	Point	50	28	28
53	Point	54	28	28
59	Point	60	28	28
62	Point	63	28	28
67	Point	68	28	28
68	Point	69	28	28
70	Point	71	28	28
71	Point	72	28	28
18	Point	19	38	38
19	Point	20	38	38
72	Point	73	38	14
80	Point	81	38	38
81	Point	82	38	38
82	Point	83	38	38
83	Point	84	38	38
84	Point	85	38	1
85	Point	86	38	1

Figure 3.6 selected points on attribute table

To determine the accuracy of the classified maps, various statistics related with classification accuracy as well as overall Kappa statistic were computed based on formulae as indicated below:

Sensitivity = $\frac{a}{a+b}$ (equivalent to Producers Accuracy')

Specificity = $\frac{d}{d+b}$

Commission error = 1-Specificity

Omission error = 1-Sensitivity

Positive Predictive Power = $\frac{a}{a+b}$ (Equivalent to User's accuracy)

Negative Predictive Power = $\frac{d}{d+c}$

where:

a = number of times a classification agreed with the observed value

b = number of times a point was classified as X when it was observed to not be X.

c = number of times a point was not classified as X when it was observed to be X.

d = number of times a point was not classified as X when it was not observed to be X.

Total points: N = (a + b + c + d)

KAPPA analysis is a discrete multivariate technique used in accuracy assessments. KAPPA analysis yields a Khat statistic (an estimate of KAPPA), that is a measure of agreement between two raters or accuracy. The Khat statistic is computed as;

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + Xx_{+i})}{N^2 - \sum_{i=1}^{r}(x_{ii} + Xx_{+i})}$$

Where,

r = number of rows and columns in error matrix,

N = total number of observations (pixels)

X_{ii} = observation in row i and column i,

Xi+ = marginal total of row i, and

X+i = marginal total of column i

A Kappa coefficient can range between 0 and 1. 1 means perfect agreement whereas a value close to zero means that the agreement is no better than mere chance.

Table 4.4.1 Criteria of Kappa statistics

Kappa statistics	**Strength of agreement**
<0.00	Poor
0.00 - 0.20	Slight
0.21 - 0.40	Fair
0.41 - 0.60	Moderate
0.61 - 0.80	Substantial
0.81 - 1.00	Almost perfect

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Introduction

This chapter will be separated into three parts. The first part is the analysis and interpretation of Landsat, followed by the analysis and Interpretation of SPOT images. Lastly, the comparison of SPOT and Landsat performance using the accuracy assessment table created from ArcGIS 10.1 Software is presented.

The application of the supervised maximum likelihood in this study reveals considerable differences over time in the distribution and abundance of *P. australis*. The classification, identification and labelling were based on the experiences of the field survey, satellite images, and comparable studies. Using such subjective bases, the land cover classes were created. This chapter thus answers the research objectives about the performance of Landsat imagery as compared to SPOT imagery in mapping the abundance and distribution of *P. australis*. Overall, the results of this chapter reveal a significant change of the *P. australis* distribution over time.

Satellite data spanning a period of seven years was used for this study. Landsat Enhanced Thematic Mapper (ETM+) and Landsat Operational Land Imager (OLI) was obtained from USGS. SPOT 6 and 7 was requested from SANSA. Table 4.1.1 shows the specifications of the satellite data used in this study. The satellite images represented the entire Nylsvley Wetland area. The acquired satellite images were in geo TIFF format.

Table 4.1 Specifications of the satellite data used in this study

Sensor	Date of acquisition	Resolution (m)	Spectral Bands
Landsat 5	2011/09/12	30	Blue, Green, Red, Near Infrared
Landsat8 (Operational Land Imager OLI)	2013/08/17	15	Shortwave Infrared
	2015/08/07	15	1, Shortwave
	2017/08/29	15	Infrared
SPOT 6	2011/08/25	2.3	Blue, Green, Red
	2013/08/05	1.5	
	2015/08/18	5.5	
	2017/09/15	1.5	

4.2. Landsat image analysis and interpretation

Following Chapter 3, acquired remotely sensed data came in\single bandform. Histogram was performed after band composite on the Landsat images to aid in image visual interpretation as shown in Figure 4.1. Histogram stretching is process of increasing the contrast of an image (Kaur and Sohi, 2017). Contrast is defined as the difference between maximum and minimum pixel intensity values in an image. To increase the contrast of image the range of intensity values are stretched to cover the full dynamic range of the histogram. A histogram of an image depicts that the image is having low or high contrast. A histogram having the full range of dynamic intensity values is considered as high a contrast image .It should be noted that the above process was performed on Landsat images, SPOT images came in the form which was ready to be classified. However, images came in the form of single images which were then merged to create one single raster dataset to cover the study area, this process is called photo mosaicking.

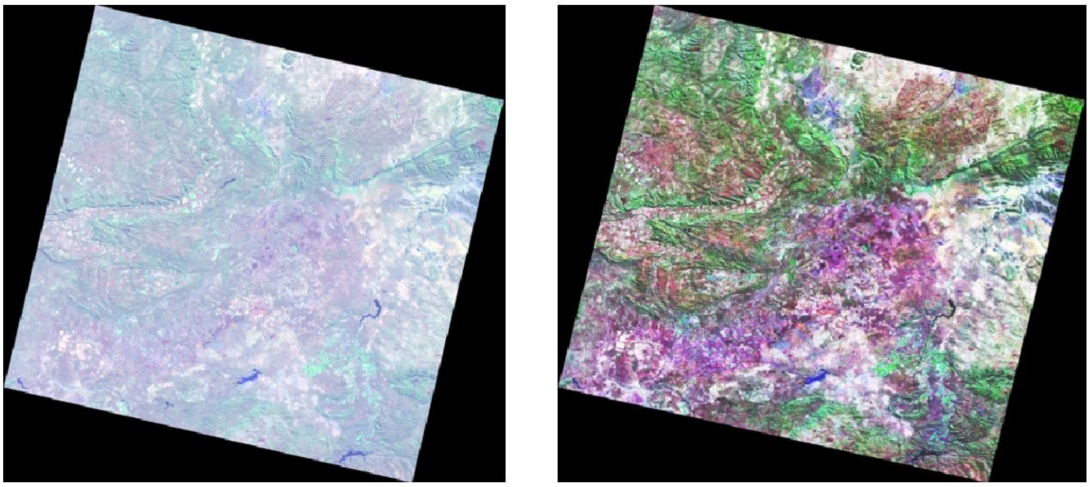

Figure 4.1 Histogram stretching

It is important to note that each image was overlaid by the Nylsvley Wetland (Figure 4.2). This is to ensure an effective extraction to cover only the study site as shown in. Exaction helps to reduce time of the classification process and to produce reliable results. Image classification was performed on individual images after the process of study area extraction.

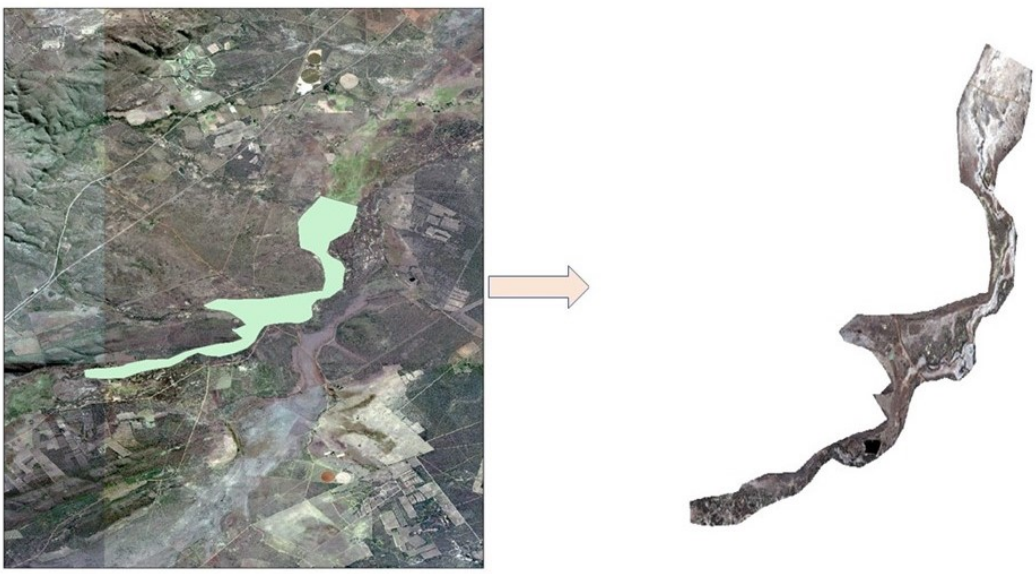

Figure 4.2 Study site extraction process

As can be seen in the Figure 4.3, trees are clearly delineated in dark green colour, grass in light green, bare land is shown in yellow, and areas which are shown to have an occurrence of *P. australis* are shown in red. More *P. australis* are observed at one side of the image; however, they cover less area as compared to other land covers shown in the image above. Approximately 117.4 ha is covered by *P. australis* stands.

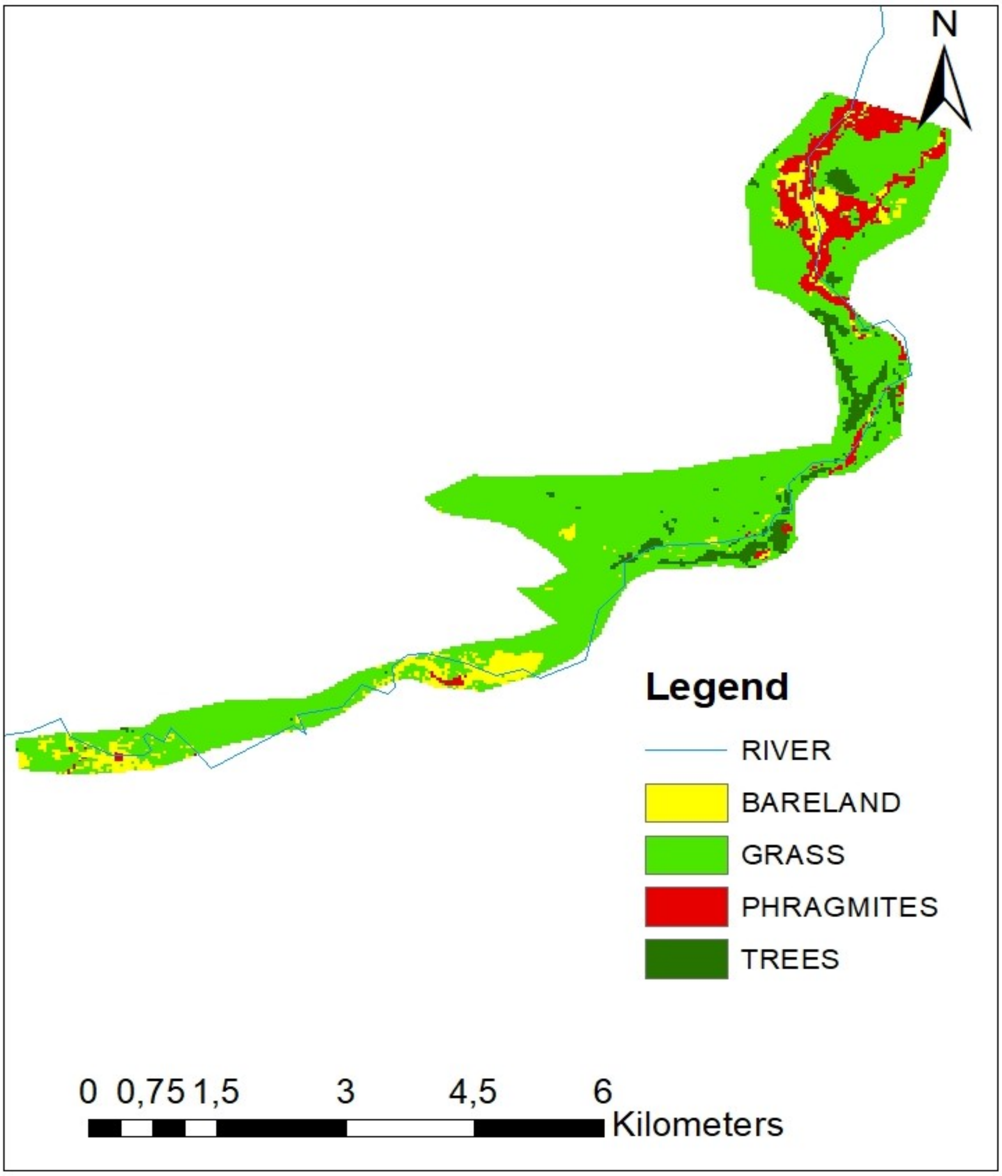

Figure 4.3. Year 2011 classified Landsat image

Year 2013 shows less *P. australis* as shown in Figure 4.4. *Phragmites australis* stands are being observed along the river, as they thrive in aquatic areas. However less red colour can be seen towards the edge of the image. This could indicate human error associated in classifying the correct *P. australis* stands.

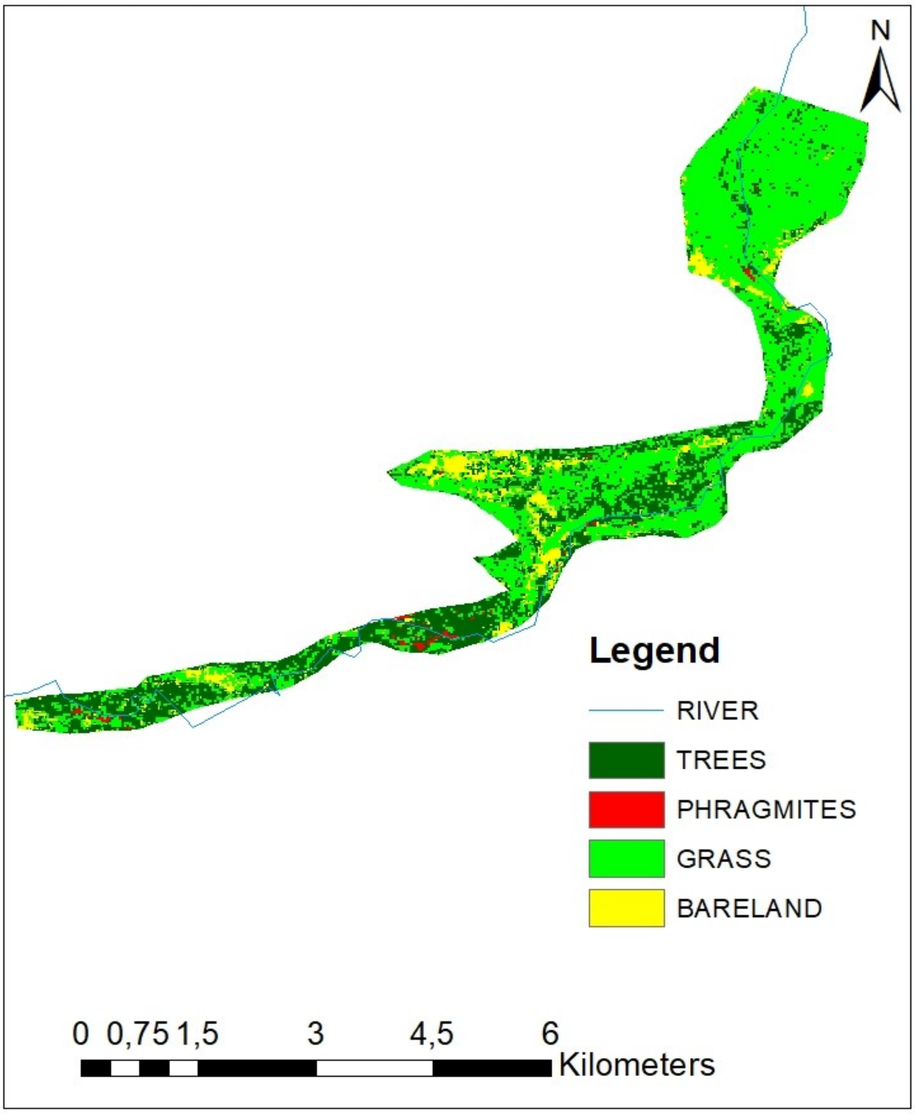

Figure 4.4 Year 2013 classified Landsat image

Less *P. australis* stands are being observed in Figure 4.5 as compared to year 2011 and 2013. *Phragmites australis* are mostly found along the river as explained in Figure 4.3. Year 2015 covers about 5 ha which is a 50% decrease from year 2013. This could be because of the management of *P. australis* from year 2013 to 2015 within the Nylsvley Wetland. Management tools and methods included burning and cutting. Other reasons may be because of the low resolution of Landsat satellite imagery used in the study. In this case, resolutions of 30 and 15 m, whereby each pixel covers 900 and 225 m^2, respectively, were used. Due to the large area that a single pixel covered, this could possibly have led to "mixed pixels" problems, where a single pixel contained a combination of several features classifying as a wrong pixel during the classifying process. This error is called "mixed pixel".

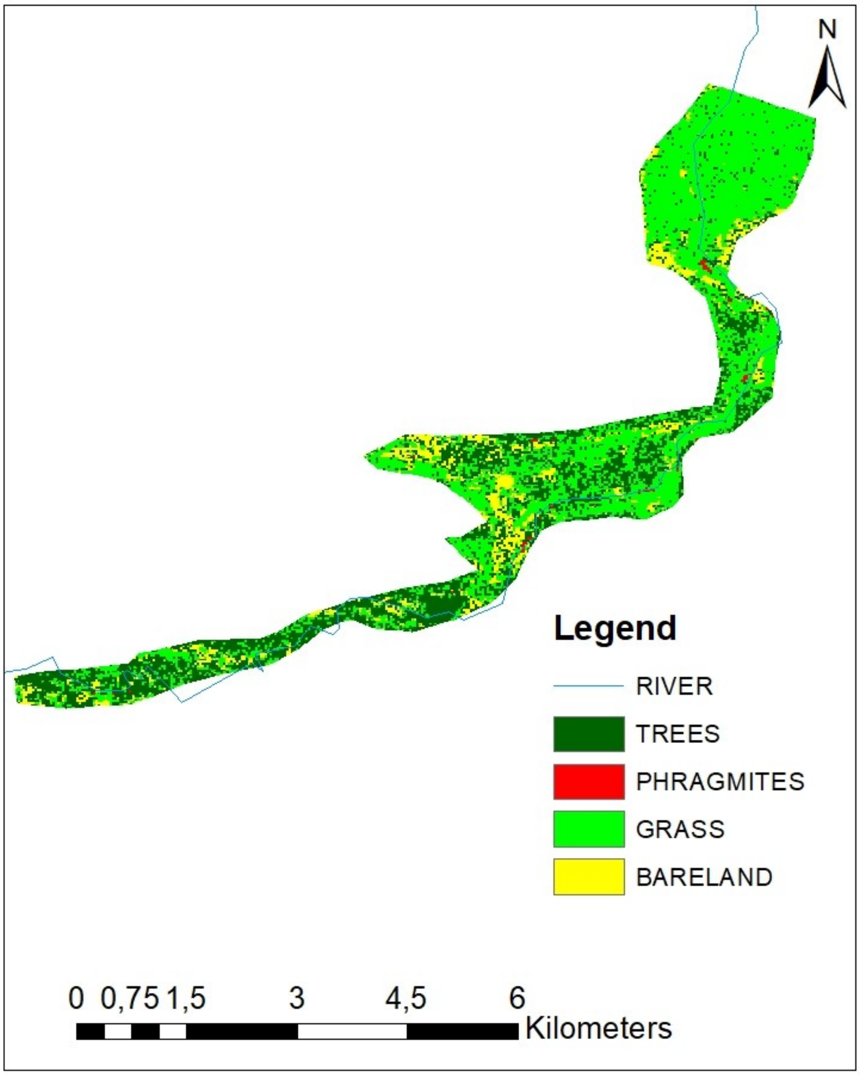

Fig 4.5 Year 2015classified Landsat image

The year 2017 showed more of the red colour at the edges of the study site as shown in Figure 4.2.6. This could mean misclassification of pixels especially from images with low spatial resolution. Another plausible reason could be that the images were acquired in spring,

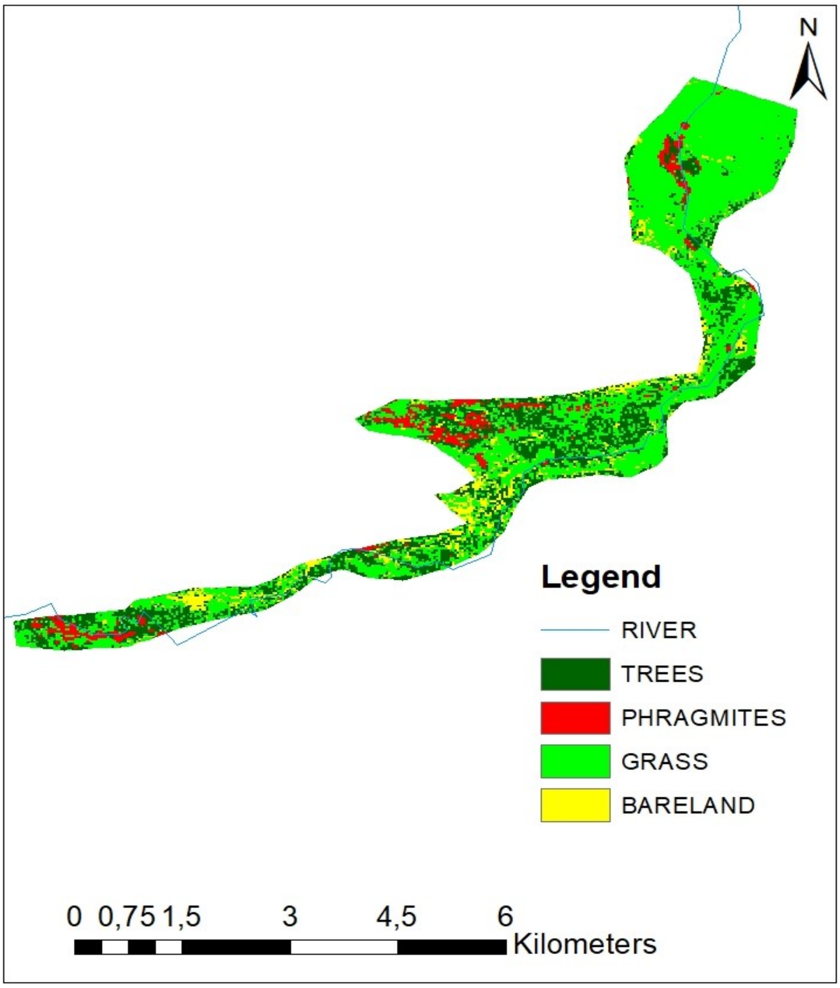

Fig 4.2.6 Year 2017 classified Landsat image

Tables 4.2.1 to 4.2.4 indicates the parameters used to calculate area of classified land covers for each year. The count column represents the number of pixels in each class. To calculate the area of each class, the number of pixels for each class were multiplied by the image resolution and divided by 10000 to get the area in hectares(ha). Since the Landsat images had different resolutions of 30×30m for 2011 and 15×15m for 2013 to 2017, the pixel number was multiplied by $900m^2$ for 2011 and $225m^2$ for 2013, 2015 and 2017. Figure 4.2.6 shows that *P. australis* covers less area in every successive year compared to other land cover classes. 2011 is the only year when *P. australis* was observed to be covering a larger area than trees.

Table 4.2 Signature editor table for year 2011 Landsat classified image.

Class	Signature name	Count	Area (ha)
1	Trees	820	73.8
2	*P. australis*	1304	117.36
3	Grass	10999	989.91
4	Bareland	1174	105.66

Table 4.3 Signature editor table for year 2013 classified Landsat image

Class	Signature name	Count	Area (ha)
1	Trees	17871	402.09
2	*P. australis*	457	10.28
3	Grass	34029	765.65
4	Bareland	4868	109.53

Table 4.4 Signature editor table for year 2015 classified Landsat image

Class	Signature name	Count	Area (ha)
1	Trees	820	419.94
2	*P. australis*	265	5.96
3	Grass	32026	720.59
4	Bareland	18664	141.07

Table 4.5 Signature editor table for year 2017 classified Landsat image

Class	Signature name	Count	Area (ha)
1	Trees	15180	341.55
2	*P. australis*	3542	79.69
3	Grass	33790	760.28
4	Bareland	4713	106.04

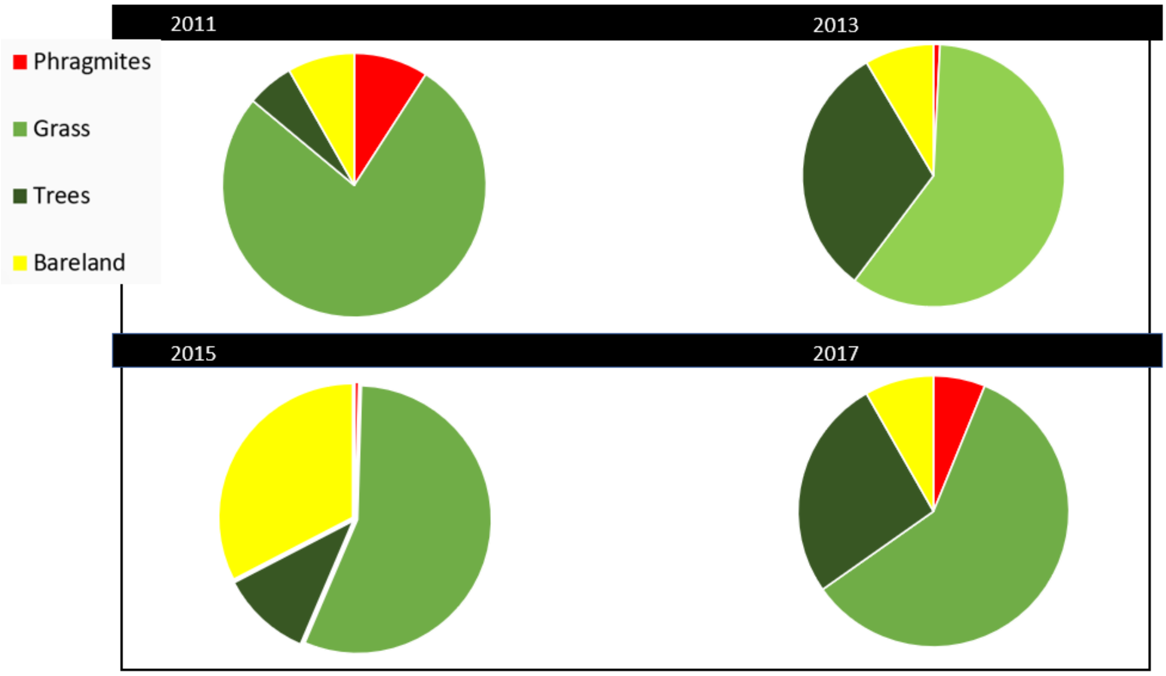

Figure 4.7 Pie chart showing area covered by each land cover classes

Figure 4.8 shows the changes in prevalence of *P. australis*. From year 2011 to 2013 a sharp increase of 37% is observed, followed by 2% of decrease from 2013 to 2015. A sharp increase of 43% is observed again from year 2015 to 2017. The average increase of *P. australis* over the 7-year time span is 4%. Although slight changes in areas were observed over the years, according to Kruskal-Wallis analysis no significant differences (H = 0.066, p = 0.987) were observed across years, whereas significant differences (H = 10.919, p = 0.012) were observed among the different vegetation land classes.

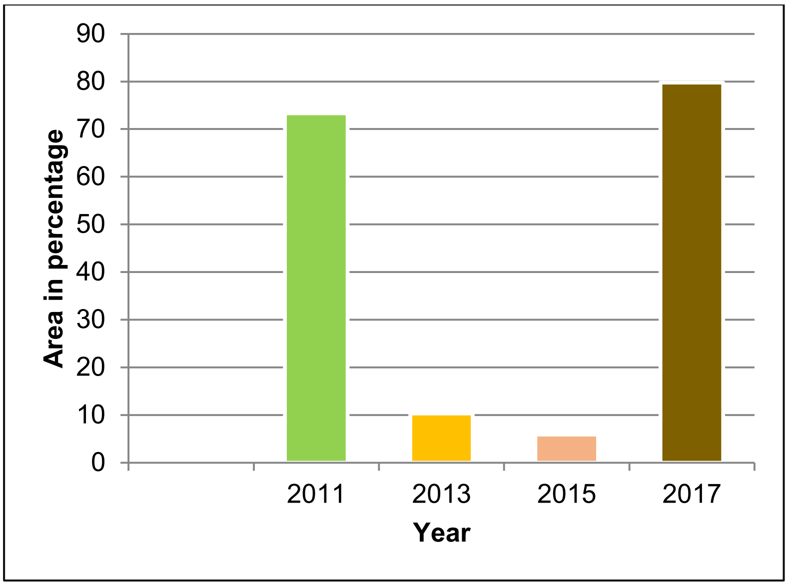

Figure 4.8 Bar graph showing total area (%) covered by *Phragmites australis*

4.3 SPOT image analysis and interpretation

SPOT consisted of different images which had to be merged through mosaicking to produce one dataset (details of which are elaborated on in the Chapter 3). It should be noted that spatial resolution of SPOT images is higher than that of Landsat. SPOT images used in this study have high spatial resolution that ranges from 1.5 to 5.5m. Hence, mixed pixel problems are minimised. Figure 4.1 shows that *P. australis* cover less area and are more visible along the river.

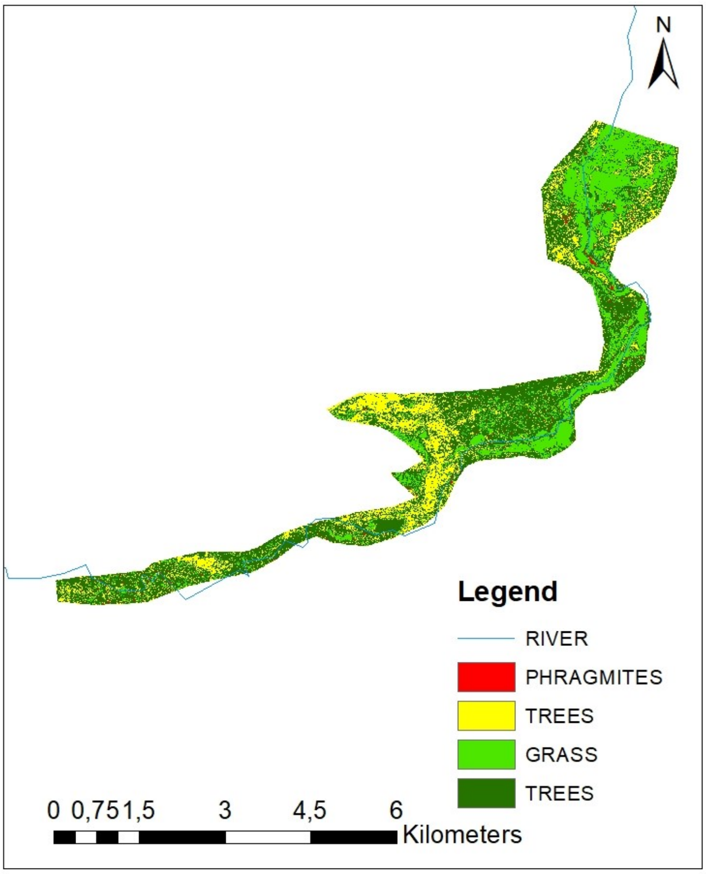

Figure 4.9 Year 2011classified SPOT Image

More *P. australis* are observed in Figure 4.10 as compared to Figure 4.9 There has been a slight observed increase of *P. australis* from year 2011 to 2013.

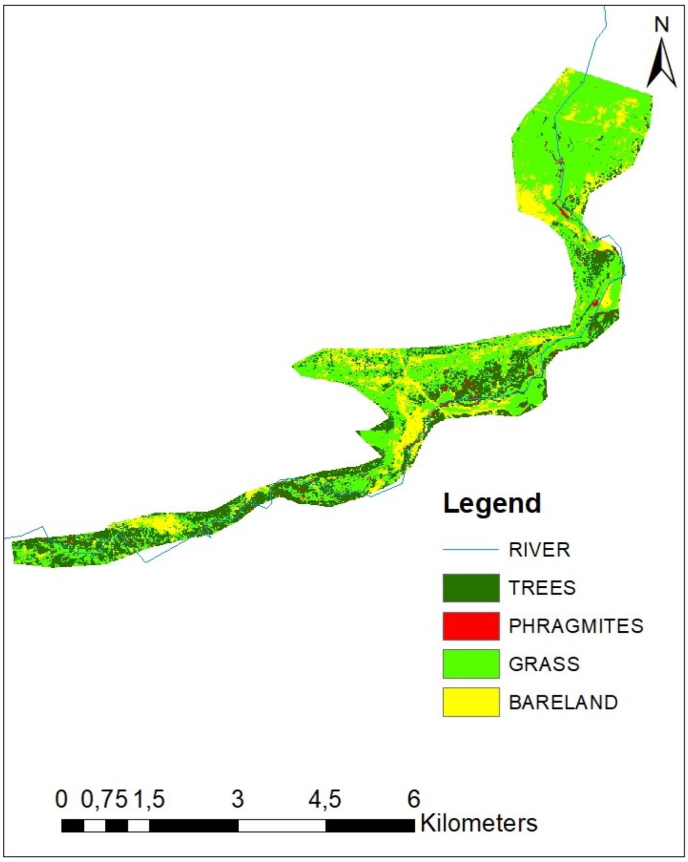

Figure 4.10 Year 2013 Classified SPOT image for SPOT.

Figure 4.11 shows less *P. australis* as compared to year 2011 and 2013. More of the *P. australis* are observed along the river and this is because they have preferable conditions which include aquatic and semi aquatic areas.

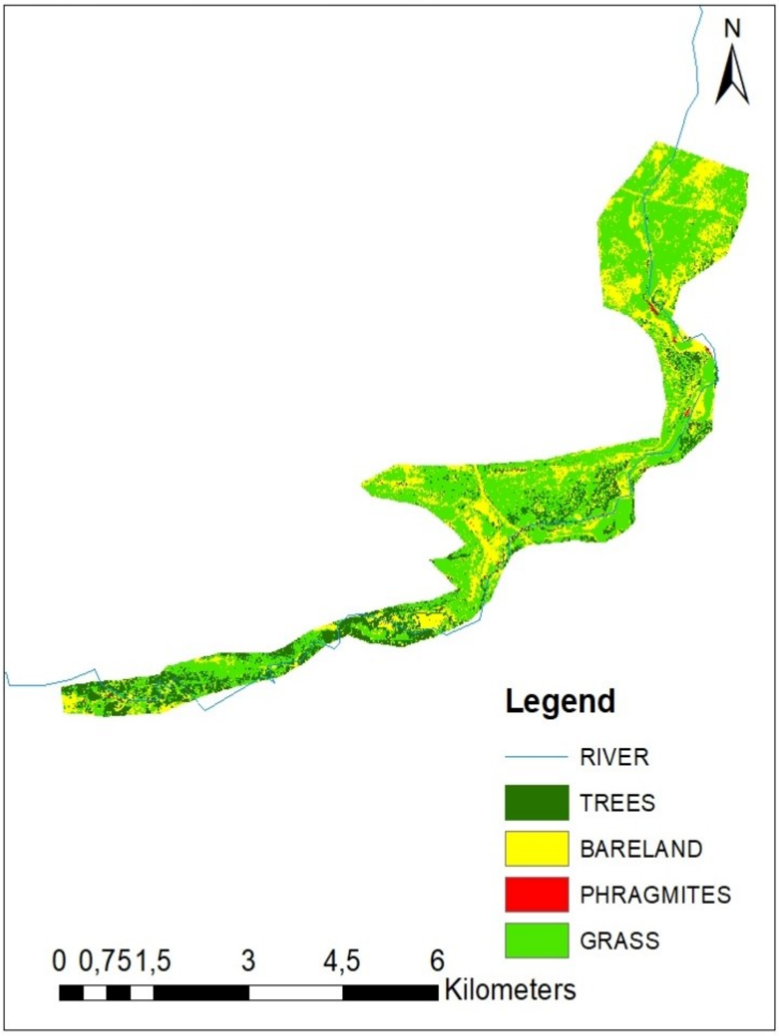

Figure 4.11 Year 2015 classified SPOT Image.

Year 2017 shows significant increase in *P. australis* stands as compared to years 2011, 2013 and 2015. This is suspected to be due to mixed pixels and same reflectance of different features on the ground. The red colour is observed along the river and at the edge of the study site (Figure 4.12).

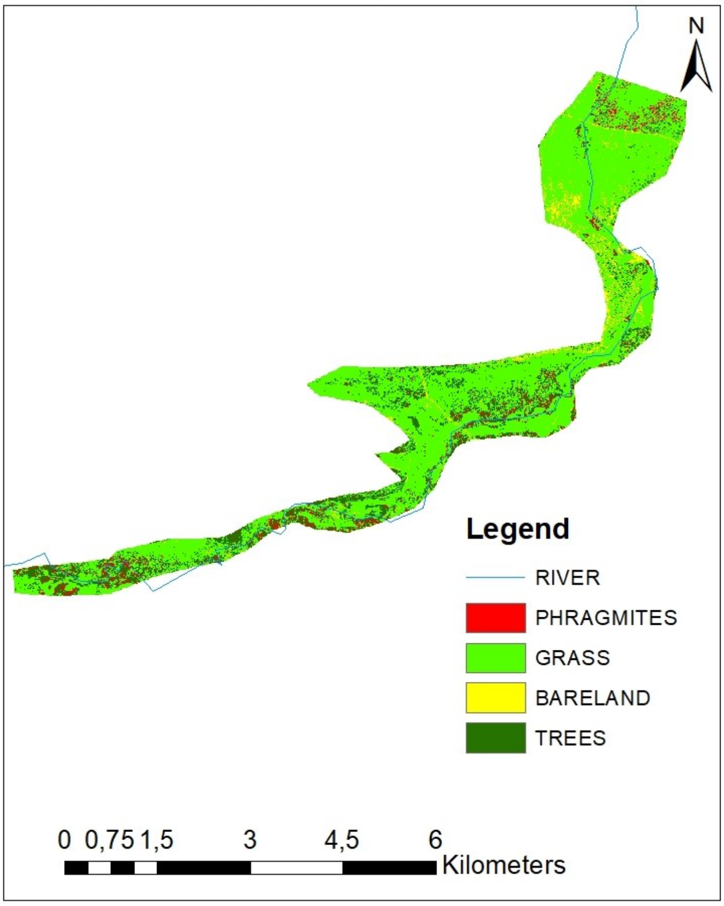

Figure 4.12 Year 2017 classified SPOT image

Figure 4.13.5 shows that *P. australis* covers a smaller part of the study area compared to other land covers classes. An increase of 10% *P. australis* area coverage from year 2011 to 2013 was observed (Figure 4.11) and a noticeable decrease of 15% from year 2013 to 2015. A significant increase of 52% from year 2015 to 2017 was also observed (Figures 4.11 and 4.12).

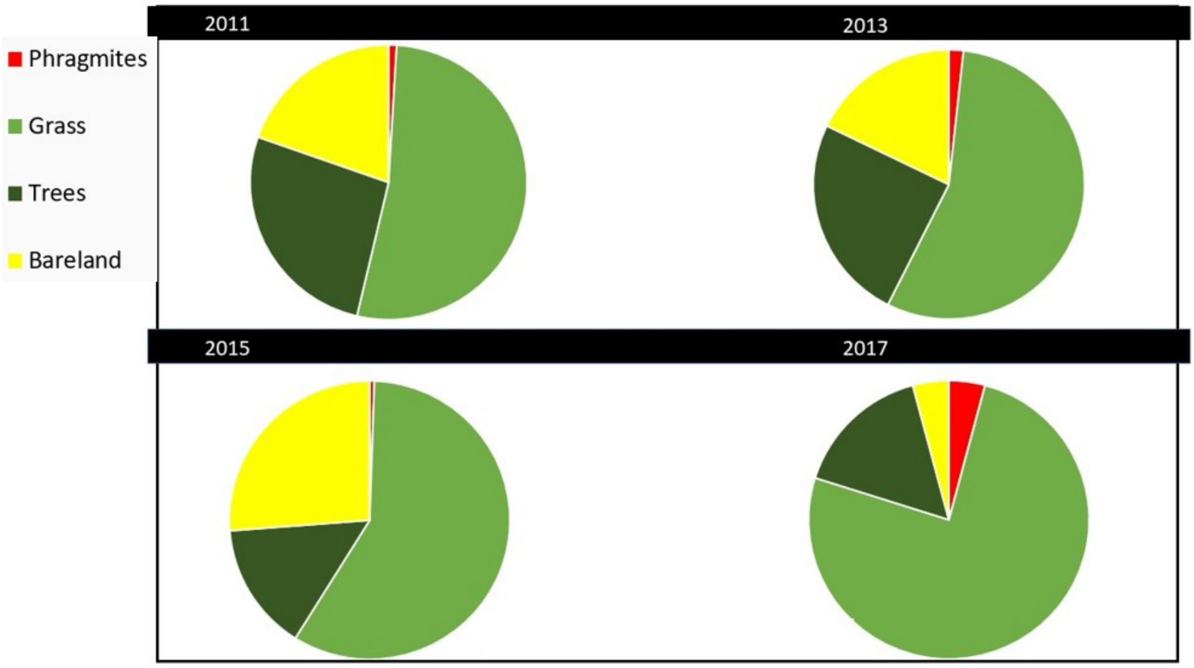

Figure 4.13 Area (ha) covered by each landcover class

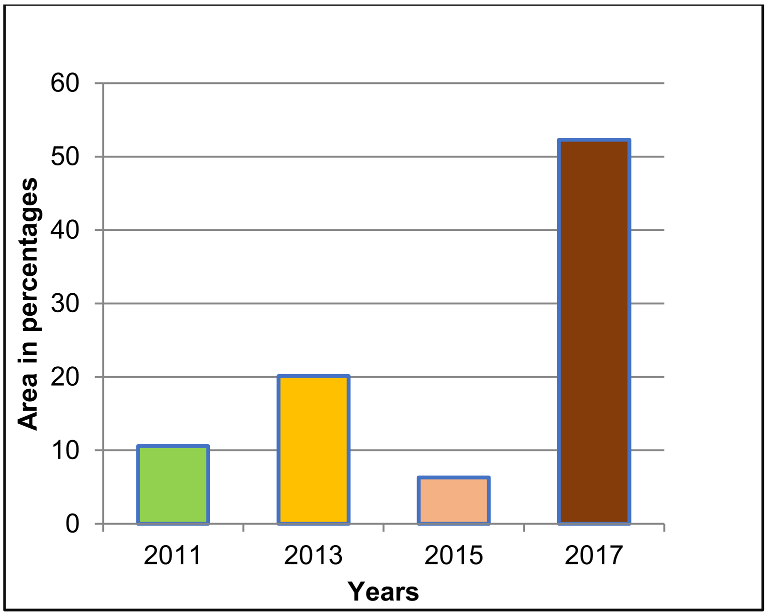

Figure 4.14 Bar graph showing total areas covered by *Phragmites australis*

The area of land cover classes was computed using pixel count shown from the signature (Tables 4.2 and 4.5). As SPOT images had different spatial resolutions (Table 4.1), different calculations were used for each spatial resolution. Higher resolutions produced the more reliable results. Similar to Landsat imagery, slight changes in areas were observed over the years, however, according to Kruskal-Wallis analysis no significant differences ($H = 1.833$, $p = 0.596$) were observed across years, whereas significant differences ($H = 11.735$, $p = 0.008$) were observed among the different vegetation land classes.

Table 4.6 Signature editor for year 2011 classified image

Class	Signature name	Count	Area (ha)
1	Trees	113972	598.35
2	*P. australis*	20101	10.56
3	Grass	576158	302.48
4	Bareland	424442	222.83

Table 4.7 Signature editor for year 2013 classified image

Class	Signature name	Count	Area (ha)
1	Trees	92054	288.68
2	*P. australis*	6420	20.13
3	Grass	207295	650.07
4	Bareland	66307	207.93

Table 4.8 Signature editor for year 2015 classified image

Class	Signature name	Count	Area (ha)
1	Trees	55421	173.8
2	*P. australis*	2004	6.28
3	Grass	217127	680.91
4	Bareland	97524	305.83

Table 4.9 Signature editor for year 2017 classified image

Class	Signature name	Count	Area (ha)
1	Trees	893627	201.06
2	*P. australis*	232494	52.31
3	Grass	423463	952.79
4	Bareland	265904	59.82

A comparison of the two satellite imagery types revealed similarities ($F = 1.071$, $Df = 3$, $p = 0.495$) across the study years in terms of area based on ANOVA analysis, with significant differences ($F = 34.321$, $Df = 3$, $p = 0.008$) being observed across the different land classes for the two satellite imagery types.

4.4. Accuracy assessment

Accuracy assessment was used to quantitatively assess how effectively the pixels were sampled into the correct land cover classes (Congalton, 1991). It was used to compare the performance of classified images for both SPOT and Landsat data in mapping the distribution and abundance of *P. australis*.

Accuracy table used was the theoretical confusion matrix (error matrix) of classified images. These tables are important in determining whether the classified image is fit to be used or the need to be reclassified (Stehman, 2004). The columns of the confusion matrix show to which classes the pixels belong in the validation set and the rows show to which classes the image pixels have been assigned in the image. The diagonal shows correctly classified pixels. Pixels that are not assigned to the class they belong to are not represented diagonally and give an indication of the confusion between the different land-cover classes in the class assignment (Yan et al., 2006).

One of the objectives of the study was to use both Landsat and SPOT accuracy assessment to determine which sensor is more suited for mapping the distribution of *P. australis*. Using different formulas, accuracy evaluating parameters were calculated and represented in accuracy Tables 4.4.1 and 4.4.2. Landsat images showed an average overall accuracy and average kappa coefficient of 61.20% and 0.337, respectively. The 2011 images, however, showed the lowest overall classification accuracy likely due to their low spatial resolution at 30m.

SPOT images have an average overall accuracy of 71.50% and an average Kappa coefficient of 0.567. For the year 2015 the producer's accuracy ranged from 56% to 88% and 33% to 97% for Landsat and SPOT, respectively. SPOT images had a user's accuracy that ranged from 18% to 90%, whereas Landsat images ranged from 60% to 75%. Producer's accuracy is a measure for how often features on the ground are correctly classified on the classified image. User's accuracy reflects how often features on the map will be present on the ground (Foody, 2010). The area coverage for year 2015 in both images shows similar results, requiring a further analysis of accuracy from both SPOT and Landsat images. The user's accuracy for *P. australis* is 63% for SPOT and 60% for Landsat images. Omission error refers to reference sites that were left out in the classified image. *P. australis* had omission errors of 30% and 33.3% for SPOT and Landsat, respectively.

The commission error reflects the points which are mistakenly included in a specific category to which they do not belong. Commission error is Landsat and SPOT implies that there are several points which are classified as *P. australis* in the classified map but are actually not *P. australis* on the reference map, accounting for "mixed pixels". The overall classification accuracy was81.4% and 68.6% for SPOT and Landsat, respectively. An overall Kappa coefficient of 0.53 for Landsat which is considered moderate according to the criteria of Kappa statistics was observed. The Kappa coefficient for SPOT was 0.73 and rated to be substantial.

Table 4.4.1 Accuracy of classification for year 2011 Landsat image

	Trees	Grass	*P. australis*	Bareland	Total	Commision Error	User's accuracy
Trees	0	4	0	3	7	57.14%	0.00%
Grass	20	37	3	2	60	36.67%	61.67%
P. australis	1	3	7	0	11	36.36%	63.64%
Bareland	5	3	0	0	8	37.50%	0.00%
Total	26	47	10	5	86		
Omission Error	80.77%	21.28%	30.00%	100.00%			
Producer's Accuracy%	0.00%	78.72%	70.00%	0.00%			
Overall classification Accuracy	51.16%						
KAPPA COEFIENT	0.14887						

Table 4.4.2 Accuracy of classification for year 2013 Landsat image

	Trees	Grass	*P. australis*	Bareland	Total	Commision Error	User's accuracy
Trees	18	16	3	0	37	51.35%	48.65%
Grass	0	34	0	3	37	8.11%	91.89%
P. australis	2	0	4	0	6	33.33%	66.67%
Bareland	0	6	0	0	6	100.00%	0.00%
Total	20	56	7	3	86		
Omission Error	10.00%	39.29%	42.86%	100.00%			
Producer's Accuracy%	90.00%	60.71%	57.14%	0.00%			
Overall classification Accuracy	65.12%						
KAPPA COEFIENT	0.4298						

Table 4.4.3 Accuracy of classification for year 2015 Landsat image

	Trees	Grass	*P. australis*	Bareland	Total	Commision Error	User's accuracy
Trees	18	4	2	0	24	25.00%	75.00%
Grass	11	27	0	1	39	30.77%	69.23%

P. australis	3	1	6	0	10	40.00%	60.00%
Bareland	0	4	1	8	13	38.46%	61.54%
Total	32	36	9	9	86		
Omission Error	43.75%	25.00%	33.33%	11.11%			
Producer's Accuracy%	56.25%	75.00%	66.67%	88.89%			
Overall classification Accuracy	68.60%						
KAPPA COEFIENCY	0.53711						

Table 4.4.4 Accuracy of classification for year 2017 Landsat image

	Trees	**Grass**	***P. australis***	**Bareland**	**Total**	**Commision Error**	**User's accuracy**
Trees	15	10	2	0	27	44.44%	55.56%
Grass	6	30	1	3	40	22.50%	75.00%
P. australis	3	1	7	0	11	36.36%	63.64%
Bareland	1	6	0	1	8	75.00%	12.50%
Total	25	47	10	4	86		
Omission Error	36.00%	36.17%	30.00%	75.00%			
Producer's Accuracy%	60.00%	63.83%	70.00%	25.00%			
Overall classification Accuracy	61.63%						
KAPPA COEFFIENT	0.39608						

Table 4.4.5 Accuracy of classification for year 2011 SPOT image

	Trees	**Grass**	***P. australis***	**Bareland**	**Total**	**Commision Error**	**User's accuracy**
Trees	19	20	1	0	40	52.50%	47.50%
Grass	3	17	1	4	25	28.00%	68.00%
P. australis	2	0	8	0	10	20.00%	80.00%
Bareland	1	0	10	0	11	90.91%	0.00%
Total	25	37	20	4	86		
Omission Error	20.00%	54.05%	60.00%	100.00%			
Producer's Accuracy%	76.00%	45.95%	40.00%	0.00%			
Overall classification Accuracy	51.16%						
KAPPA COEFFIENT	0.30893						

Table 4.4.6 Accuracy of classification for year 2013 SPOT image

	Trees	**Grass**	***P. australis***	**Bareland**	**Total**	**Commision Error**	**User's accuracy**

Trees	19	4	3	0	26	26.92%	73.08%
Grass	3	34	0	2	39	12.82%	87.18%
P. australis	2	1	7	0	10	30.00%	70.00%
Bareland	0	9	0	2	11	81.82%	18.18%
Total	23	48	10	4	86		
Omission Error	21.74%	29.17%	30.00%	50.00%			
Producer's Accuracy%	82.61%	70.83%	70.00%	50.00%			
Overall classification Accuracy	72.09%						
KAPPA COEFFIENT	0.56834						

Table 4.4.7 Accuracy of classification for year 2015 SPOT image

	Trees	Grass	*P. australis*	Bareland	Total	Commision Error	User's accuracy
Trees	18	1	1	0	20	10.00%	90.00%
Grass	1	35	1	2	39	7.69%	89.74%
P. australis	4	0	7	0	11	36.36%	63.64%
Bareland	2	3	1	10	16	25.00%	62.50%
Total	25	39	10	12	86		
Omission Error	20.00%	10.26%	30.00%	16.67%			
Producer's Accuracy%	72.00%	89.74%	70.00%	83.33%			
Overall classification Accuracy	81.40%						
KAPPA COEFIENCY	0.728828						

Table 4.4.8 Accuracy of classification for year 2017 SPOT image

	Trees	Grass	*P. australis*	Bareland	Total	Commision error	User's accuracy
Trees	19	20	1	0	40	52.50%	47.50%
Grass	3	17	1	4	25	28.00%	68.00%
P. australis	2	0	8	0	10	20.00%	80.00%
Bareland	1	0	10	0	11	90.91%	0.00%
Total	25	37	20	4	86		
Omission Error	20.00%	54.05%	60.00%	100.00%			
Producer's Accuracy%	76.00%	45.95%	40.00%	0.00%			
Overall classification Accuracy	51.16%						
KAPPA COEFIENCY	0.30893						

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Mapping the distribution and abundance of *P. australis* in the is of importance to the environmental managers. The study aim was to assess the distribution and abundance of *P. australis* comparing two different types of satellite images, SPOT and Landsat. This research served to fulfil the objectives established in this thesis, which were to show any changes in distribution and abundance of *P. australis.* Remote sensing has been used since the 1970s for different purposes including the mapping of *P. australis* distribution (Adam et al., 2010). However, the reliability of remote sensing can be increased using additional classification, analysis and interpretation of satellite images using reference data (Yuan et al., 2005). In the case of this study, reference data took the form of collected field data. The main aim of the field work was to gain familiarity with the area. Measuring *P. australis* also provided insight into what could be expected on the satellite images during the classification process.

Supervised classification was chosen as the best classification method for the study. Maximum likelihood classification was then applied after training site selection to complete the classification process. The classification method chosen was best suited for the study because prior knowledge about the area studied was available, which also made training sites selection easier. Eight images were used in this study consisting of four Landsat and four SPOT images spanning seven years between years 2011 and 2017.

It was observed in this study, that the total cover of *P. australis*had increased between years 2011 and 2017. More *P. australis* stands were observed along the river, as they thrive in wet conditions. There, however, *P. australis* were observed on the edges of study site, due to the problem of “mixed pixels” wherein pixels fall in the category they do not belong. The problem of mixed pixels is common, and in some cases, it is caused by low spatial resolution

(Villa et al 2010). Landsat images showed a sharp decrease in *P. australis* from years 2011 to 2013, whereas SPOT images showed a slight increase for the same period. Year 2015 both SPOT and Landsat showed similar area coverage by *P. australis* which was 6.3ha and 5.9ha, respectively.

The study demonstrated the advantages of using SPOT image over Landsat to map landcover especially small patches of *P. australis*stands, evidenced by a considerably higher overall accuracy of classification. SPOT produced the highest overall accuracy (OA = 81.4%) and the lowest error of omission (OE = 1.59%) as well as a relatively low error of commission (CE = 30%) for *P. australis*. Landsat produced an overall accuracy of 68.6% and an error of commission of 33.3% for year 2015. Correlation between the classified image is shown by the overall kappa coefficient average of 0.5648 and 0.37 for SPOT and Landsat, respectively.

As a consequence of the satellite images selected for this study having been acquired during the early spring there was an issue of incorrectly classifying *P. australis* with other land cover classes. According to Arzandeh and Wang (2003), this was attributed to other wetland vegetation and *P. australis* having similar reflectance responses in spring season. Another limiting factor was the spatial resolution of the remote sensing imagery in comparison to the size and shape of *P. australis* stands within the area. The year 2011 classified image has the lowest spatial resolution of 30m meaning that a pixel covered $900m^2$. This caused less reliable results as more pixels were classified into incorrect categories. Given the aerial coverage of the satellite images, these images may have not be applicable for small stands of *P. australis*. Future research with a small aerial coverage of *P. australis* would therefore not benefit from using satellite imagery in the analysis due to the poor resolution of the sensors. Therefore. it will be ideal to use satellite images with high spatial resolution.

In this study remote sensing data was used to map the distribution and abundance of *P. australis*. Two satellite sensors namely SPOT and Landsat were selected for this purpose. The reason behind the selection of the two sensors was there being limited literature of both being used together to map the distribution of *P. australis*. The study shows an increasing trend in *P. australis* when using SPOT images, whilst no trend is depicted from using Landsat satellite images. The other objective of the study was to assess the performance of both sensors in mapping *P. australis*. This was achieved by individually assessing their classification accuracy. From the results it can be concluded that SPOT performance is better than that of Landsat. This is supported by the overall accuracy of 71.20 and kappa coefficient of 0.56, which is said to be substantial according to the criteria of Kappa statistics. The better performance of SPOT over Landsat might be attributed to its high spatial resolution that ranges from 1.5 m to 5.5 m and 30 m to 15 m, respectively. Remote sensing has proven to be a suitable tool in mapping *P. australis* as the study has yielded promising results.

5.2. Recommendations

Future studies should consider using machine learning such as random forest regression to minimise misclassification of pixels. An extensive field work should be done before the actual classification processes. Future research should consider the use of sensors with high spatial resolutions to detect small patches of *P. australis*. More points should be chosen for accuracy assessment of classification to increase the overall accuracy of the classification.

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Appendices

Appendix A Remote sensing timeline (adapted from Aggarwal, 2004)

1800	Discovery of Infrared by Sir W. Herschel
1839	Beginning of Practice of Photography
1847	Infrared Spectrum Shown by J.B.L. Foucault
1859	Photography from Balloons
1873	Theory of Electromagnetic Spectrum by J.C. Maxwell
1909	Photography from Airplanes
1916	World War I: Aerial Reconnaissance
1935	Development of Radar in Germany
1940	WW II: Applications of Non-Visible Part of EMS
1950	Military Research and Development
1959	First Space Photograph of the Earth (Explorer-6)
1960	First TIROS Meteorological Satellite Launched
1970	Skylab Remote Sensing Observations from Space
1972	Launch Landsat-1 (ERTS-1): MSS Sensor
1972	Rapid Advances in Digital Image Processing
1982	Launch of Landsat -4: New Generation of Landsat Sensors: TM
1986	French Commercial Earth Observation Satellite SPOT
1986	Development Hyperspectral Sensors
1990	Development High Resolution Space borne Systems
1990	First Commercial Developments in Remote Sensing
1998	Towards Cheap One-Goal Satellite Missions
1999	Launch EOS: NASA Earth Observing Mission
1999	Launch of IKONOS. very high spatial resolution sensor system