

Single and multi-temporal assessment of natural resources using remote sensing

By

Mbali Mahlayeye

A dissertation submitted in partial fulfilment of the requirement for the degree of

Masters of Science in Geoinformatics

in the Department of Geography, Geoinformatics and Meteorology at the

University of Pretoria

October 2017

Declaration

This is to certify that the work is entirely my own and not of any other person, unless explicitly acknowledged (including citation of published sources). The work has not been previously submitted in form to the University of Pretoria or to any other institution for assessment or for any other purposes.

Signed:

Date:

Dissertation Supervisors:

Main Supervisor:

Dr. Joel Ondego Botai

Chief Scientist

South African Weather Services

Department of Geography, Geoinformatics and Meteorology, University of Pretoria

Co-supervisor:

Dr. Abel Ramoelo

Principal Research Scientist: Earth Observation

Council for Scientific and Industrial Research (CSIR)

ACKNOWLEDGEMENTS:

I would like to thank God for always being there in my academic journey. For always opening doors that were closed and for always reminding me that I am capable of becoming anything I ought to set my mind on. Throughout the years, His support, kindness and love became so tangible. I would also like to thank my mother, Anna Linah Mahlayeye, who always gave me the support I needed and always prayed for me. She understood why I spent few days at home during the holiday recess. I am grateful to my siblings, Mpho Tswane, Tebogo Tswane and Thandiwe Soko for always making me want to become better. I would like to give a special thanks to my grandfather, Mkhul'Skhosana, who always asked, "Palesa, kanti isikolo asipheli yini?"

I would like to give a special thanks to Dr Botai, who always believed in me and my capabilities within the field of remote sensing. His continued support has seen me push through till the completion of this project. I will forever be grateful to Dr Ramoelo who walked this journey with me from the beginning to its completion. Your encouragement, support and availability made this project a great success. I would also like to give a special thanks to GeoTerralmage for their support and encouragement. Lungile Moyo and Mark Thompson, your time and the discussions we had contributed greatly to the outcome of this project. I would like to thank Simon Moloele for always being supportive and understanding. I would like to thank Oupa Malahlela for his contribution to this study. A further thank you to the Department of Water and Sanitation for the bursary to enable me to further my studies. I am grateful to the Department of Geography, Geoinformatics and Meteorology at the University of Pretoria for their support during this journey.

I would like to thank Prof. W. Altermann for greatly contributing to my scientific writing skills. Your great level of excellence pushed me to greatly improve my writing skills. I would further like to thank Sandile Makasi, Lerato Senoko Dube, Chemist Mabena, Dr Mampho Molekane and Mpho Mkhomatha for the inspiration, motivation, support and great encouragement. A special thank you to Gaborekwe Tiro, his selfless nature and fighting spirit made this journey better. "A luta continua, vitória é certa". To my nephew and niece, Nompumelelo Jele, Samkelo Soko, and to all my friends and colleagues, thank you so much for your great support.

ABSTRACT

The study area of this project is located in Makhado Municipality, Limpopo, South Africa. The Limpopo Province is commonly known for being rich in the country's natural resources. It has a number of villages that are characterized by rich natural resources and a well-known nature reserve, Soutpansberg Mountains. Natural resources such as water, plantations, woodlands and grasslands are commonly found in these villages and are commonly used for alleviating poverty. Rural communities in this municipality are still highly dependent on natural resources. The high dependence on these natural resources subsequently affects negatively the natural environment, e.g. processes such as land degradation. Villages in this region have limited infrastructure development that influence people's livelihood. Infrastructure developments are commonly known for contributing to growing the economy and it will be no different if such developments are built in these villages. Therefore, it is imperative to find innovative and scientific techniques that provide information which can assist in finding ways of balancing the interaction between the environment and its people.

In order to successfully do so, ways of managing and monitoring of natural resources in villages such as Makhado becomes a necessity. Land cover information is required to adequately understand the extent and status of the natural resources of the Makhado region. This information is required for effective monitoring of natural resources. With the aid of remote sensing applications, land cover studies are possible. The applications always aim to provide efficient methods using low cost or freely available data. The main objective of this study was to innovatively and accurately map the land cover classes of Makhado Municipality using Landsat imagery. The study investigated the performance of single and multi-temporal assessment approach. The study found that the results of the multi-temporal approach were more accurate compared to the single-date approach for both periods. The overall accuracy of single-date classifications were 78.1% with K_c of 0.74 and 54.3% with K_c of 0.46 respectively. The classification map results of the multi-temporal approach were 72.9% with K_c of 0.68 and 79.0% and a K_c of 0.76 respectively. The multi-temporal classification maps were used for post-classification change detection. The results of these methods illustrated the major decrease in grasslands from 2006-2009 and 2013-2015 respectively. These results assisted in making further inferences of how the drastic and severe drought that occurred in 2015 till recently had a significant impact on the land cover.

Contents

CHAPTER 1: INTRODUCTION.....	1
1.1 General Background.....	1
1.2 Study Area.....	5
1.2.1 Location and study area characteristics.....	5
1.2.2 Climate.....	7
1.2.3 Topography.....	8
1.2.4 Demographics.....	8
1.3 Problem Statement.....	8
1.4 Aim & Objectives.....	10
1.5 Research Questions.....	10
1.6 Summary.....	11
CHAPTER 2: LITERATURE REVIEW OF LAND COVER, LAND COVER MAPPING AND LAND COVER CHANGE.....	12
2.1 Land cover.....	12
2.1.1 Introduction.....	12
2.1.2 The role and importance of Land cover globally and locally.....	12
2.2 Land cover Mapping.....	15
2.2.1 Introduction.....	15
2.2.2 Historical background of land cover mapping.....	16
2.2.3 History of Land cover mapping in South Africa.....	17
2.2.4 The current South African National Land cover 2013/2014.....	18
2.3 Remote sensing for land cover mapping.....	20
2.3.1 Introduction.....	20
2.3.2 The fundamentals of Remote Sensing.....	20
2.3.3 Image Classification for land cover mapping.....	21
2.3.4 Maximum-Likelihood Classification for Remotely Sensed Data.....	23
2.4 Land cover mapping challenges.....	23
2.4.1 Land cover mapping and its challenges.....	23
2.5 The innovative ways to map spatial features.....	24
2.5.1 Mapping and delineating water bodies.....	24
2.5.2 Delineating and mapping actively irrigated fields Water.....	25
2.6 Land cover change detection and its methods.....	27
2.6.1 Introduction.....	27
2.6.2 Change detection methods.....	27

2.7	Previous land cover mapping for change detection using maximum-likelihood classification and Landsat imagery	28
2.8	Single-date and multi-temporal imagery techniques for land cover classification using Landsat imagery	29
CHAPTER 3: DATA AND METHODS OF STUDY		31
3.1	Introduction	31
3.2	Data	31
3.2.1	Landsat satellite imagery	31
3.2.2	SRTM data	32
3.2.3	National land cover 2013/2014	32
3.2.4	Field data	33
3.3	Methodology	36
3.3.1	Introduction	36
3.3.2	Choice of study period	37
3.3.3	Landsat data preparation	39
3.3.4	Supervised classification	40
3.3.5	Improving classification of features	41
3.3.6	Accuracy assessment	42
3.3.7	Change detection	43
3.3.8	Mapping <i>actively irrigated</i> areas during the time of study	44
CHAPTER 4: RESULTS		48
4.1	Introduction	48
4.2	Spectral signatures that drove the choice of classes	48
4.3	Single-date and multi-temporal classification and accuracy results	51
4.3.1	Introduction	51
4.3.2	Landsat Image and classification map overall visual analysis	51
4.3.3	Single-date classification maps and accuracy assessment	53
4.3.4	Multi-temporal classification maps and accuracy assessment	56
4.4	Post-classification change detection using multi-temporal classification maps	61
CHAPTER 5: DISCUSSION		63
5.1	Introduction	63
5.2	The use of multiple techniques for image classification	64
5.3	Multi-temporal approach improved the accuracy of land cover mapping in this study	65
5.4	Monitoring irrigated fields using LST, NDVI and NDWI	66

5.5	Makhado District natural resources have changed over the 2006-2009 and 2013-2015 period	67
5.6	Major factors that affected the changes of natural resources in Makhado Municipality	68
CHAPTER 7: CONCLUSION, CHALLENGES AND RECOMMENDATIONS		71
6.1	Conclusion	71
6.2	Challenges.....	72
6.3	Recommendations.....	73
REFERENCES		75

List of Acronyms

AOI	Area of Interest
OA	Overall Accuracy
CDR	Climate Data Record
DEM	Digital Elevation Model
ENVI	Environment for Visualizing Image
K_c	Kappa Constant
TM	Thematic Mapper
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper Plus
GCP	Ground Control Points
GIS	Geographical Information Systems
GTI	Geo-Terra Image
GPS	Geographical Positioning System
Landsat	Land+Satellite
LEPADS	Landsat Ecosystem Disturbance Adaptive Processing System
LST	Land Surface Temperature
MLC	Maximum-likelihood Classification
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Differentiated Vegetation Index
NDWI	Normalized Differentiated Water Index
NIR	Near-Infrared
NLC	National Land cover
OLI	Operational Land Imager
PA	Producer Accuracy

SPOT	Satellite Probatoired'Observation de la Terra
SWIR	Shortwave Infra-red
SRTM	Shuttle Radar Topography Mission
TIRS	Thematic Infrared Sensor
TOA	Top-of-Atmospheric
UA	User Accuracy
USGS	United States Geological Sciences

List of Tables

Table 3.1 - Landsat OLI TIRS and Landsat 5 TM bands and their characteristics. (USGS, 2016).....	32
Table 3.2 - Land cover classes of this study and those of the NLC 2013/2014 and their physical appearance.....	34
Table 3.3 - Separation of the GCPs to training samples and reference samples.....	35
Table 3.4 - Different cloud-free and available Landsat imagery from 2004 to 2015.....	38
Table 4.1 - Confusion matrix of MLC, 2009 single-date classification map illustrating % of OA, PA and UA.....	55
Table 4.2 - Confusion matrix of MLC, 2015 single-date classification map illustrating % of OA, PA and UA.....	55
Table 4.3 - Confusion matrix of the 2006-2009 multi-temporal MLC classification map.....	58
Table 4.4 - Confusion matrix of 2013-2015 multi-temporal classification map.....	58
Table 4.5 - Illustrates the values of NDVI, NDWI, LST and area size for both periods.....	60
Table 4.6 - Classes area size in ha and percentages for both 2006-2009 and 2013-2015 periods.....	61

List of Figures

Figure 1.1 - A map illustrating the area of study, Makhado in Limpopo.....	6
Figure 1.2 - Average temperature and precipitation of the Vhembe district annually (source: worldweatheronline)	7
Figure 2.1 - Distribution of water consumption by different sectors in South Africa. (Source: NWRS 2013).....	15
Figure 2.2 - Illustration of how foundation classes were sub-divided. (Source: NLC 2013/2014 report)	18
Figure 2.3 - The National Land cover 2013/2014 of South Africa and its 72 classes. (Source: DEA)	19
Figure 2.4 - Electromagnetic spectrum illustrating different wavelength regions. (Source: Lillesand et al., 2004)	21
Figure 3.1 - Makhado map illustrating ground control points.....	33
Figure 3.2 - Field photos illustrating some of the classes of the study across the Makhado area.	35
Figure 3.3 - Methodological framework of the study.	37
Figure 3.4 - Original Surface Landsat 5 TM (26 May 2006) and Landsat 8 OLI TIRS (27 May 2015) both on a 432 false colour band combination and on a WGS 84 coordination system.....	40
Figure 3.5 - The two images are the original stacked Landsat 8 imagery.....	41
Figure 3.6 - The left image is the original 30m DEM and the right image is the processed one. The red parts of the image represent highly elevated areas and the green is the low-lying areas.....	42
Figure 3.7 - The workflow of the innovative approach to extract actively irrigated fields.....	45
Figure 4.1 - Landsat 8 imagery with a 432 false colour composite band combination.....	49
Figure 4.2 - Spectral profile of the classes' best suited for this study.....	49
Figure 4.3 - Histogram illustrating some overlaps of some of the classes.....	50
Figure 4.4 - 2-D scatter plot of Red (x) and NIR (y) illustrating classes of the study for the Landsat 8 (OLI)(TIRS).....	50
Figure 4.5 - Spies dam and unknown dam of the study area.....	52

Figure 4.6 - The top two are the original stacked Landsat 8 imagery and below the classified image, with some areas which are misclassified.....52

Figure 4.7 - Classification map for Landsat 5 (May 2009) generated through the ML classifier.....53

Figure 4.8 - Single-date classification map of Landsat 8 (May 2015) through the ML classifier.....54

Figure 4.9 - 2006-2009 Multi-temporal classification map generated by the ML classifier.....56

Figure 4.10 - 2013-2015 Multi-temporal classification map generated by the ML classifier.....57

Figure 4.11 - Processed Landsat image illustrating the area of study for the irrigation approach.....59

Figure 4.12 - Illustrates the results for both 2009 and 2015 actively irrigated fields.....59

Figure 4.13 - Area sizes in Ha for both 2009 and 2015 study periods.....60

Figure 4.14 - Area in percentage illustrated for 2006-2009 and 2013-2015 for all the classes of the study.....62

Figure 5.1 - Dried-up Nsami dam and cattle drinking water from the dam.....67

Figure 5.2 - 2009 and 2015 maximum daily temperatures.....69

Figure 5.3 - 2009 and 2015 monthly rainfall in mm.....69

CHAPTER 1: INTRODUCTION

1.1 General background

In a global perspective, land cover changes contribute to accelerating the impact of climate change. Change in land cover is also an indicator of human activities which ultimately have an influence on the climate (Haines *et al.*, 2006). Despite such facts, it is important to note that, natural resources play a humongous role in the livelihoods of the rural communities. In South Africa, Limpopo is one of the commonly known provinces that even after apartheid it remained impoverished (Jeeves, 1998). It still struggles to be part of the rural reconstruction from the injustices of the past. Restrictive land policies, skewed agricultural facilities, and racially motivated marketing arrangements favoured white commercial farmers (Jeeves, 1998).

The Limpopo province is commonly known to be rich in natural resources which play a major role for both the livelihoods of the rural and the urban communities (Mpandeleli and Maponya, 2013; Oberhauser, 2015). It is not only the direct use of the natural resources by the people in the villages that causes an increase in demand. Also, the increase in the number of people migrating from rural to urban areas turn to indirectly cause an increase in the demand of natural resources (Oberhauser, 2015). For example, wood is used as energy in different forms for the urban communities. The same wood is collected from the same rural environments that the village people use for their own survival. Oberhauser (2015), further highlights the link in the livelihoods of both rural and urban people through the reliance of natural resources for local and economic activities. These are some of the fundamental factors that led to the studies of land cover mapping and land cover change in communities such as that of Makhado Municipality. The mapping and classification on vegetation become important for the communities and also for environmental management. In a global perspective, vegetation is a base for all living organisms and is a key factor in global climate change studies (Xie *et al.*, 2008). It is because of such key factors that the need to monitor natural resources using efficient and improved accurate methods arises. As a result, innovative ways of mapping and analysing the changes of land cover in Limpopo, South Africa becomes imperative and of great significance.

Natural Resources such as water, plantations, grasslands, forests, fertile land (cultivated areas) in the livelihoods of rural villages in South Africa provides fuel for energy, shelter, food and medication (Hunter *et al.*, 2014; Paumgarten and Shackleton, 2011). The subtropical climate of the study area enables the communities to produce fruits, coffee, tea, sunflower, tobacco, maize, groundnuts, beans and wheat which contributes to the economic

growth of the province (Maponya and Mpandeli, 2012; Moeletsi *et al.*, 2013). Through small-scale business projects, many families use natural resources to alleviate poverty. For example, the communal land provides space for livestock grazing and crop cultivation; such provides food and jobs through the small-scale business projects (Hunter *et al.*, 2014). The role of water is pivotal for all living organisms. All living things depend on water for survival. In the rural areas of Limpopo, the few major uses of water resources are livestock, irrigation, fishing, reeds collection for roofing and brick making (Senzanje *et al.*, 2008). Agriculture plays a major role in the rural villages. It uses a large amount of water volumes compared to other water-requiring activities such as the industrial sector and domestic use (NWRS, 2013). These key factors further emphasize the need to continuously monitor the changes of the natural resources. Further, in a previous study by Guerra *et al.* (1998), illustrated how human activities induce degradation in vegetated areas. Thus, the pressing land degradation problem facing the country (Murithii, 2015; Ramoelo, 2007) does create a necessity to focus on various efficient ways to monitor these natural resources.

Natural resource monitoring is important for environmental sustainability and remote sensing does provide a better solution. Remote sensing is the study of an object, area, or phenomenon without coming into physical contact with that object, area or phenomenon (Campbell, 2007). It entails the use of acquired satellite datasets to collect information about the Earth's surface for land cover studies. In the early 1900s, ground surveys and aerial photographs were widely used for land cover mapping. They were the main source of land use and land cover information (Anderson *et al.*, 1978). The increase in the availability of free Landsat imagery over time led to more use of satellite imagery for land cover mapping and monitoring (Campbell, 2007; Jewitt *et al.*, 2015). Remote sensing technologies have become less expensive compared to collecting the same type and quantity of data using aerial photographs and ground surveys. Further, field based studies are tedious and time consuming. They are also costly and the study areas are commonly in remote areas which are inaccessible. This may be due to the fact that many natural resources are part of objects governance containing new rules with property relations (Hanse *et al.*, 2015). Despite such challenges, natural resources need to be monitored in order to know what we are managing and how we can manage better. The continuous availability of satellite imagery provides a better solution to the abovementioned challenges.

The use of remote sensing applications using satellite imagery provides better methods and efficient platforms that assist in monitoring natural resource changes at wider scales. Satellite imagery is commonly differentiated by its attributes viz. spectral, spatial, temporal

and radiometric (Xie *et al.*, 2008). In this study, Landsat imagery was suitable to study the changes of the natural resources of Makhado Municipality. Satellite imagery dataset such as Landsat is freely available, repetitive every 16 days with a spatial resolution of 30 m (USGS, 2016). Landsat imagery has been widely and successfully used for Land cover mapping in many projects abroad and in South Africa (Kleynhans *et al.*, 2016). It is one of the longest existing datasets that allows long-term Land cover studies (Xie *et al.*, 2008). Land cover change studies require the repetitive acquisition of satellite imagery, and the use of freely available Landsat imagery is cost-effective. The availability of this datasets ensures a more accurate and precise mapping and analysis of land cover. This also enables a process of creating and compiling multi-temporal land cover maps which are used to study the changes that have occurred over time. This emphasizes on the importance of land cover for planning, legislation, management as well as for science studies (Murithii, 2015).

Image classification in remote sensing is one of the majorly used techniques for land cover mapping (Foody, 2002). There are various methods of image classification that have been explored through a number of different studies. There are two broad image classification techniques, supervised and unsupervised classification (Bruzzone *et al.*, 2002). A large variety of classifications developed through statistical methods exists within these two broad classification techniques (Kumar and Sahoo, 2012). In both classification techniques, pixels are grouped based on reflectance properties of the pixels. Unsupervised classification is known as clustering and the technique does not require training samples for land cover mapping. Supervised classification technique requires distinctive known location through collection of training data sets. This type of classification consists of three stages which are (i) training stage, (ii) classification stage and (iii) output stage (Lillesand and Kiefer, 1999). There are various types of supervised classification that can be utilised for image classification in order to create Land cover maps. In this study a supervised approach was undertaken using maximum-likelihood classifier.

Multi-temporal assessment of land cover using maximum-likelihood has been studied by Tottrup (2004), Meddens *et al.*, (2013) and Bodart *et al.* (2011) amongst other researchers. The multi-temporal approach entails the stacking of satellite imagery of the same area but different dates. Ideally, for land cover mapping using dates of the growing period of vegetation is more beneficial. Land cover such as grasslands and agricultural fields are then easily detected from the stacked images. In this study, this approach worked successfully as the study looked at images that were within the growing period of vegetation. Tottrup (2004), confirmed that the multi-temporal assessment approach enhanced the classification

of the image. The approach provides spectral information that is related to the changing seasonal growth of the vegetation. Further, image classification in areas such as Makhado Municipality where the area consists of a large escarpment, have shadows. As it is commonly known, shadows within the satellite imagery affect the accuracy of the classification. The multi-temporal assessment approach has been used in this study to improve areas that consist of shadows. The multi-temporal approach seems to minimise the appearance of and hence improve the classification output. Both single-date and multi-temporal Landsat satellite imagery approach was explored in this study.

In this study, additional, input variables such as Normalised Differentiated Vegetated Index (NDVI), Normalized Differentiated Water Index (NDWI), Land Surface Temperature (LST) and Shuttle Radar Topography Mission (SRTM) 30m were also used to map and improve the accuracy of the land cover mapping. The NDVI and NDWI are commonly used indices in vegetation and agricultural studies. These two indices have been best used for enhancing and delineating healthy vegetation and water features (Bhandari *et al.*, 2014). The two bands used to calculate NDVI are the red and Near-Infrared bands. Likewise with NDWI, it is an index that at a specific threshold it delineates water features. The formation of how the index works, focussed on where water is mostly absorbed in the electromagnetic spectrum. Water features absorb energy in the NIR region (Bhandari *et al.*, 2014). In this study, these indices were successfully explored. The use of the SRTM 30m digital elevation model is also one of the valuable input variables in such studies where the land surface is not flat. The use of DEM to understand the topology of the area has been explored. The ability of using such dataset to delineate the highly elevated areas from the low lying areas adds more value to such studies. It provides information about the differences in vegetation land cover of the area of study.

There exists a wide-range of methodologies for change detection studies using satellite imagery (Mas, 1999). Mas (1999) grouped change detection procedures into three broad headings viz. image enhancement, multi-temporal data classification and comparison of two independent Land cover classification. Image enhancement involves the use of thresholds from mathematical combination of different bands using different dates. Multi-temporal data classification on the other hand, is based on performing a single analysis of combined imagery datasets of different dates. Lastly, the comparison of two independent land cover classifications, also known as post-classification which uses satellite imagery obtained at different period for comparative analysis (Mas, 1999). Post-classification approach is simple

to implement while providing clear land cover change results. This method was used for change detection purposes in this study.

1.2 Study area

1.2.1 Location and study area characteristics

The study is within Vhembe District Municipality, the northernmost part of Limpopo, South Africa (see Figure 1.1). The district is one of the five districts of the Limpopo province. Vhembe District is known for its fruit industry, whereby large-scale commercial farms produce avocados, mangoes, and bananas (Ziervogel *et al.*, 2006). The district consists of four local municipalities viz. Mutale, Thulamela, Collins Chabane and also Makhado. Makhado local municipality consists of villages which form part of the southwestern part of the Vhembe District Municipality. It is generally known for its livestock farming and the southern parts for its timber plantations. The eastern part runs through to the Kruger National Park game reserve. The total area of Makhado is approximately 8 300 km². Variation in the vegetation type of the area is a result of different altitudes and soil types within the area. According to Tlou *et al.* (2015), the type of vegetation existing in the area are, Arid Low Veld (ALV), Mopane veld (MOV), North eastern mountain sourveld (NMC), Sourished mixed bushveld (SMV), Arid sweet bushveld (ASV) and Lowveldsourveld (LSV).

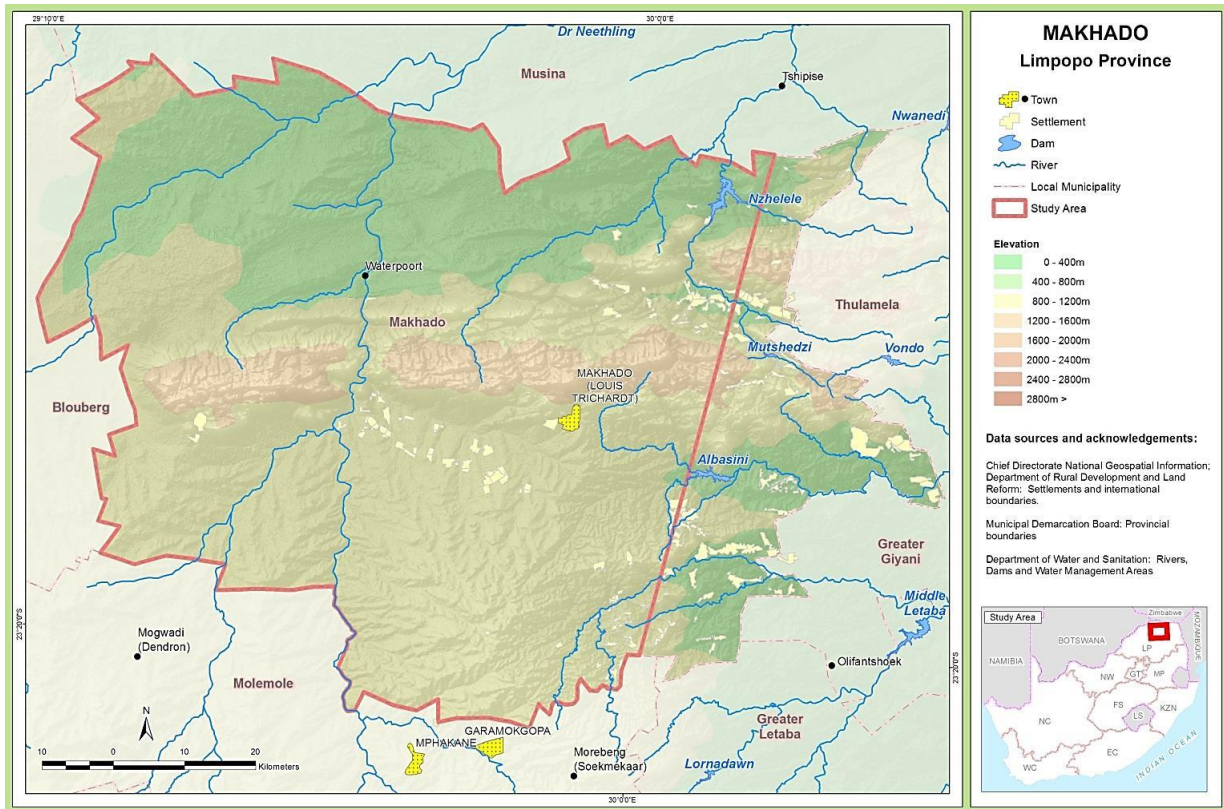


Figure 1.1- The area of study, Makhado in Limpopo

The study area also consists of Nzhelele catchment basin with a capacity of 55.3 cubic meters. It provides ecosystem services for formal agriculture and also for the coal mine. Coal deposits are found in the Karoo sediments which rest on the northern part of the Soutpansberg mountain range. The Soutpansberg Mountain Range also consists of quartzites and granite. Granite and the Karoo sediments reach the Limpopo River all the way up. The Quartzites Mountains consist of indigenous forest which to the local people is highly valued culturally and it's known for its old tales and legends of the past. According to van Riet (2015), the catchment has insufficient water and a need for innovative ways of managing the basin is of great necessity. The demands of water in the area have increased and that is the result of urbanisation in the upper catchment (van Riet, 2015).

The choice of the study area was motivated by the undergoing land cover changes caused by infrastructure developments and population growth which was highlighted in Kundu *et al.* (2015). The study also expressed how water resources are affected due to the rapid increase in environmental degradation. The hills and mountains of the Soutpansberg make it one of the crucial areas of the Limpopo province that must be monitored over time for nature conservation.

1.2.2 Climate

According to Koppen Climate Classification System, Limpopo province consists of five different climates viz. Cfa, Cwa, Cfb, BWh and BSh. The dominant climate in Limpopo Province is that of BSh, which is characterised by semi-arid conditions. Other parts of the province possess the climatic conditions of Cfa and Cwa, which is characterised by humid subtropical climate. Also, desert-like climatic conditions (BWh) are found in some parts of the province. In Makhado, the climatic conditions are that of Cfb which is characterised by oceanic climate. The annual average temperature is approximately 18°C, with an average rainfall of approximately 790mm. The climatic conditions of the Vhembe district illustrate wide range of variability as a result of climate change. The municipality experiences rainfall season between October to April.

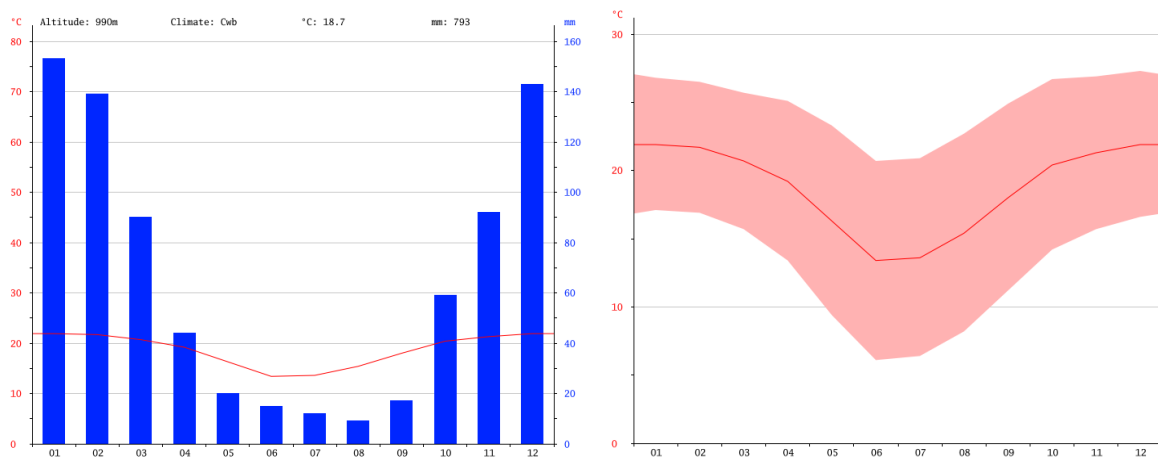


Figure 1.2- Average temperature and precipitation of the Vhembe district annually (Source: worldweatheronline)

Environments consisting of such climate variability are prone to harsh weather conditions. Studies done in several villages of the provinces by Maponya and Mpandeli (2012) have illustrated that severe climatic condition such as drought have occurred and are prone to occur in such climatic environments similar to those of the Limpopo province. It is known the negative impact of such a disaster on the environment. Since the early 80's till now, almost every year there is a shortage of rainfall and this has negatively affected the agricultural production (Maponya and Mpandeli, 2012; Maponya *et al.*, 2015). During 2003 and 2004 Limpopo Province, Vhembe district experienced drought and this illustrates the extreme variability of rainfall and runoff in the Limpopo Province (Mpandeli and Maponya, 2013; Nel and Nel, 2009). The extreme variation in weather conditions affects natural resources. Drought conditions result to land and soil degradation which largely affects crops and

livestock production. The district is mainly characterized by high climatic variability which as a result there is a significant decrease in agricultural productivity (Moeletsi *et al.*, 2013).

1.2.3 Topography

The topography of the area is fairly flat in the northern, western, and central areas whilst the eastern, north-eastern and south-eastern areas consist of undulating hills and rocky outcrops. It consists also of the Limpopo River which has large drainage patterns and floodplains with an eroded valley bottom on the eastern border (Nel and Nel, 2009).

1.2.4 Demographics

The Vhembe district's total area is 8 300 km² and a total population of 516 013, with black people dominating by 97.3 % followed by 2% of white people and the rest is Asian coloured, Indian and other nationalities (StatsSA, 2011). Tshivenda is the majorly used language in the area, followed by Xitsonga, with younger people dominating the population. A highest education level in the area of most people is primary school that is about 43% of the people in the area have primary education, while 37% have secondary education with only 1.3% of the people with post secondary education (StatsSA, 2011). The living conditions are mostly (88.3%) traditional with most households using woodfire for cooking and heating (StatsSA, 2011). Over 80% of the families in the community depend on natural resources for survival. This high reliance in natural resources does subsequently affect the land cover of the area over time.

1.3 Problem statement

Land cover change has become one of the most dominant global phenomena that enormously affect the environment (El-Hattab, 2016). As a result, land cover change studies have become more significant because their availability assists in understanding the link between land cover changes and environmental changes. In South Africa, one of the major environmental problems is land degradation (Murithii, 2015). The northern part of the country is classified as degraded. In these areas there are communal villages that are highly dependent on both plant and water resources for survival (Wessels *et al.*, 2004). Land degradation decreases soil organic carbon and nitrogen and as a result the quality of soil becomes poor and also affects its fertility. Excessive use of plant resources result in soil erosion and water pollution (Murithii, 2015). The environmental changes also pose a threat in the water resources of the country. Considering that South Africa is currently facing a water crisis, water pollution will speedily contribute in further decreasing the already scarce

natural resource. The high dependence on these natural resources is a result of poverty, urbanization and increase in population which subsequently, changes the land cover (Twine, 2003). In a broader view, the decrease in plant and water resources affects the whole ecosystem. Reduction of plant resources through deforestation result in less to no habitat for terrestrial creatures. Also, water pollution not only affects humans but also aquatic life which plays a big role in the ecosystem. This study is motivated by these environmental concerns. Reliable Land cover change information can assist in such rural environments to thoroughly understand the interaction of the environment with its people. This ultimately contributes in making informed decisions about the ever changing environment (El-Hattab, 2016).

The application of remote sensing in the northern part of the country, which is rich in agriculture, indigenous forest and commodities has not been extensively studied or explored. There is still a need to derive detailed information for most parts of the country. Especially in the northern part of the country where there is South Africa's Biosphere Reserve, rich wildlife and drastic variation in weather conditions (Mpandeli and Maponya, 2013; Nel and Nel, 2009). Remote sensing applications' contribution in exploring and understanding such rich parts of the country is important in order to monitor and preserve what is left. The approach in improving Land cover mapping using Landsat imagery is important and contributes to the natural science research of the remote sensing environment. Furthermore, the South African history of land cover mapping illustrates the need for constant and continuous mapping of natural resources. Only four national land cover maps (Ngcofe and Thompson, 2015) have been produced, despite the increasing availability of satellite imagery (Campbell and Wynne, 2011). This affects the effectiveness of monitoring land cover change over a time period.

In earth observation studies, image classification methods have not been fully explored for areas/location such as that of Limpopo, South Africa. Moreover, the use of multi-temporal dataset for improving image classification has not been fully explored. The use of multi-temporal datasets, band ratios and DEM in order to improve the land cover mapping the Makhado area is the new and innovative approach of this study, especially for water bodies and active irrigated area delineation. Most work has been done on the livelihoods of the people (Hunter *et al.*, 2014; Rasethe *et al.*, 2013; Wessels *et al.*, 2004) but very few on the changes of natural resources in the province.

1.4 Aim & objectives

The aim of this study it is to use different methods to determine an innovative approach for improving land cover mapping and land cover change in Makhado Municipality. The innovative use of single and multi-date Landsat imagery from 2006-2015 will be explored.

The objectives of this study were;

- 1) To investigate the accuracy of single-date vs. multi-temporal land cover mapping approach
- 2) To detect and analyse changes in natural resources of the study period in Vhembe district, South Africa
- 3) To determine possible natural drivers of the detected (*in objective 2*) natural resource changes

1.5 Research questions

The research questions discussed and answered in this study using relevant literature, multi-sensor satellite imagery, remote sensing software and also data collected from Makhado Municipality;

- (i) Does the multi-temporal land cover mapping approach improve the classification performance or accuracy as compared to the single-date approach?
- (ii) Has natural resources of Makhado municipality changed over the period of this study?
- (iii) What are the major factors that affect the changes of natural resources in Makhado municipality?

1.6 Summary

Changes in the natural resources largely affect rural communities in the northern part of Limpopo and as a result poverty, droughts, pollution, and other environmental issues arise. Remote sensing provides an effective and efficient approach to map and analyse natural resources in locations with such rich natural resources. Improving the methods of remote sensing applications is important in order to develop advanced image classification techniques. Better and improved methods of image classification become more accurate and efficient and as a result, this contributes in better understanding of the natural and social-economic processes. These processes have a probability of impacting the sustainability of heavily relied-on natural resources. The study is aim at highlighting what methods work best in such environments. It further explores innovative ways of mapping spatial features such as water bodies and active irrigated areas.

CHAPTER 2: LITERATURE REVIEW

2.1 Land cover

2.1.1 Introduction

Land cover is the biophysical cover on the earth surface which forests, agricultural land, and water and other natural surfaces form part of the land cover (Gregorion and Jansen, 2000). Globally, land cover plays a huge role in the ecosystem services as it provides shelter, recreational spaces, food, fossil fuel and medication. It is important to note that land use and land cover are often used interchangeably (Dimiyati *et al.*, 1996). Despite the existing link of land use patterns reflecting the interaction anthropogenic activities on the land cover they still are different. Land use focuses on the use of land by humans while land cover has no emphasize on the activities that exists on the land surface (Campbell, 1996; Gregorio and Jansen, 2000). It is anthropogenic activities that are associated with a land unit within the land cover and how it is utilized for local and economic purposes (Campbell, 1996). Food and Agricultural Organization (n.d.) further indicates that it is debatable whether water areas form part of the land cover and researchers commonly defines the class under land cover (Gregorio and Jansen, 2000). The purpose of this chapter it is to bring to light the importance and role of land cover globally and locally. It is to further understand land cover mapping using remote sensing on a national and local scale. Lastly, seek an understanding of the importance of land cover change detection methods and their contribution to better understanding our environment.

2.1.2 The role and importance of land cover globally and locally

Globally, in an ecosystem, there is a relationship and a great dependence amongst living organisms. If a key part of an ecosystem gets extinct or damaged, the whole ecosystem suffers and the ecosystem becomes unsustainable. Land cover type such as vegetation plays a key role as primary producers in a food pyramid. Primary producers are at the initial stage of the food pyramid, they convert light energy from the sun through photosynthesis into food for primary consumers. Primary consumers are mainly animals that feed on plants and secondary consumers depend on primary consumers for food. Lastly, at the top of the food pyramid are tertiary consumers which feed on secondary consumers. It is important to note that human beings and other animals feed both on plants and animals for survival. This whole process plays a huge role in sustaining the biodiversity systems that exist within our environment.

In Limpopo, South Africa, there are different types of vegetation species utilized to meet the daily needs of the rural villages (Rasethe *et al.*, 2013). Plant resources are at the core of the livelihoods of the rural people. There exist a high dependence on plant resources for food provision, crafting, medication, fuelwood and fibre (Rasethe, 2013). These are the fundamental factors that drive the continuous use of natural resources. Different vegetation species are utilized for different purposes. Within the botanical family, trees are the most preferred. They are used for crafting, fuelwood and medicine (Rasethe, 2013). Multi-usage of such plant species is common in these villages. Rasethe (2013), illustrates how the species recorded in the villages were utilized; firewood (40%), Fruits (36 %), crafting (12%), timber (2%) and medicine (29%). These findings correlated to the findings that were done in other areas of Limpopo by Shackleton *et al.* (2002) and Shackleton and Shackleton (2004). The common use of these types of plant species is mainly due to their availability and long-lasting heat with little smoke. Other plant species are used for extracting chemical compounds for healing different sicknesses and diseases. Plant species such as *Sclerocaryabirrea* are commonly used for a different purpose not only in Limpopo but also in various southern African cultures (Rasethe, 2013). They are believed to be more effective and hence their multi-purposeful use.

Plant resources also play a significant role in providing habitat for wildlife, they use mostly trees for shelter, food, mating and nesting. Also, natural areas which consist of vegetation provides parks which can be used for family and friend gatherings, nature enjoyment, space for physical exercise, a place where some people find tranquillity and solitude (Lynn, 2003). Scientifically, land cover changes affect the biogeochemical cycles, where semi-arid ecosystems such as that of Limpopo Province play a major role. These ecosystems occupy 47% of earth's land cover, and according to Allen-Diaz *et al.* (1996), one 3rd of global vegetation is carbon storage. There are three major biogeochemical cycles, namely; water cycle, nitrogen cycle and carbon cycle (Zhang *et al.*, 2013).

- The carbon cycle is a process whereby carbon is exchanged amongst the lithosphere, atmosphere, hydrosphere and biosphere (Rickie, 2011). Carbon element is crucial for life on earth. It forms major components of many minerals and also exists in different forms in the atmosphere. Both terrestrial and aquatic vegetation plays a significant role in the carbon cycle (Huang *et al.*, 2016).
- The nitrogen cycle is another biogeochemical cycle that has a global impact on the environment. It plays an important role in ecological processes. The supply of nitrogen plays a crucial role in nature and plant diversity. Further, it is also

fundamental in the population dynamics of grazing of animals and their predators. The importance of vegetation availability is further highlighted in the nitrogen cycle studies. It is evident that nitrogen cycle will not be a success if there is no existence of croplands and forestry.

- The water cycle is another cycle that plant resources play a major role in. This is through a process called transpiration, which is evaporation of water from plant leaves to the atmosphere (USGS, 2016). Studies have shown that 10% of the moisture found in the atmosphere is released through transpiration from plants (USGS, 2016). Plant resources' availability is a key factor in regulating atmospheric chemistry and climate (Arneth *et al.*, 2011).

There is a strong natural link that exists between the above-mentioned biogeochemical cycles and plant resources play a significant role in their sustainability. In a nutshell, plant resources play a key role in supporting living organisms on the earth's surface and the whole linkage can be best described as biodiversity.

Water is one of the most indispensable natural resources for all life on the earth's surface. The previously discussed water cycle illustrated how water is important for plant resources. The three cycles depend on one another for environmental sustainability. In South Africa, a country with arid and semi-arid environments contributes to the land surface water supply of ~79% annually (Hedden and Celliers, 2014). The country's biggest water-use sector is agriculture with a total usage of 57% (Hedden and Celliers, 2014). In South Africa, most agricultural activities occur in rural areas. This further highlights the motivation of this study. It is then followed by domestic use with a total of 35% and 8% of usage by the industrial sector (Hedden and Celliers, 2014). According to National Water Resource Strategy 2013, 2% of the water is utilised for generation of electricity. Livestock and the mining industry utilize approximately 2.5% separately. Lastly, afforestation uses 3% (NWRS, 2013).

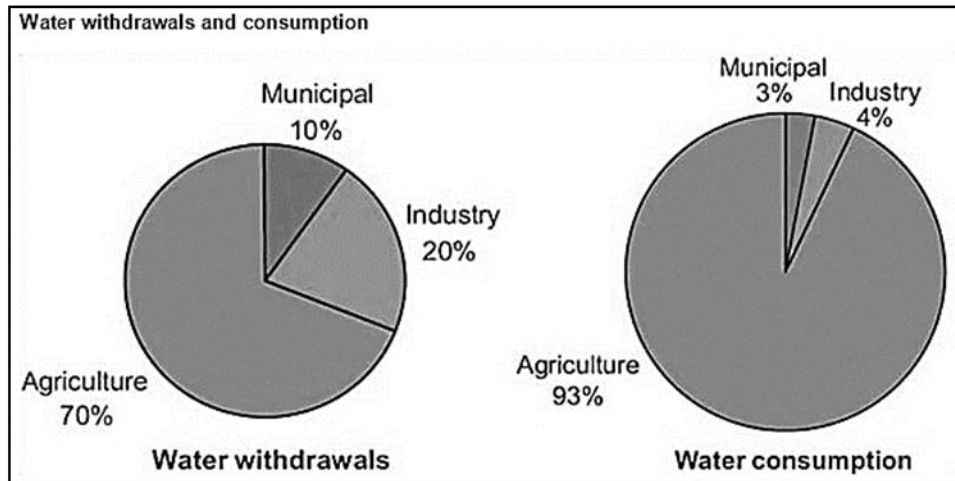


Figure 2.1- Distribution of water consumption by different sectors in South Africa. (Source: NWRS 2013)

Water resources also provides habitat for marine creatures, plants and animals. Reduction of water resources in South Africa will have a great consequence on the food production (Juana, 2012). The availability of water resources plays a role in food security, alleviating poverty and also to the wealth and wellbeing of different communities (McCafferty *et al.*, 2012). There is a need to investigate what will be the possible consequences of water scarcity. Short-term policies will then be implemented to minimise the consequences. Such studies/research requires analysis of the impact of climate change on water resources (Juana, 2012).

2.2 Land cover mapping

2.2.1 Introduction

The mapping of the land cover is important for management of natural resources and ecosystem services. A need arises for comprehensive planning of the interactions of the finite natural resources and the communities as population increases (Campbell, 1996). Land cover maps are produced on a local, national and global scale and they assist in monitoring land cover changes (Lilliesand and Keifer, 1999; Jewitt, 2015). Land cover information is also important in biodiversity and conservation planning. The maps further assist in better understanding the natural and human-induced drivers of change (Clark and Kilham, 2016). Campbell (1996) mentions that on a national level, land cover/land use information contribute to creating policies concerning environmental, economic and demographic issues. As a result, it forms a big part of the decision making on various issues pertaining to land cover and land use. In socioeconomic studies, it is important to understand and know the land patterns for land use planning. In hydrological studies, pre-knowledge of

the distribution of trees, grass, pavements and roofs contributes to understanding rainfall run-off characteristics (Lilliesand and Keifer, 1999).

Landsat imagery which consists of a wealth of information for identifying and monitoring land cover changes is free and the entire archive is available to the scientific communities (Rawat and Kumar, 2015). Moreover to its repetitive coverage of the same area, it includes multispectral data, relatively fine spatial resolution and multi-angular viewing geometries, attributes that drive the land cover mapping methods (Friedl and Brodley, 1997; Rawat and Kumar, 2015). Sobrino and Raissouni (2000) further emphasize that mapping, quantifying and monitoring changes of land cover are key elements in global change studies. This is possible through multispectral data sets that contain spectral bands such as the visible, near-infrared, and thermal infrared bands (Sabrino and Raissouni, 2000; USGS, 2016).

The tremendous role that land cover plays in the ecosystem forces the need to spatially map or record what is taking place on the earth's surface and conduct change detection studies in order to understand how the land cover changes over time. In order to effectively and successfully manage the environment and its landscape, land cover information is imperative and this emphasizes the importance of what Peter Drucker once said: "You can't manage what you can't measure".

2.2.2 Historical background of land cover mapping

The historical origins of land cover mapping dates back to the early use of aerial photography (Hansen and Loveland, 2012). In 1910, Wilbur Wright began to use aeroplanes for acquiring aerial photographs and this was an opportunity for human to explore and understand the information carried through by aerial photographs. During the mid-1900s, curiosity led to the use of kites and balloons to capture and record the aerial view of the land surface, which subsequently led to the earliest synoptic depiction of the land cover (Campbell, 1996). The use of commercial aerial photographs significantly increased after the United States made the data available and this was one of the earliest sources of imagery that captured the land feature characteristics remotely (Lilliesand and Keifer, 1999; Campbell, 1996 and Browning *et al.*, 2009). As a result, there was a need for trained image interpreters. Training was based on acquiring, processing and interpreting aerial photos (Campbell, 1996 and Lilliesand and Keifer, 2000). The training was based on visually interpreting the aerial photographs through different image textures, complex shapes and size of features and also by understanding the depth of the image (Campbell, 1996; Lilliesand and Keifer, 1999). A procedural method of improving the level of confidence in

producing aerial maps that were correct and accurate was designed and followed. There were four different procedural methods/functions;

- (i) classification
- (ii) enumeration
- (iii) measurement
- (iv) delineation (Campbell, 1996; Lilliesand and Keifer, 1999).

Aerial photographs still play a crucial role in change detection studies as its datasets dates back to the 1900s. Their usefulness ranged from water resource management, urban planning, forestry and agriculture (Hansen and Loveland, 2012). Maps were generated quickly and directly from the aerial photographs. Despite its merits, aerial photography had its disadvantages related mainly to how humans handle the data from acquisition to map drawing. Also, the scale was one of the significant specifications on any aerial photos and an ideal scale for the land cover purpose was between 1: 12 000 and 1: 15 000, a relatively a large scale as it covers a small area. In order to map a larger area, more aerial photographs were required and subsequently increases the costs of a project (Spurr, 1948). During the 1970s, space-based land cover mapping initially started and has rapidly increased since then. Digital land cover mapping became the primary method for projects (Hansen and Loveland, 2012).

2.2.3 History of land cover mapping in South Africa

Land cover mapping in South Africa has drastically increased as there has been a continuous increase in satellite datasets. In South Africa, land cover mapping of the whole country using satellite imagery has been previously done for the years 1994, 2000, 2005 and 2013/2014.

(i) National land cover 1994 (NLC 94)

The NLC 94 map was constructed manually using copies of Landsat image 1:250 000 scale maps (Schoeman *et al.*, 2013). The map consists of 31 land cover classes with an accuracy of 79.4% with kappa index of 74.8 (Fairbanks *et al.*, 2000).

(ii) National land cover 2000 (NLC 2000)

The 2000 national land cover was also generated from Landsat dataset which was acquired between 2000 and 2001. This map was generated digitally and has an accuracy of 65.8% with a 57 kappa index (Van den Berg *et al.*, 2008).

(iii) National land cover 2005 (NLC 2005)

The NLC 2005 was mapped generated through the combination of other land cover datasets. Some parts of the country were mapped using SPOT satellite imagery whilst the areas which had no SPOT coverage in 2005 were mapped using Landsat dataset. The accuracy of the NLC 2005 is reportedly between 80% and 83%.

(iv) National land cover 2013/2014 (NLC 2013/2014)

This is the currently latest land cover dataset that was generated using multi-seasonal Landsat 8 satellite imagery. The land cover dataset consists of 72 classes (Ngcofe and Thompson, 2015).

2.2.4 The current South African national land cover 2013/2014

The latest National land cover 2013/2014 (NLC 2013/2014) was developed by GeoTerralimage (GTI). The dataset was created through the use of multi-seasonal Landsat 8 and Landsat 5 imagery. Landsat 5 imagery was used for areas which had no suitable scenes within the period of April 2013 and March 2014. The NLC 2013/2014 consists of 72 classes of both land cover and land use information (Ngcofe and Thompson, 2015). The modelling of the land cover was automated and was based on spectral indices such as Normalised Difference Vegetation (NDVI), Normalised Difference Water Index (NDWI) and other algorithms that were developed using ERDAS Imagine in-house. The automated modelling approach GTI used was based on multi-temporal imagery for each scene. The dates ranged from April 2013 to March 2014, this is a period that illustrates different seasonal periods. The 16-day overpass schedule contributed to the rapid, accurate, repetitive and reliable generation of this land cover dataset.

The spectral modelling approach created firstly the foundation covers which were spectrally distinctive. The foundation cover classes are water, bare, burnt, grass and tree/bush and were combined to generate basic land cover. Below is a process diagram that illustrates how foundation classes were further sub-divided based on both spectral characteristics and seasonal permanence.

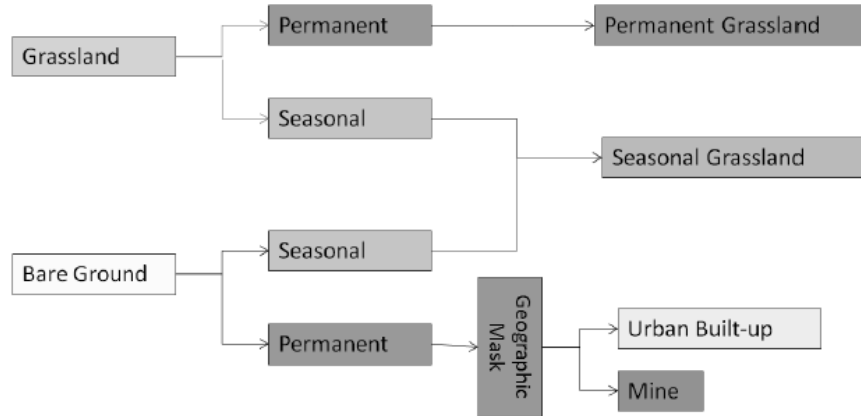


Figure 2.2- Illustration of how foundation classes were sub-divided. (Source: NLC 2013/2014 report)

The overall map accuracy is 81.73% with a K_c of 80.31%. The most significant classes had an accuracy of greater than or equal to 80%. Few classes had accuracies below 80% viz. Indigenous forest (72.6%), dense bush/thicket (53.86%), woodland/open bushland (54.13%), grassland (69.82%), low shrubland for Fynbos and other (79.64% and 70.59%) and bare ground (73.54%).

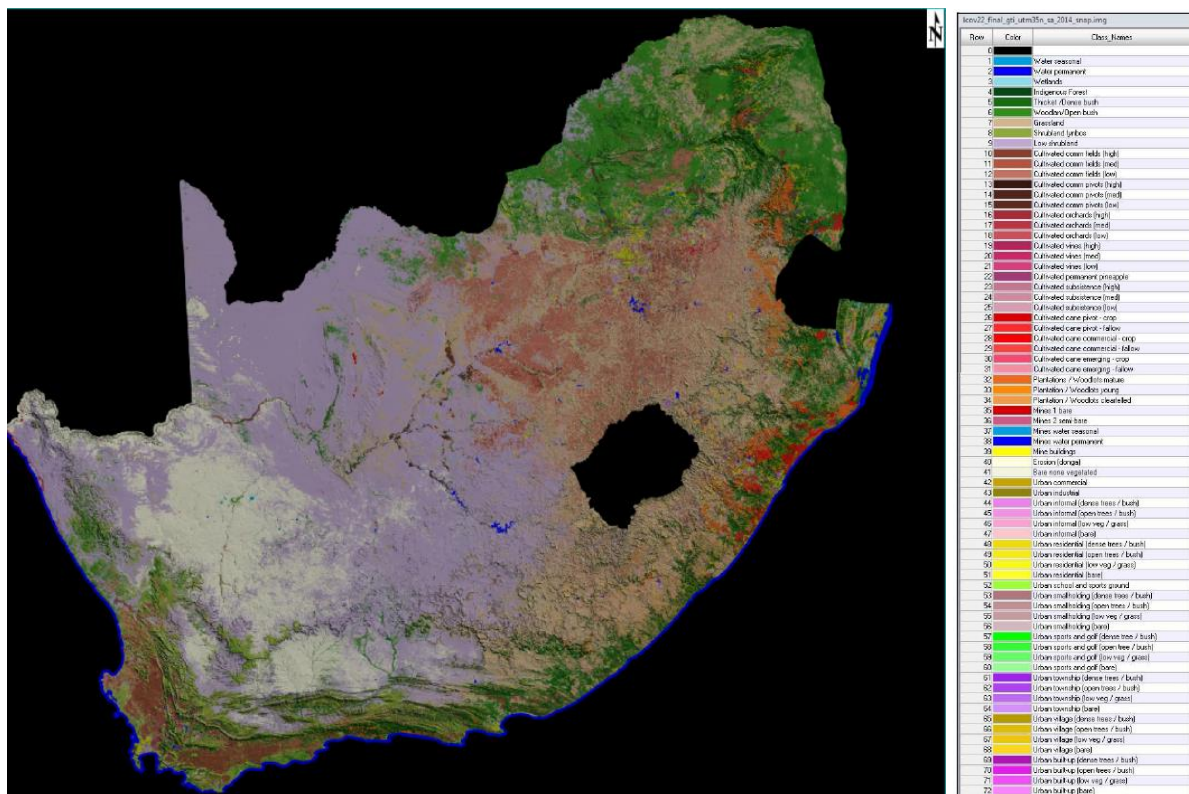


Figure 2.3- The National land cover 2013/2014 of South Africa and its 72 classes. (Source: DEA)

2.3 Remote sensing for land cover mapping

2.3.1 Introduction

Over the years the invention of both remote sensing and Geographical Information System (GIS) methods have advanced and improved land cover mapping (Rawat and Kumar, 2015). Remote sensing provides a platform that is less time-consuming with improved accuracy at a lower cost. Remote sensing applications not only provide a platform for data analysis but also the ability to create local, national and global maps continuously. Satellite dataset such as Landsat played a big role in the rapidly increasing study of land cover mapping and analysis (Rawat and Kumar, 2014; Butt *et al.*, 2015). The basics of remote sensing studies enable researchers to continue developing new methods that advances and improves their applications.

2.3.2 The fundamentals of remote sensing

Remote sensing is based on a set of principles. There are four sets of principles that are pivotal for remote sensing applications viz. spectral, spatial, radiometric and geometric (Campbell, 1996). The above principles are relative to the type of sensor used. Different sensors have different sensor properties and as a result, the output image is different. In this study, Landsat satellite imagery was utilised and the image properties will be discussed in the methodology chapter. Sensors consist of different wavelengths ranges which are derived from the electromagnetic spectrum. They can be divided into two groups, passive or active sensors. In passive, the source of energy is the sun whereas in active the sensors provide their own source of energy. Optical remote sensing (passive) is the most commonly used for image classification. Most of the optical remote sensors such as SPOT 5, Landsat 5 and Landsat 8 consist of information that is from the visible and infrared regions (Gibson and Power, 2002). The visible range starts from 0.4 μ m to 0.7 μ m and infrared is from 0.7 μ m to 15 μ m (see Figure 6).

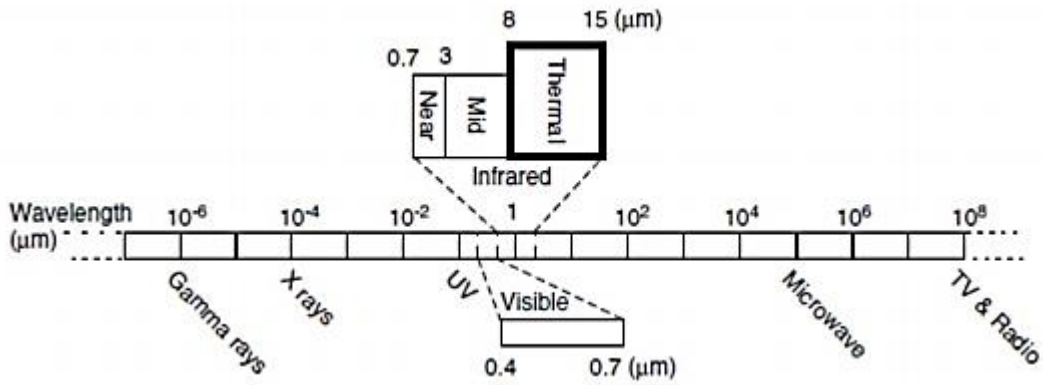


Figure 2.4- Electromagnetic spectrum illustrating different wavelength regions. (Source: Lillesand *et al.*, 2004)

Different earth surfaces are reflected, refracted or absorbed depending on their spectral characteristics. The surface differences behave differently on different wavelength ranges (bands). For example, water has high reflectance on the blue band but low reflectance on Near-infrared (NIR). On the other hand, vegetation has a high reflectance on the NIR region and low reflectance on the Mid-Infrared (MIR) (Gibson and Power, 2002). The spectral characteristics enable a distinction in features which is used to classify different features of an image.

2.3.3 Image classification for land cover mapping

Remote sensing plays a key role globally in image classification. The different methods and satellite data have been used to classify and map land cover changes (Butt *et al.*, 2015). Landsat satellite imagery, in particular, have played a tremendous role in image classification of several land cover components at a larger scale and has been continuously recording the land surface during the last 30 years for global coverage (Butt *et al.*, 2015; USGS, 2016). There are numerous classification techniques that can classify satellite imagery into meaningful categories illustrating different land cover features (Horning, 2004). The majorly used techniques are automated and utilises the spectral band information. There are two majorly used image classification methods; supervised classification and unsupervised classification (Horning, 2004; Friedl and Brodley, 1997; Campbell, 1996). The classification methods are capable of producing reliable results as that is primarily based on determining how spectral signatures are assigned to different land cover classes (Horning, 2004).

Unsupervised classification is a classification method that naturally classifies group pixels into clusters of initially unknown pixels. Unsupervised classification requires no training samples to produce results, only a general knowledge about the area is necessary (Campbell, 1996). This minimises the opportunity of human errors as there are no predetermined classes and uniform classes are produced (Lillesand and Keifer, 1999). There are also limitations with the classification method. The classifiers identify classes according to spectral signature and it is unable to focus on classes that are of interest to the researcher (Campbell, 1996; Lillesand and Keifer, 1999). Researchers have limited control towards the classes and identification thereof. Also, considering how spectral signatures change over time, the classes classified in winter may appear different in summer. So these limitations affect land cover classes that already have predetermined classes over time (Campbell, 1996; Lillesand and Keifer, 1999).

Supervised classification, on the other hand, requires known pixels for image classification. It uses training dataset to group pixels into different classes. The user identifies the pixels in an image to use as representative of different classes and training data set is used to identify similar pixels in an image (Chuvieco and Huete, 2010; Lillesand and Keifer, 1999, Campbell, 1996). The results will be all the pixels that were selected as a particular land cover type by the user (Butt, 2015; Campbell, 1996). Unlike unsupervised classification, the method permits the user to control the data set and classes are tailored to the user's needs. Prior knowledge of the area is known as field data was collected, also the results can be compared and analysed using the field data set, so errors are easily detectable (Campbell, 1996; Lillesand and Keifer, 1999).

Despite the merits, there are also limitations with this classification as well. Training data sets are collected from the field of interest and this task is commonly time-consuming, expensive and also tedious and adding also the challenge of matching training data sets from the maps with those classes on the image (Campbell, 1996). Also, the use of training data sets imposes a particular classification structure which may sometimes clash with the natural structure or pattern of the classes and the results may not be a true representation of the data in the multidimensional space (Lillesand and Keifer, 1999; Campbell, 1996). The whole procedure of imposing a specific classification structure through the use of the training data sets commonly do not represent the classes that may be unknown to the user, which could be a special or a unique class (Campbell, 1996). Lastly, the training data sets are defined commonly through the field information rather than the spectral information of the

image and this, especially in land surfaces that are diverse; this classification method leads to poor results (Campbell, 1996; Lilliesand and Keifer, 1999).

2.3.4 Maximum-likelihood classification for remotely sensed data

In this study, Maximum-likelihood classification (MLC), a supervised method was employed. MLC is one of the widely used supervised classification methods in image classification (Shafri *et al.*, 2007; Campbell, 1996; Jensen, 2005; Otukey and Blaschke, 2010). It is commonly known as a Gaussian Maximum Classifier, as the method assumes the probability of each class is that of a normal distribution (Gaussian distribution) (Shafri *et al.*, 2007; Petropoulos *et al.*, 2012; Heisl *et al.*, 2009). It uses a Bayesian equation to calculate the probability of a class belonging to a specific class (Otukey and Blaschke, 2010; Petropoulos *et al.*, 2012). The function or estimate uses the means and variances from the training data and computes the probability (Petropoulos *et al.*, 2012); the mean and covariance matrix describes the response patterns (Shafri *et al.*, 2007). As mentioned earlier, the MLC decision rule is based on the probability of belonging to the specific class and if the highest probability is smaller than the threshold specified (if the threshold is specified) the pixels of that image remains unclassified (Petropoulos *et al.*, 2012). If no threshold is selected, all the available pixels will be classified and each of the pixels will be assigned to a class that has a high probability (Shafri *et al.*, 2007). The decision rule further considers the variability of brightness values in each class (Petropoulos *et al.*, 2012). An important advantage of this method compared to its other parametric classifiers is that it provides an estimate of overlap areas through the use of the MLC density function by computing probabilities of pixel values belonging to different class categories (Campbell, 1996; Petropoulos *et al.*, 2012). Automation has its own limits and the introduction of using data sets such as digital elevation model, slope, aspect and soil type improves the accuracy of the results (Horning, 2004; Friedl and Brodley, 1997).

2.4 Land cover mapping challenges

2.4.1 Land cover mapping and its challenges

According to Campbell (1996), few of the major factors that drive accurate land cover mapping are the selection of images, assignment of spectral classes to informational classes and selection of classification algorithm. The selection of the algorithm plays a tremendous role in dictating how the classifier will perform. In an area such as that of Makhado, which consists of a landscape largely dominated by rugged mountainous areas and agricultural landscapes, specific algorithms will perform better than others (Campbell, 1996; Lu and

Wung, 2006). Especially, in mapping and monitoring land cover, the dates and seasons of the images play a tremendous role. The land cover changes drastically from one season to the next, which subsequently affects the land cover mapping (Swift, 2008). Despite such challenges, other innovative methods can improve the mapping of different classes. The old traditional methods of image classification do not attend to all the challenges that are encountered during image processing. Furthermore, the dynamic nature of land covers creates a challenge, especially in monitoring land cover (Swift, 2008). Thus, there is more focus on improving the land cover classification accuracy (Lu and Weng, 2006).

In this study, challenges such as similar spectral signatures but different features were encountered (see Chapter 4). Secondly, in some areas, water bodies had different colours. This was due to the depth of the water and sediment availability. In some water bodies, the high concentration of sediments reflects differently when compared to normal fresh water (See Chapter 4). Lastly, monitoring irrigated areas using remote sensing applications is still a challenge in South Africa. There have been a number of developments in using evapotranspiration and band ratios for mapping irrigated areas (Jarman, 2016; Ramoelo *et al.*, 2014). Irrigated fields in this study are defined according to Pervez *et al.* (2014), which are agricultural areas that receive enough water according to the water requirements for each individual crop on an annual basis. Actively irrigated fields in this study are the agricultural areas that are actively irrigated on the satellite image acquisition date.

2.5 The innovative ways to map spatial features

2.5.1 Mapping and delineating water bodies

According to Ji *et al.* (2009), normalized difference water index (NDWI) has been used successfully to extract water features. This is one of the band ratios used to assist in accurately extracting water features. Such a method of using two multispectral bands to enhance features of interest has been growing as more similar arithmetic methods are studied (Ji *et al.*, 2009; Xu, 2006; Gao, 1996; Wilson and Sader, 2002; Dupigny *et al.*, 1999; Singh *et al.*, 2015; Bhagat and Sonawane, 2015). In this study, McFeeters's NDWI was used for delineating water features. McFeeters adopted the format of the NDVI format to develop NDWI which is expressed as followed;

$$NDWI(McFeeters) = \frac{GREEN - NIR}{GREEN + NIR} \dots\dots\dots (1)$$

where green is the green band and NIR is near infrared band. This index was designed from the knowledge that water absorbs energy in the near-infrared and short-wave infrared region (Ji *et al.*, 2009). According to McFeeters (1996), the index is designed to minimize low reflectance NIR by water areas. Also, maximise water reflectance by using green wavelength. A successful extraction of water feature significantly depends on the thresholds established. The NDWI value ranges are similar to those of NDVI which range from -1 to 1. For water extraction, Ji *et al.* (2009), stipulates that if the values of NDWI are less than 0, the cover type is water.

Despite the common use of Normalized Difference Vegetated Index (NDVI) for vegetation studies, the index can also be useful for delineating water features. The NDVI is used for measuring the greenness of leaves through the amount of chlorophyll a plant/crop contains (Pervez *et al.*, 2014). It is derived from satellite imagery that scans both the visible and the near-infrared bands of the electromagnetic spectrum. Its designated bands vegetation enhancement allows the separation between water features and vegetation (Dupigny *et al.*, 1999). The NDVI developed by McFeeters (1996) can be expressed as follows;

$$NDVI = \frac{NIR - R}{NIR + R} \dots\dots\dots (2)$$

where NIR is the near-infrared and R is the red reflectance respectively. The NDVI value ranges from -1 to 1. The thresholds of NDVI assist in delineating different types of features. For vegetation, the values are greater than 0 and vegetation that is denser such as forest have a maximum value of 0.45 (Bhagat *et al.*, 2011). Features like water, barren and rocky land the value ranges are below 0 (Wilson and Sader, 2002; Dupigny *et al.*, 1999).

Both NDVI and NDWI can be successfully used to accurately and efficiently delineate and map water features. The above discussed thresholds will be useful to find correlation between NDVI and NDWI. Bhagat *et al* (2011) used NDVI and Surface Wetness Index to delineate water features. In this study, a combination of NDVI and NDWI thresholds were used to delineate water bodies of the land cover map of Makhado municipality.

2.5.2 Delineating and mapping actively irrigated fields

An accurate and efficient approach to continuously mapping and monitoring of actively irrigated fields is yet to be discovered. The use of band indices has been widely used to analyse remotely sensed data. The combination of different indices which consists of minimal bands has been very useful in understanding different spectral properties of different

spatial features. The indices always enhance the spectral properties of spatial features, in both natural and man-made features. Studies focussing on NDWI, NDVI and LST have been done previously for drought, irrigation and water distribution studies. In a drought study done by Son *et al.* (2012), the use of NDVI and LST played a pivotal role. The NDVI has been used previously to evaluate drought conditions. There is an indication that the variations in NDVI values are also affected by weather and ecosystem components (Son *et al.*, 2012). Due to these variations, the derivations of indices such as NDWI and Normalised multi-band drought index (NMDI) were configured. The NDWI formulated by Gao (1996) is more sensitive to any changes in liquid water content of vegetation canopies. It is the measure of liquid water molecules in vegetation canopies that interacts with solar radiation. Gao (1996) further stated that NDWI completes NDVI and does not necessarily substitute it. The NDWI can be expressed as follows;

$$NDWI(GAO) = \frac{NIR - MIR}{NIR + MIR} \dots\dots\dots (3)$$

where NIR is the near-infrared and MIR is the mid-infrared. This index consists of two near-IR channels one at 0.86 μm (NIR) and the other at 1.24 μm (MIR). This vegetation index is suitable for mapping irrigated fields.

In another study, Land surface temperature (LST) and NDVI were used for the drought monitoring. LST information is derived from the thermal band which provides temporal and spatial variations of the surface equilibrium state (Li *et al.*, 2013). In a study done by Pervez *et al.* (2014) actively irrigated areas were mapped using NDVI and LST. The study illustrated that irrigated areas generally had lower temperatures compared to non-irrigated areas (Pervez *et al.*, 2014). There were thresholds formulated which were dependent on the date of the acquisition date of the image. These thresholds successfully delineated the irrigated areas from the non-irrigated areas. LST is related to water stress and NDVI provides vegetation and moisture information (Son *et al.*, 2012). The LST formula can be expressed as:

$$LST = \frac{T}{1} + W \times \left(\frac{T}{P}\right) \times \ln(LSE) \dots\dots\dots (4)$$

which is further discussed and used in Chapter 3. In Son *et al.* (2012) study, LST and NDVI have an indirect proportional relationship. Low NDVI values and higher LST values are associated with non-vegetated areas such as bare ground/soil. Furthermore, areas covered in vegetation such as forests, grasslands have low LST values and high NDVI values (Son *et*

al., 2012). Whereas in Gao (1996), NDVI and NDWI have a more direct proportionality relationship. The higher the NDVI values, the higher the NDWI values and vice versa. Combining the three parameters in order to map the irrigated areas is the innovative approach and the results and further analysis will be discussed later.

2.6 Land cover change detection and its methods

2.6.1 Introduction

The increasing impacts of land cover change have become imperative in the research environment. The link to global, regional and local climate change and variability has elevated the importance of change detection studies (Lui *et al.*, 2014). The earth's surface has always been and will continuously change. There are seasonal changes, climate changes, global changes, economic changes, evolutionary changes that one way or the other affects the earth's surface (Gregory, 2010). Land cover changes play a major role in the current study of global change. The current environmental problems are often linked to land cover change. Land cover change studies provide critical information for decision making in environmental issues (Reis, 2008). The land cover and land use patterns are an outcome of both natural and socio-economic factors (Rawat and Kumar, 2015). Thus land cover and its changes are imperative aspects of socioeconomic studies and in most scientific research (Xian *et al.*, 2009). Change detection studies assists in understating the impacts of these changes in our natural ecosystem (Rawat and Kumar, 2015).

Change detection majorly involves the ability to quantify temporal effects using imagery from different dates. This process can be defined as the identification of the state of the objects/phenomena analysed at different times (Singh, 1989). Change detection is mainly based on multi-temporal images as a result of a change in the environmental conditions and human activities (Odindi *et al.*, 2012). Using optical multi-temporal satellite imagery such as Landsat, change in features can be detected. Major reflectance value changes occur mostly due land cover change. There is very low detection of changes in soil moisture, due to the difference in sun angles (Mas, 1999; Singh, 1989).

2.6.2 Change detection methods

Change detection methods are widely used in different fields because they are applicable to a broad range of disciplines. Change detection methods are based on multi-temporal imagery. The methods are used to identify changes in land cover between two or more dates (Chuvieco and Huete, 2010). Singh (1989) also mentioned how changes in land cover must

result in changes in radiance values. In literature, there are different types of change detection methods that have been developed. The techniques use conventional image differencing, image ratios, image regression, principal component analysis and post-classification comparison (Reis, 2008). Numerous studies found post-classification method to be more accurate and presented advantage of illustrating the nature of changes (Reis, 2008, Odindi *et al.*, 2012; Rawat, 2015).

Post-classification comparison method has been employed in this study. This is due to its success in a variety of studies. The method uses already classified images to detect any changes in land cover types via a comparative study (Singh, 1989; Canty, 2007; Rawat, 2015). Post-classification approach compares already classified images independently. The method is done through properly coding the classification results for the two periods. A complex matrix can then be derived showing changes in classes (Singh, 1989). This approach relies on the classification accuracy of the classified datasets. The higher the accuracy of each classified dataset the better the change analysis.

The quality of change detection is determined by thematic, spectral, spatio-temporal limitations and hence it is crucial to carefully select appropriate techniques (Odindi *et al.*, 2012). In this study, post-classification change detection technique was used and applied for two land cover maps at a time. A two-way table shall be created to show the land cover change in terms of area and percentage.

2.7 Previous land cover mapping for change detection using maximum-likelihood classification and Landsat imagery

Previous land cover studies using multi-temporal Landsat imagery for change detection studies have been explored. Rawat and Kumar (2015), Reis (2008), Muriithi, (2016) and Yang *et al.*, (2015), explored land cover change studies using maximum-likelihood classification. This approach is motivated by less time, low cost and better accuracy. Their accuracy results were a success which contributed to the decision to use a similar approach for the study in the Vhembe district, Limpopo.

Following are several successful studies of land cover change using Maximum-likelihood and Landsat imagery;

- In Rawat and Kumar (2015) study, the use of post-classification comparison was employed. Comparing change in land cover for the year 1990 and 2010 and the overall accuracy was 90.29% with K_c of 0.823 and 92.13% with K_c of 0.912

respectively. The main classes being vegetation, agriculture, barren land, built-up and water body. The misclassifications in this study were rectified using recode on ERDAS Imagine software.

- In north eastern of Turkey, a land cover change study was done with its main land cover classes as agriculture, urban, pasture, forestry, bare soil, coniferous and water (Reis, 2008). The overall accuracy of this study for the year 1976 and 2000 was 84.4% with K_c of 82.3% and 87.1% with K_c of 83.6% respectively.
- Another study which was done by Muriithi (2016) produced high accuracy results using Landsat imagery and the maximum-likelihood classifier. The main classes in this study were water, forest, agricultural land, woodland and grasslands, settlement/urban, dark bare soil, bright bare soil. The overall accuracy results for the year 1989 and 2009/2010 were above 80% with K_c of 0.78% and 0.84% respectively.
- Yang *et al.*, (2015) used a rule-based classification that compared single-date classification dataset and multi-temporal classification dataset. Despite using a different satellite sensor, the result illustrated that combining seasons improves the accuracy of the classification. Overall accuracy for single-date dataset 78.9%, 82.8% and 82.0% (winter, early summer and autumn). The overall accuracy for the multi-seasonal dataset was 87.9 % with $K_c = 0.85$.

There are a number of methods used to improve the accuracy of the land cover classification. The use of the recode function on ERDAS Imagine for easily identifiable classes e.g. water, plantations and dense vegetation commonly in escarpment areas. Digital Elevation Model (DEM) input variable is another input variable that improves the accuracy of the land cover classification (Reis, 2008).

2.8 Single-date and multi-temporal imagery techniques for land cover classification using Landsat imagery

Multi-temporal imagery consists of rich information about the land cover. The widespread use of satellite imagery of the same area contains phenological and structural properties (Tottrup, 2004). In areas such as that of Vhembe district, which consists of an escarpment, pose a challenge while using remote sensing for land cover classification. The complex topography and heterogeneous surfaces become a challenge when features within these

surfaces are classified using the remote sensing approach (Tottrup, 2004). The illumination angle and ecological zones can obscure the different spectral responses of features in such surfaces (Helmar *et al.*, 1999). The multi-temporal classification approach for land cover has been proved to be a success in previous studies done by Tottrup (2004), Conese and Maselli (1991), Driese *et al.*, (2004), Meddens *et al.* (2013) and Bodart *et al.* (2011).

Remote sensing satellite imagery provides repetitive data acquisition, a synoptic view of inaccessible areas as well as consistent image quality (Bodart *et al.*, 2011). The methods to improve image classification accuracy are feasible and are available at a low cost. Landsat imagery with its medium-resolution offers good value when considering its spectral and spatial resolution. Multi-temporal acquisition of Landsat imagery is believed to enhance classification because collectively, they provide spectral information that is related to the changing phenological stages as well as the canopy roughness (Tottrup, 2004). Canopy roughness is imperative for highly vegetated areas where the different heights of the trees can be distinguished using satellite imagery. According to Conese and Maselli (1991), land cover classes have different angular reflectance and that is also related to surface roughness. A combination of spectral information with different sun angle provides a particular spectral pattern which can be linked to canopy roughness (Tottrup, 2004). Phenological cycles also provides well defined spectral responses in vegetation thus the acquisition of satellite imagery of different seasons improves and greatly enhances the image classification (Conese and Maselli, 1991).

Single-date and multi-temporal imagery classification is vital in understanding the type of study area, the behaviour of different classes during different seasonal periods and also provides a good comparative study. Such different approaches do improve and simplify the different classification methods and accuracy approach.

CHAPTER 3: DATA AND METHODS OF STUDY

3.1 Introduction

This chapter focuses on the data, software and methods applied during the study. The objectives of the study were drivers of the data and methods used and explored in this section. The study focussed on addressing the objectives highlighted in chapter 1. This study utilised various types of data that aid in addressing the objectives. The data sources differ and were utilised for different purposes. It is also important to note that the study area was critical in determining suitable data and methods. The highly elevated and mostly agricultural areas of Vhembe District require suitable methodology for better image processing performance.

3.2 Data

3.2.1 Landsat satellite imagery

In this study, Landsat satellite imagery was suitable for conducting land cover change and detection studies. The freely available, 30m medium spatial resolution dataset provide sufficient information for more accurate land cover mapping. Due to the availability of the satellite imagery suitable Landsat sensors were Landsat 5 TM and Landsat 8 OLI TIRS (See Table 5 for acquisition dates). The study dates from 2006 to 2015 which falls in Landsat 5, 7 and 8 satellite timeline. The choice of imagery depended on the dates (seasons), cloud cover and any other effects (detector failure). Imagery of Landsat 7 (ETM+), experienced detector failure in 2003, and as a result the images that were collected had a malfunction (USGS, 2009). The images consist of black stripes of missing data, therefore unusable. The Landsat 5 TM and Landsat 8 (OLI)(TIRS) satellite imagery consists of all the bands that are required for image processing and analysis for this study. The imagery acquired from USGS is surface reflectance high level data products. This means the data has been pre-processed to top-of-atmosphere (TOA) and surface reflectance (USGS, 2016).

The Landsat 5 TM satellite was launched in 1984 and is the longest-operating observation satellite, which still delivers high quality earth's surface global data (USGS, 2015). In November 2011, the Landsat 5 TM satellite ended its operation. Landsat 8 satellite was launched February 2013 and the satellite carries two-broom instruments the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) (USGS, 2015). The OLI sensor consist of two new spectral bands namely, coastal/aerosol and new infrared band. The TIRS

sensor also consists of two spectral bands, namely Thermal Infrared 1 and Thermal Infrared 2, which measure surface land temperature.

Table 3.1- Landsat OLI TIRS and Landsat 5 TM bands and their characteristics. (USGS, 2016)

Band Description	Landsat band wavelength (μm)					
	L8 OLI/TIRS			L4-5 TM		
	Band	Wavelength (μm)	Spatial Resolution (m)	Band	Wavelength (μm)	Spatial Resolution (m)
Coastal/Aerosol	1	0.43-0.45	30	-	-	
Blue	2	0.45-0.51	30	1	0.45-0.52	30
Green	3	0.53-0.59	30	2	0.52-0.60	30
Red	4	0.64-0.67	30	3	0.63-0.69	30
Near-Infrared	5	0.85-0.88	30	4	0.76-0.90	30
Shortwave Infrared-1	6	1.57-1.65	30	5	1.55-1.75	30
Shortwave Infrared-2	7	2.11-2.29	30	7	2.08-2.35	30
Panchromatic	8	0.50-0.68	15	-	-	
Cirrus	9	1.36-1.38		-	-	
Thermal	10	10.60-11.19	100*(30)	6	10.40-12.50	60
Thermal	11	11.50-12.51	100*(30)	-	-	

3.2.2 SRTM data

The Digital Elevation Model is imperative for various land surface analysis. DEM is a 3D representation of the land surface without any land cover. Shuttle Radar Topography Mission (SRTM) acquires the 30m DEM on a near-global scale. Its spatial resolution is compatible to the spatial resolution of the Landsat imagery. As a result, this input variable is suitable for any techniques in this study. The data was used to identify different elevation slopes of the area of study which, will later assist in separating classes from different slopes.

3.2.3 National land cover 2013/2014

The NLC 2013/2014, with a 30m spatial resolution was used for accuracy assessments of the classification dataset. It also assisted in defining the classes of the study. In chapter 2, the history and more information about this dataset was discussed.

3.2.4 Field data

In supervised classification approach, training dataset form part of the image classification process. It was imperative to collect field points that represent the classes of interest of our study. On the 26 - 30 September 2016, field work was done in Makhado, Vhembe District. Collection of random points in accessible areas was employed. Most of the areas of the study were inaccessible. Some further points were then derived using SPOT 6 data in conjunction with the NLC 2013/2014. The main points that were dominant and accessible in the field were agricultural fields and grasslands. These field points were preselected using SPOT imagery and Google Earth and added unto a global position system (GPS).

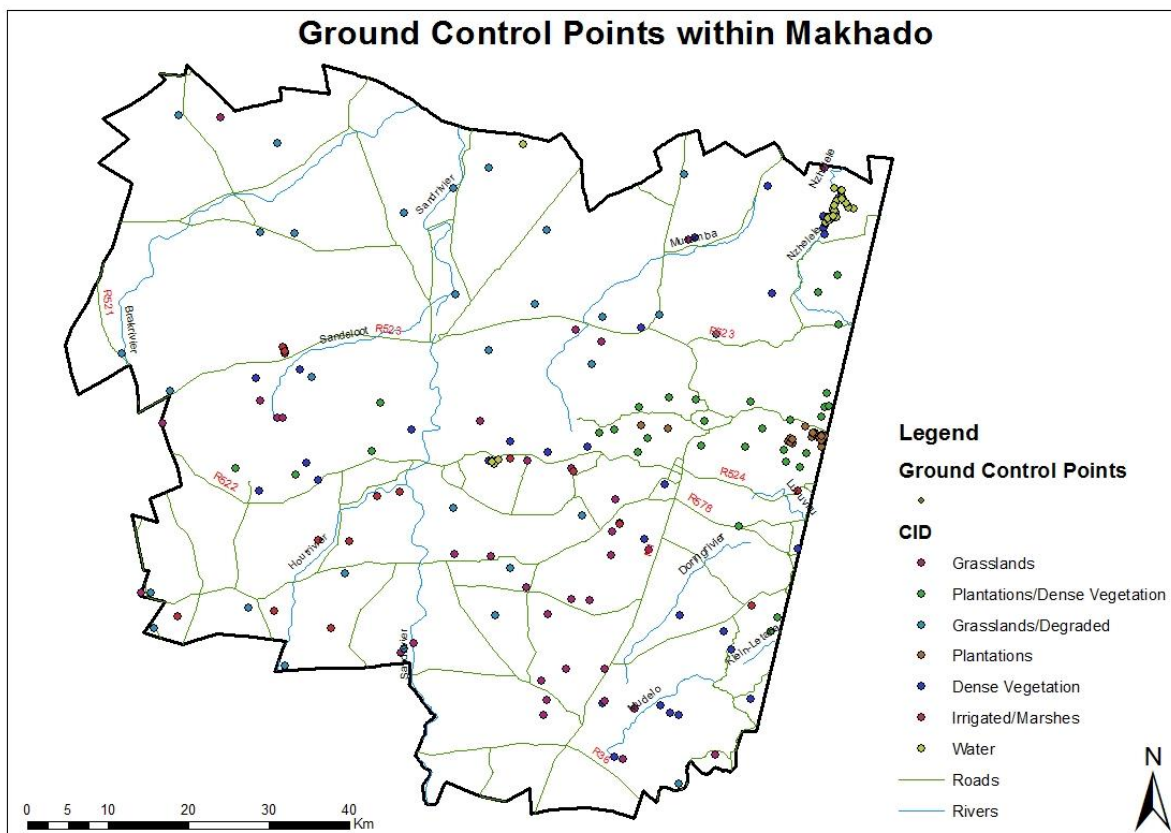



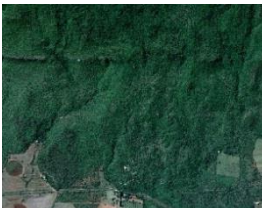
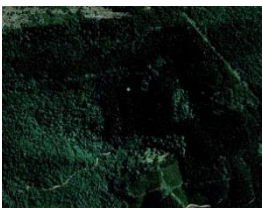



Figure 3.1- Makhado map illustrating ground control points

3.2.4.1 Targeted classes

As previously mentioned, the study focussed on natural resources. In Makhado after field visits and visually analysing the area using SPOT 5 imagery and Google Earth the following classes were derived; Grassland/Degradation, Plantations/Dense Vegetation, Plantations, Dense Vegetation, Grasslands, Irrigated/Marshes and Water.

Table 3.2- Land cover classes of this study and those of the NLC 2013/2014 and their physical appearance

Classes	SA_Land cover_2013-14_Classes	SPOT5 Imagery
Water	<ul style="list-style-type: none"> - Water permanent - Mines Water Permanent - Water Seasonal 	
Grasslands	<ul style="list-style-type: none"> - Grassland - Woodland/Open bush 	
Grasslands/Degraded	<ul style="list-style-type: none"> - Urban built-up - Cultivated subsistence (low) - Low Shrubland - Urban Village - Erosion - Bare Non Vegetated 	
Dense Vegetation	<ul style="list-style-type: none"> - Indigenous Forest - Thicket/Dense bush - Urban Village (dense trees/bush) 	
Plantations/Dense Vegetation	<ul style="list-style-type: none"> - Indigenous Forest - Plantations/Woodlots mature - Cultivated Orchards - Thicket/Dense bush 	
Plantations		

- Irrigated/Marshes**
- Cultivated Commercial Pivots
 - Plantations/Woodlots
 - Cultivated orchards



Several of photos of accessible areas were taken, with written notes in some points. All information was recorded on a spread sheet and later exported into ArcGIS software. Missing classes were then added randomly using the ArcGIS software and SPOT 6 imagery. The total number of points for the whole study area was 210 samples (See Table 3.3). The points were later divided into training (10 samples) and reference (20), totalling to 30 samples for each class.



Figure 3.2- Field photos illustrating some of the classes of the study across the Makhado area

Table 3.3- Separation of the GCPs to training samples and reference samples.

No.	Class Names	Training Samples (70%)	Reference Samples (30%)	Total no. of samples
1	Grassland/Degradation	20	10	30
2	Plantations/Dense Vegetation	20	10	30
3	Plantations	20	10	30
4	Dense Vegetation	20	10	30
5	Grasslands	20	10	30
6	Irrigated/Marshes	20	10	30
7	Water	20	10	30
	TOTALS	140	70	210

Most classes were not easily accessible as they were in a private property. As a result, access was a challenge as most of the sites in Makhado were difficult to map. Also, few places could be visited due to limited budget from researcher's side.

All the maps in this study were created in ArcGIS 10.2 or ENVI 5.3 and all image analysis were done in ENVI 5.3 and ERDAS Imagine 2014 software.

3.3 METHODOLOGY

3.3.1 Introduction

The section aims to explain the different methods used to achieve the results that were analysed and discussed in Chapter 4. Methods were employed using the data in section 3.2 and ERDAS Imagine, ENVI and ArcGIS used for the generation of the results. Figure 3.3 shown below is an overview illustrating the steps that were used to achieve the project results.

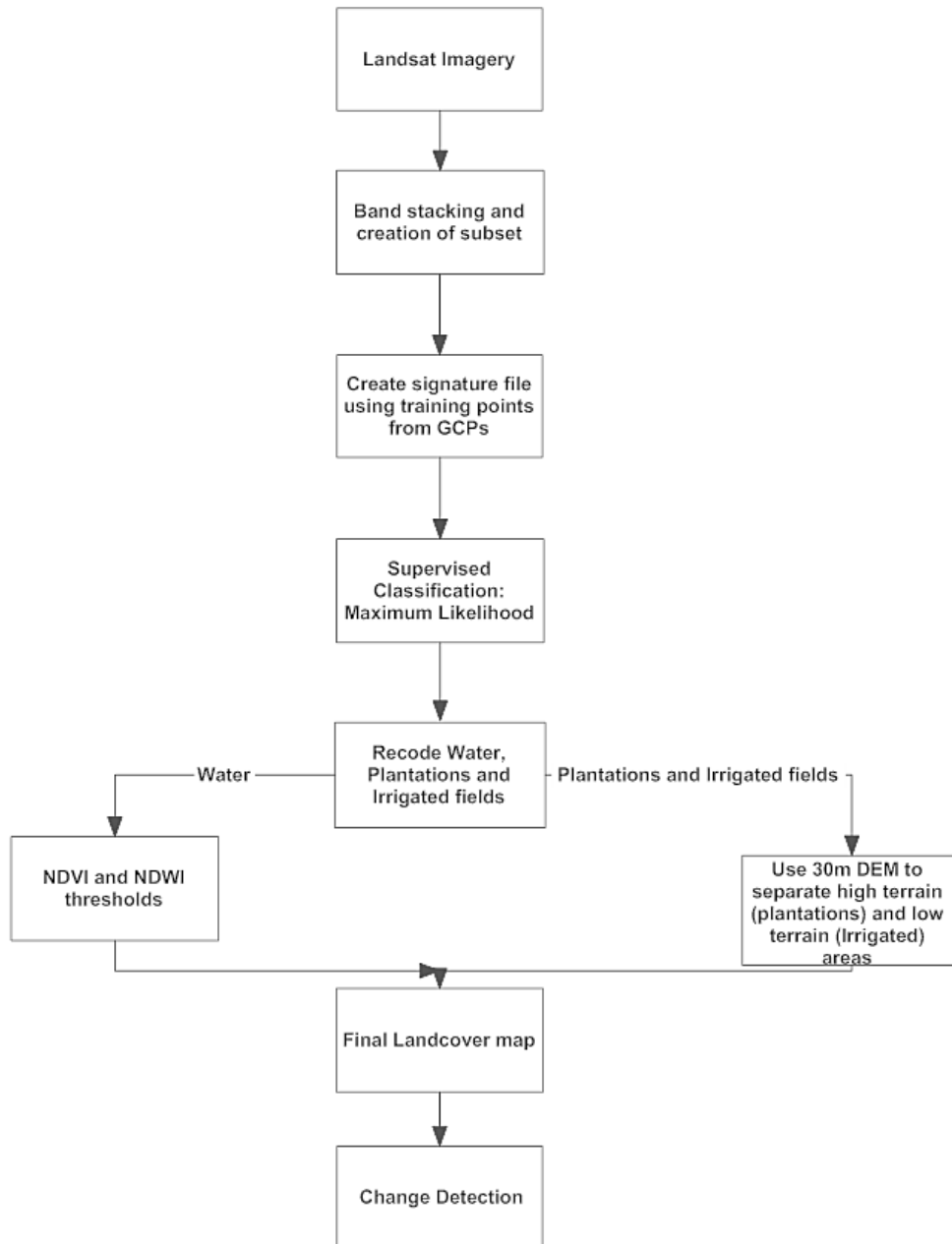


Figure 3.3- Methodological framework of the study.

3.3.2 Choice of study period

The availability of good quality satellite imagery majorly determines the period of most studies. Despite predefined dates that may have been motivated by environmental related issues, their availability depends on a number of key factors. In this study these periods 2006-2009 and 2013-2015 were motivated by the following factors.

- *Seasonal Variations*

The period of study that was chosen is April and May, which is the autumn season in South Africa. During this season, there are less burn scars in the land cover due to moderate temperatures. Also, forest mapping is best done during this season because the areas have low to no burn scars that may be misclassified. Climate during this season has a low to no rainfall, which increase in the availability of cloud-free imagery.

- *Satellite Imagery*

Images with free cloud cover that fall in the same time period were selected with the focus on natural resources mainly cultivated areas, dense bushes and water. It is pivotal to choose areas that fall in the same period for change detection studies. The images below fall in autumn, which is the harvest time and also there is a clear distinction of woody vegetation and grass. During this period, there are no burnt scars in images as compared to winter (dry conditions).

The table below illustrates the cloud free imagery that was available in the *Earth Explorer* Landsat downloading site (<https://earthexplorer.usgs.gov/>). The chosen Landsat imagery dates best represented the interested study period.

Table 3.4 - Different cloud-free and available Landsat imagery from 2004 to 2015.

Month/Year	1	2	3	4	5	6	7	8	9	10	11	12
2004						13						
2005		8					18		20	31		
2006							<u>21</u>	<u>22</u>	<u>23</u>			
2007					21							<i>Landsat 5</i>
2008				21								
2009			23	<u>24</u>	<u>26</u>							
2010											23	
2011						17				23		
2012	<i>No Landsat 5 & Landsat 8 data except Landsat 7 data (striped)</i>											
2013					21	22	24			12		
2014					24	<u>25</u>	<u>11</u>	<u>28</u>				<i>Landsat 8</i>
2015					<u>27</u>		30	31	<u>16</u>	<u>12</u>		

Landsat 5 (TM) and Landsat 8 (OLI)(TIRS) images were obtained for two periods. The years, 2006 and 2009 were for the first period. Then 2014 and 2015 images were for the second period (see Table 3.4). The choice of the images within these years assisted in providing more time to map land cover changes of the Makhado municipality over time.

Challenges of acquiring cloud-free, throughout the seasonal period were encountered and hence the multi-temporal classification became more viable to cover the growing periods of the land cover. The approach in choosing the dataset focussed on the growing season (March to October) for both the old (2006-2009) and recent period (2013-2015).

The main drivers of choosing the relevant datasets were location, season and availability of imagery. The careful consideration of all these factors contributed in producing reliable and accurate results. There are always limitations in doing land cover change studies and taking into account these factors in one's study minimises the effect of these limitations.

3.3.3 Landsat data preparation

3.3.3.1 Image corrections

Change detection studies require spatial registration and radiometric calibration. Minor registration errors can introduce errors in the change analysis (Prenzel, 2004). The data used in this study is already corrected to surface reflectance and it is freely available from the USGS website. Climate Data Record (CDR) was generated from Landsat Ecosystem Disturbance Adaptive Processing System (LEPADS) and this system applies MODIS atmospheric correction routines to Landsat TM and ETM+ data. It uses water vapour, ozone, DEM, Geo-potential height aerosol optical thickness as some of its inputs (USGS, 2016). These inputs enables the software to generate top of the atmosphere (TOA) reflectance, surface reflectance, brightness temperature, masks for clouds, cloud shadows, adjacent clouds, land and water data which are all delivered as Land Surface Reflectance CDR (USGS, 2016).

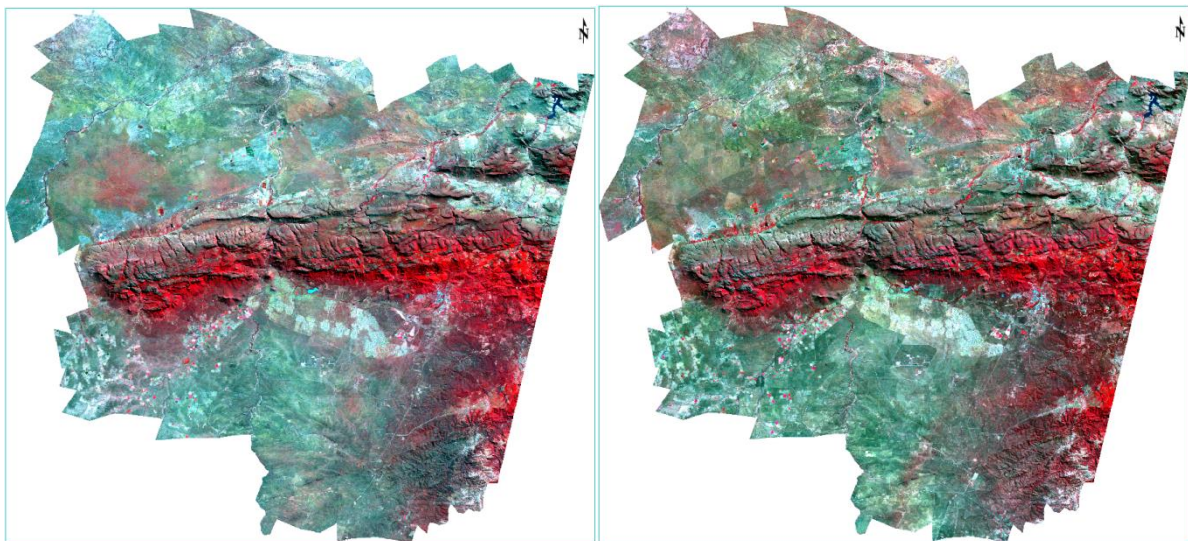


Figure 3.4- Original Surface Reflectance Landsat 5 TM (26 May 2009) and Landsat 8 OLI TIRS (27 May 2015) both on a 432 false colour band combination and on a WGS 84 coordination system. (Source: USGS)

The surface reflectance correction reduces any constraints that may be caused by unfavourable conditions such as hyper arid/snow covered regions, low-sun angle conditions, coastal regions with big adjacent water but small land and also those with extensive cloud contamination (USGS, 2016). The panchromatic band is not processed to TOA or SR.

3.3.3.2 Single-date imagery

Two images from both periods were used 26 May 2009 (Landsat 5 TM) and 27 May 2015 (Landsat 8 OLI TIRS) for the single-date imagery approach. Each image was stacked and clipped according to the area of study. A false colour composite band combination was employed in order to enhance the appearance of features from the Landsat images. The surface reflectance products already come with only the bands required for image classification. The thermal bands found in both Landsat 5, cirrus and panchromatic bands in Landsat 8 are not part of the datasets. A total of six bands for Landsat 5 TM and seven bands for Landsat 8 OLI TIRS image were stacked and clipped separately.

3.3.3.3 Multi-temporal imagery

In both periods, 2006 – 2009 and 2013 – 2015, all the bands of the images of each period were stacked together. A total of five different dates for the 2006-2009 period and six different dates for 2013-2015 period (see Table 3.4). The total number bands for 2006-2009 were 30 and for 2013-2015 were 42. Landsat 8 OLI TIRS images have more bands due to the new coastal band. The false colour composite band composite was employed for each of the stacked images for both periods.

3.3.4 Supervised classification

In ERDAS Imagine, training sets were derived from the GCPs (Figure 7) to create a signature file. Areas of interests (AOIs) for all seven classes were created using the eleven training points from each class (see Table 4). The AOIs were then saved as a signature file which was used in employing the MLC function. In the single-date mapping approach, 26 May 2009 Landsat 5 TM and 27 May 2015 Landsat 8 OLI (TIRS) satellite imagery were used. The maximum-likelihood classifier was then used separately for both images, creating single-date classification maps. For each period, the maximum-likelihood classifier was employed using the above mentioned parameters on the ERDAS software. For both innovative approaches the same signature file was used to classify the images.

3.3.5 Improving classification of features

The land cover map produced consisted of misclassified areas such as water being classified as dense vegetation or plantations or irrigated/marshes class being classified as plantations as a result of similar spectral characteristics. Using other data and methods to distinguish between these classes is possible and has been previously successfully done by other researchers. Below are illustrations of some water bodies not appearing the same colour (see Figure 3.5)

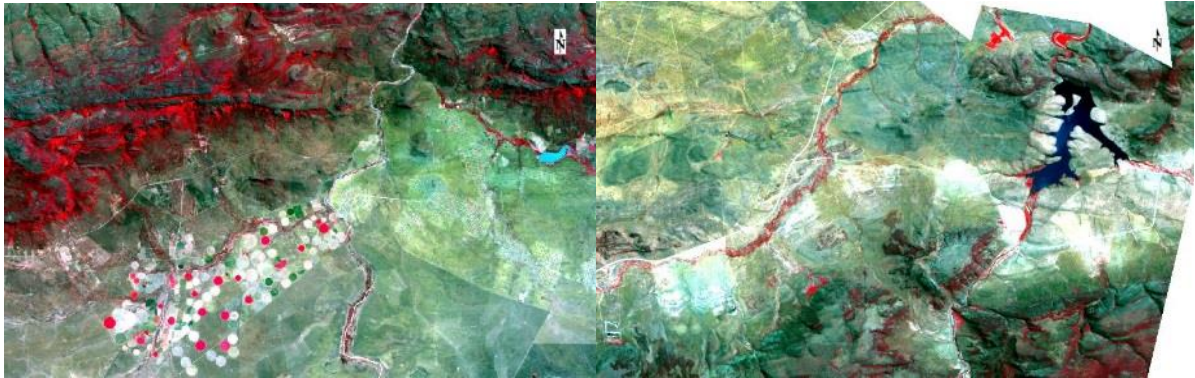


Figure 3.5- The two images are the original stacked Landsat 8 imagery

3.3.5.1 Mapping of water bodies

Both NDVI and NDWI were used to extract water feature. The best thresholds that extracted the water features completely were;

- $NDVI \leq 0$
- $NDWI \geq 0$

3.3.5.2 Plantations and irrigated areas

Extraction of irrigated/marshes class within the plantations class was a success after using the SRTM 30m. Plantations are commonly found in highly elevated areas and most agricultural activities occur on flat land. The use of SRTM data was to assist in distinguishing the irrigated areas from plantations. Both these classes have similar spectral signatures thus misclassifications.

The DEM was processed using topographic modelling tool on ENVI which produced six classes that allowed a clear distinction of different topography namely; peak, ridge, pass, plane, channel and pit and the two most topographic features that were essential for this exercise were the pass and ridge features. The unclassified parts were then reclassified using the moving window method of the neighbourhood operator from ERDAS Imagine. The

neighbourhood tool from ERDAS Imagine was run repeatedly until all the unclassified pixels were classified.

The output data was unsigned 16 bit, with the majority as a function definition and ignoring 0 and applying the function at 0 on a 7x7 kernel size (See Figure 3.6).

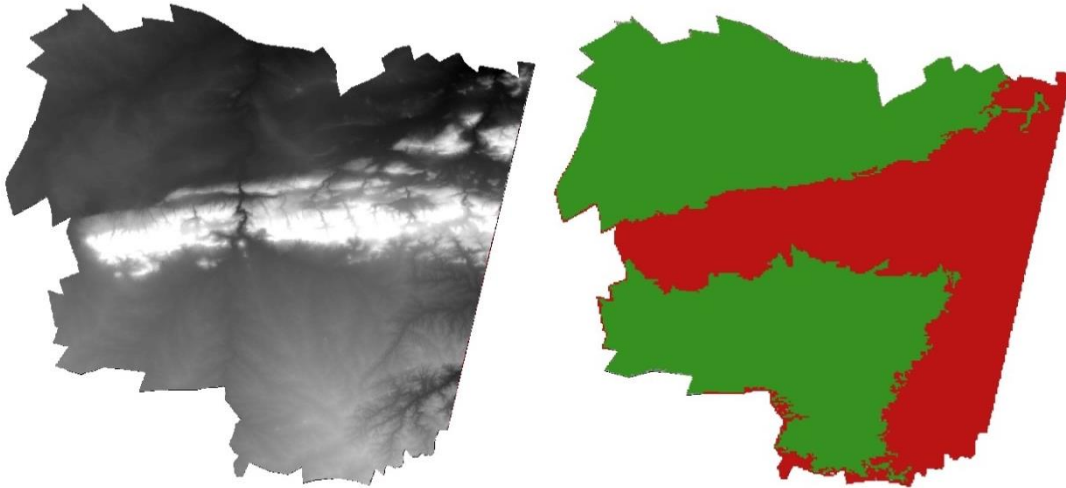


Figure 3.6- The left image is the original 30m DEM and the right image is the processed one. The red parts of the image represent highly elevated areas and the green is the low-lying areas.

3.3.6 Accuracy assessment

In change detection studies, accuracy assessment is imperative as it drives the results of any change detection technique. The classification data can be only useful and accurate if the classified datasets has high accuracy. The high accuracy results provide high level of confidence of the change detection results. The accuracy assessment of this study was carried out using a total of 168 points, 24 for each class. These points were derived from the ground control points. The GCPs were collected following a simple random sampling approach. This was also driven by inaccessibility in some areas of the study. Comparison of these reference points against the classified maps were carried out using the error matrix. The total map accuracy is a function of both positional and thematic accuracy. Positional accuracy measures distance between reference data classes and corresponding map features. Thematic accuracy measures the degree of agreement between the reference data and corresponding map features.

The error matrix or aka confusion matrix consists of three accuracies, viz.

- *Overall accuracy* which is the total of the correctly classified features/the total number classes (average of completeness and correctness)
- *Producer's accuracy* is the correctness of the classification
- *User's accuracy* is more of a guide to how reliable a map is

Further, there are errors of omission which are defined as, the total correct class/total number of classified class from reference data (Producer's accuracy). Errors of commission are the total number of correct class/total number of classified class (User's accuracy).

There is also Kappa analysis which is a measure of agreement between predefined producer ratings and assigned user ratings (Gwet, 2002). Kappa is calculated using this formula;

$$K = \frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r X_{i+} \times X_{+i}}{N^2 - \sum_{i=1}^r (X_{i+} \times X_{+i})} \dots\dots\dots (5)$$

Where:

r = rows

X_{ij} = observations in row i and column j

X_{i+} and X_{+i} = marginal totals of row i and column i respectively

N = total observations

This method was employed on both the multi-temporal imagery dataset and as well as the single-date imagery dataset.

3.3.7 Change detection

The main objective of this study was to detect any changes that may have occurred during 2006 and 2015. To also look at how the change has influenced the rural community of Vhembe district, Makhado. In this study post-classification change detection approach was adopted. Post-classification is a method that uses two accurate and already classified images to detect change. It has been successfully and widely used by researchers. Its efficiency in detecting the location, nature and rate of changes makes it one of the popularly

used change detection methods (Butt et al, 2015). The detection was done using the multi-temporal imagery dataset of the two different periods (2006-2009 and 2013-2015). A new layer was produced illustrating information from the two compared datasets and it illustrated all the classes with different combination of 'from- to' change class.

In the classification maps were further analysed using ArcGIS software. The attribute table consisted of the count field which represent the area for each class. The values were used to calculate the area of the different classes using the calculate geometry tool. The results of the table showed the total area for each class for both periods, (2006-2009) and (2013-2015). These results are then converted into a graph that was analysed and further correlated with the results from highlight change method.

3.3.8 Mapping *actively irrigated* areas during the time of study

This section will focus on the methodology of the actively irrigated fields using Landsat satellite imagery, calculating LST, NDWI and NDVI. The bands used in this innovative approach are the RED, NIR, MIR and thermal band. Figure 3.7 below illustrates the methodological process.

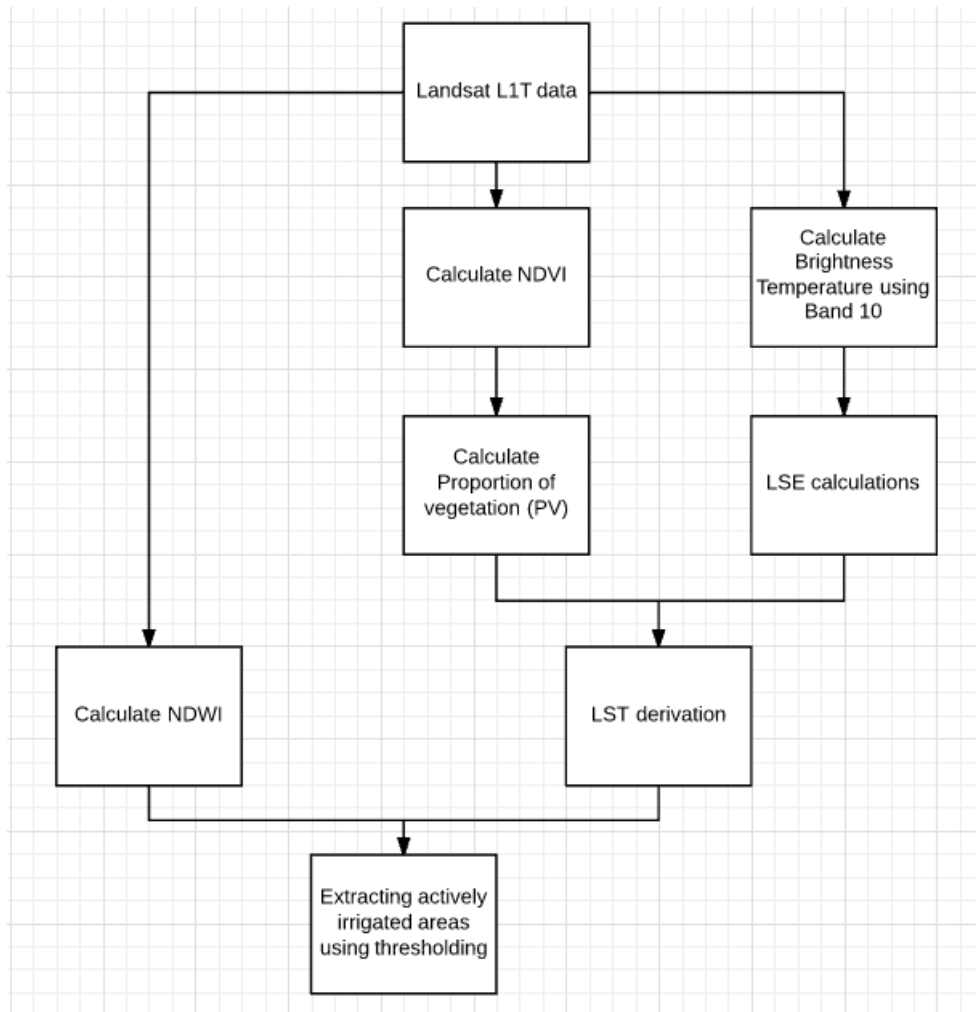


Figure 3.7- The workflow of the innovative approach to extract actively irrigated fields

3.3.8.1 Land surface temperature derivations

In deriving Landsat Surface Temperatures (LST) 3 parameters are required viz. At-Satellite Brightness Temperatures (T), proportion of vegetation (PV) and land surface emissivity (LSE). Refer to formula 4 for the LST formula.

(i) At-Satellite brightness temperatures (T)

$$T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \dots\dots\dots (6)$$

Where:

T = At-satellite brightness temperature

Lλ = TOA spectral radiance

K_1 and K_2 = Band-specific thermal conversion constant from metadata file

Derivation of: $L\lambda$ (TOA spectral radiance)

$L\lambda = (DN \times RADIANCE_MULTI) + RADIANCE_ADD$ (These values are from metadata file)

(ii) Proportion of vegetation (PV)

$$PV = \frac{(NDVI - NDVI_{min})}{(NDVI_{max} - NDVI_{min})^2} \dots\dots\dots (7)$$

where:

PV = Proportion Vegetation

NDVI = Normalised Difference Vegetation Index

$NDVI_{min}$ = Minimum NDVI value

$NDVI_{max}$ = Maximum NDVI value

(iii) Land surface emissivity (LSE)

$$LSE = 0.004PV + 0.986 \dots\dots\dots (8)$$

Refer to equation (7) for PV formula

3.3.8.2 Derivation of NDVI and NDWI

The NDVI and NDWI formulae have been briefly discussed in Chapter 2 and in this chapter, they will be used to assist in determining suitable thresholds that will delineate irrigated fields of the Makhado Municipality.

3.3.8.3 Thresholding using LST and NDWI

The two parameters are better suited to delineate actively irrigated fields, with NDWI being better suited than NDVI. NDWI is more sensitive to crops moisture or water content, whereas NDVI is more of an indicative of vegetation greenness and not necessarily crop canopy moisture. The thresholding process looked at NDWI values which were greater than 0, as that is illustrative of crop with high water content. The approach of LST thresholds focussed on the lower temperatures of the crops. The LST values that are more representative of a wet/moist spatial feature commonly had lower temperatures than those with high LST values. The two were then combined using the AND boolean operator.

3.3.8.4 Accuracy assessment of actively irrigated fields

Assessing the accuracy of this approach became a challenge as the two study periods are within the 2006-2015 range. The field work for this study was undertaken in 2016 and using the points for 2016 to calculate the accuracy of the 2009 and 2015 images would have been inaccurate. It is thus ideal to collect sample points and test the accuracy of the results using the same acquisition date. In that way, we minimise any inaccuracies or changes that may have occurred before or after the image acquisition date. Despite such, using the field data collected in September 2016, three actively irrigated fields were visited and two out of the three in the 2015 image were mapped accurately.

3.3.8.5 Change detection of actively irrigated areas

Change detection study for this approach was undertaken through calculating the area of all actively irrigated fields in ArcMap. The raster results of the maps were converted to polygons, which were then used to create an area field that assisted in calculating the area in hectares. These results were represented in a table and also shown graphically.

CHAPTER 4: RESULTS

4.1 Introduction

In this chapter all the results from the employed methods in chapter three will be analysed and shown. The spectral profiles of the different classes will be illustrated and analysed based on their choices. The results of the classification maps together with their confusion matrix will be assessed. Lastly, the post-classification change detection results using the multi-temporal imagery approach will be shown.

4.2 Spectral signatures that influenced the choice of classes

The spectral signatures of the Landsat imagery of the study area were different as seen in Figure 13 below. The study area consists of a mountain range. The south slope of the mountain consists majorly of plantations and tightly packed tall trees (dense vegetation). This is due to the shade on the southern side of the slope in the southern hemisphere. Most farmers plant their trees on the southern side as the temperature is cooler and there is more moisture for trees to grow. Cooler temperatures keep the soil moist for longer periods as compared to hot temperatures. As a result, most vegetation on the southern slope in the southern hemisphere will be greener and healthier compared to the northern part of the slope. This is what drives most classes to possess the same spectral characteristics in areas such as that of Makhado. The southern part of the slope consists of plantations, indigenous forest and thicket or dense bush which consists of similar spectral characteristics. Also, irrigated fields of this study area also shared similar spectral characteristics. Through a number of different tests of differentiating classes, the following classes' best suited the study area (see Figure 14).

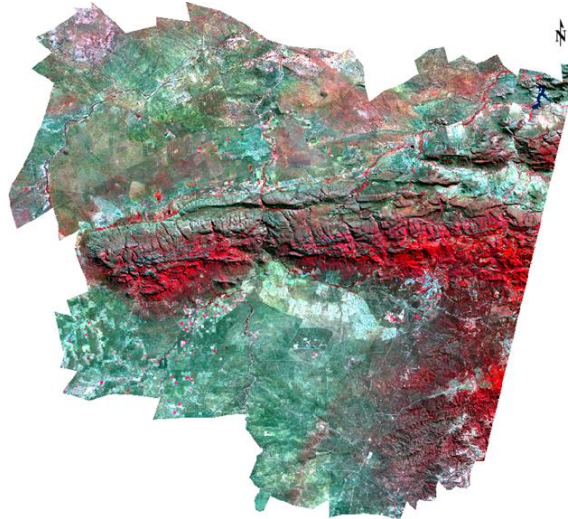


Figure 4.1- Landsat 8 imagery with a 432 false colour composite band combination

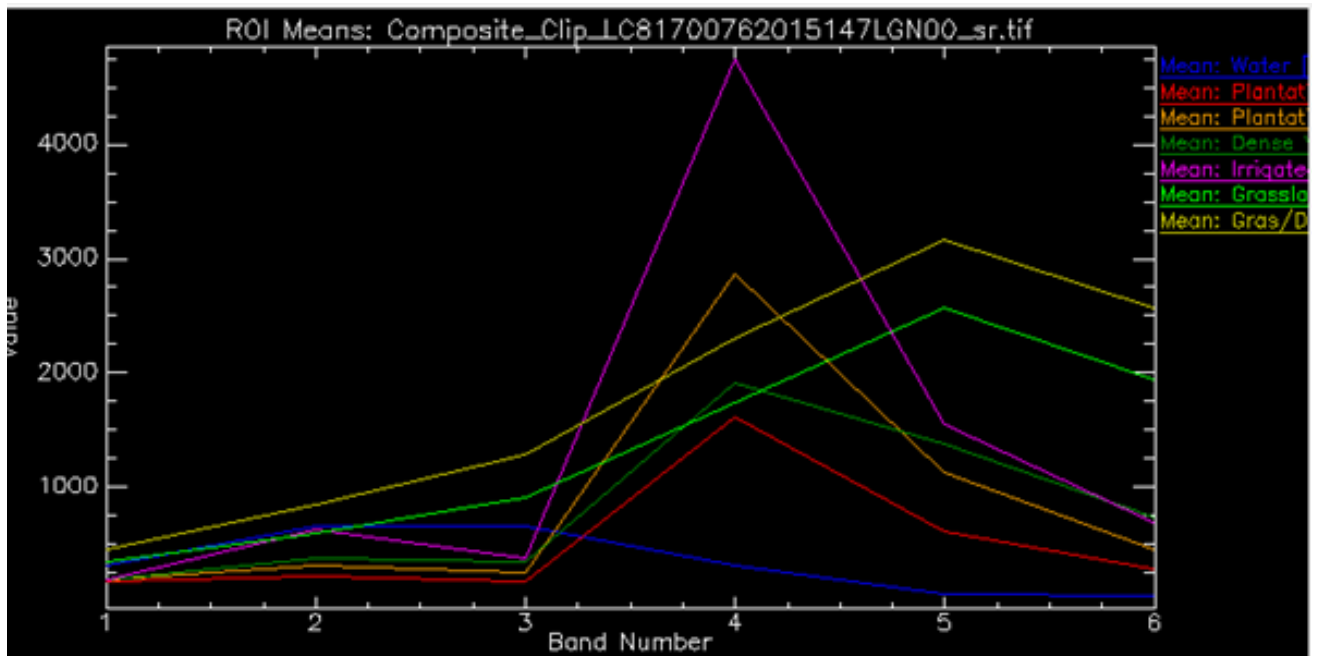


Figure 4.2- Spectral profile of the classes' best suited for this study

In Figure 4.2 the spectral profiles of the seven chosen classes are shown within the respective bands with their reflectance value range. Despite the clattering of some classes in band 1, 2 and 3 the profile does illustrate good class separability in other bands. For example, in band 4 and band 5 there is good class separability. Classes such as water, plantations, dense vegetation, plantations/dense vegetation and Irrigated/marshes are easily separable. Grasslands and grassland/degraded show good separability in band 5 together with the other classes.

Furthermore, a histogram that clearly illustrates some overlaps in some of the classes. There is an overlap of classes viz. plantations/dense vegetation, dense vegetation and irrigated/marshes class. This is due to what has been a previously discussed, similar spectral signature. Also a slight overlap in grassland and grassland/degraded which is expected. One of the classes that have no overlaps and is quite distinctive is the water class.

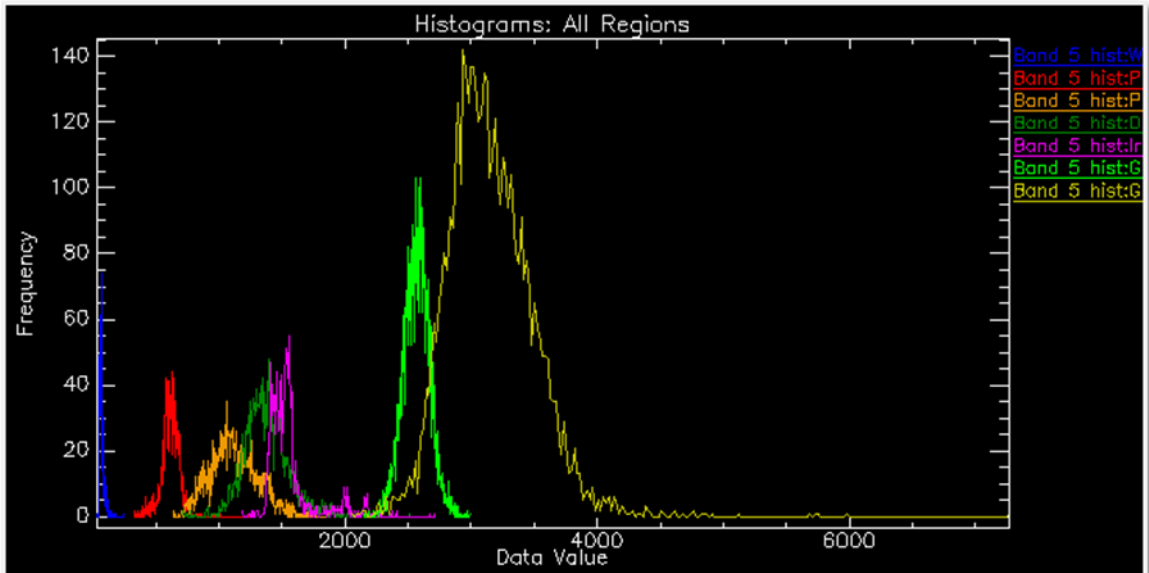


Figure 4.3-Histogram illustrating some overlaps of some of the classes

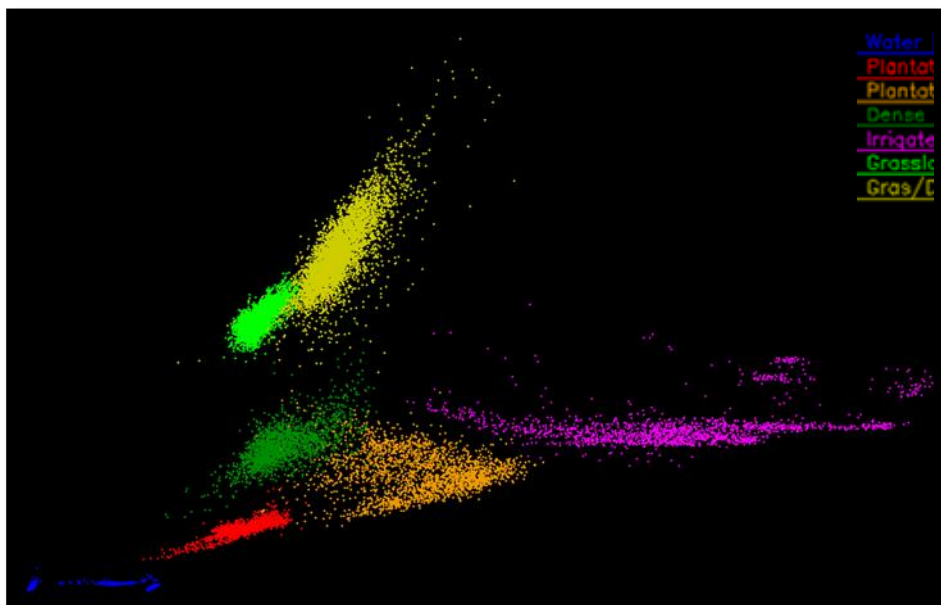


Figure 4.4-A 2-D scatter plot of Red (x) and NIR (y) illustrating classes of the study for the Landsat 8 OLI TIRS.

The n-D visualizer illustrates the two major bands (band 4, RED and band 5, NIR) that showed distinct spectral profiles of the different classes of the study. It also assisted in further analysing the ROIs that were used for the image classification. The above diagram

illustrates the degree of overlap of the classes used in this study. It still shows the slight overlaps between classes such as grassland and grassland/degraded, dense vegetation and plantations/vegetation (see Figure 16).

The above spectral profiles were sufficient to conduct supervised classification using the ROIs of the study. The ROIs well-represent the classes of the study, and thus they were utilised for maximum-likelihood classification.

4.3 Single-date and multi-temporal classification and accuracy results

4.3.1 Introduction

The objective of this study was to identify the best technique that produced better classification maps. The two techniques were then employed and results produced. Both multi-temporal and single-date technique produced different results which are shown in the Figures below. The overall area of study had three major water bodies, river and streams that were more vegetated (marshes), dense vegetation and plantations along the Soutpansberg Mountain, irrigated fields, grasslands and degraded areas which had grasslands as well.

4.3.2 Landsat Image and classification map overall visual analysis

The Landsat images of the area of study in the 432 in Landsat 5 and 543 in Landsat 8 false colour band combination showed a variety of colours. Hues of red were the most dominant colours found on the Soutpansberg Mountain. The dark red colour dominated the southern part of the image which is the southern slope of the Soutpansberg Mountain. The area showed healthier vegetation and broad leaf with some parts of the study showing lighter reds which commonly indicate grasslands or sparsely vegetated areas. Agricultural areas, as in Makhado are commonly situated in flat land. Some agricultural fields had similar shades of red as the area of the southern slope. Other colours that were visible from image were shades of brown, cyan and yellow. All these colours represented features such as bare ground, soils, low cultivated subsistence, low shrubland, urban village, erosion and bare non-vegetated. Further, most water areas appeared dark blue or black because of the higher green band reflectance.

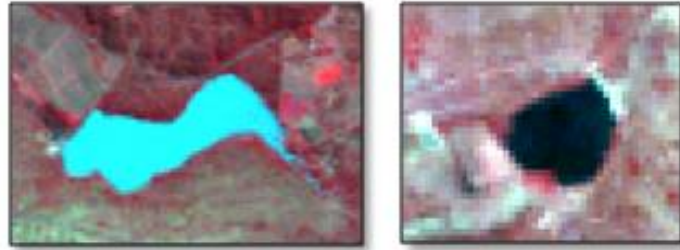


Figure 4.5:- Spies dam and unknown dam of the study area

Spies dam (see Figure 4.5) on the other hand appeared cyan which was a confirmation of what was observed from the field. The dam had turbid water which indicated the dense presence of sediment hence different reflectance. All the different colours gave an indication of how the classification algorithm will perform.

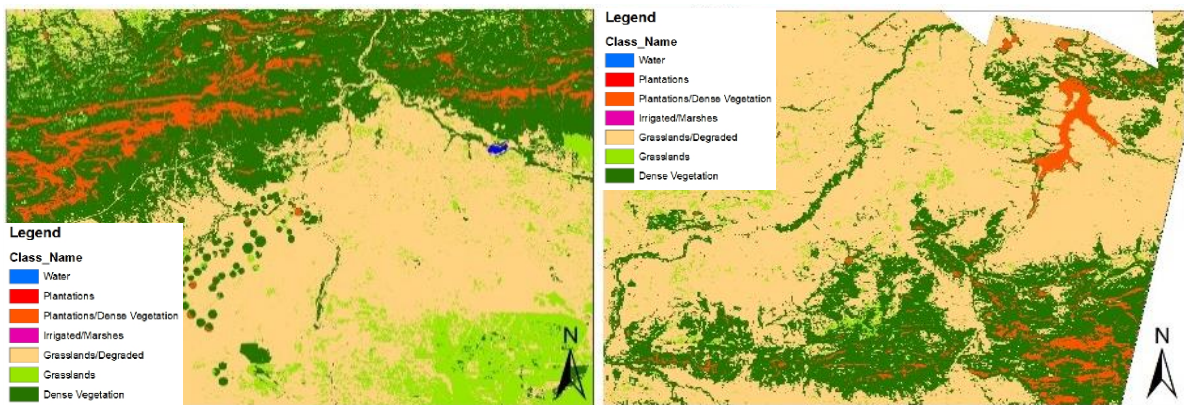


Figure 4.6 - The top two are the original stacked Landsat 8 imagery and below the classified image, with some areas which are misclassified.

The results of the MLC classifier classified most classes correctly with other classes such as the Nsami Dam (water) and agricultural areas being misclassified due to the classes sharing similar spectral features with other features as explained above. The result of the classification was then analysed and further re-classification was done using band ratioing and thresholding the DEM. For example, plantations (red) are mostly found in the eastern part of the image with few plantation/dense vegetation around the same area. The plantations/dense vegetation class mainly consists of the shaded areas that are commonly found on the southern part of the Soutpansberg Mountain. Using high resolution imagery some of these shaded areas belonged to both plantations and dense vegetation. Due to their special spectral signatures they best suited the plantations/dense vegetation class. The grassland/degraded class which includes NLC 2013/2014 classes such as urban built-up, cultivated subsistence (low), low shrubland, urban village, erosion and bare non vegetated

areas. Despite having such a wide variety of classes in one class, in this area the different classes had similar spectral signatures and thus they were easily grouped together. One would have expected the areas close to dense vegetation to be grasslands rather than grassland/degraded but this may be due to the more light cyan areas (from false colour image) around the mountain. The water areas reflected differently with most of them being dark blue or black due to the absorption of all the colours. Other water features such as Spies dam remained cyan and hence recoding from ERDAS Imagine was employed (see Figure 4.5). Also, with water features, some river streams and the outside part of the rivers were rather marshes than water and hence the inclusion of marshes in the water class.

4.3.3 Single-date classification maps and accuracy assessment

The results of the two single-date image classification map showed quite distinct results. The 2009 classification map (Figure 4.7) illustrated grassland/dense vegetation class dominate around the Soutpansberg Mountain. Whilst, in the 2015 classification map (Figure 4.8) most of the area shows most of the low lying areas are covered with grasslands. In the 2009 map, plantations are low and there is high dense vegetation. On the 2015 map, the southern part of the slope is majorly covered in plantations and plantations/dense vegetation classes whilst the distribution of dense vegetation is low. The water areas showed no distinct changes from a visual perspective. The accuracy results were distinctive. Though, considering the visually interpretation of these two Landsat images, the classification produced accurate results.

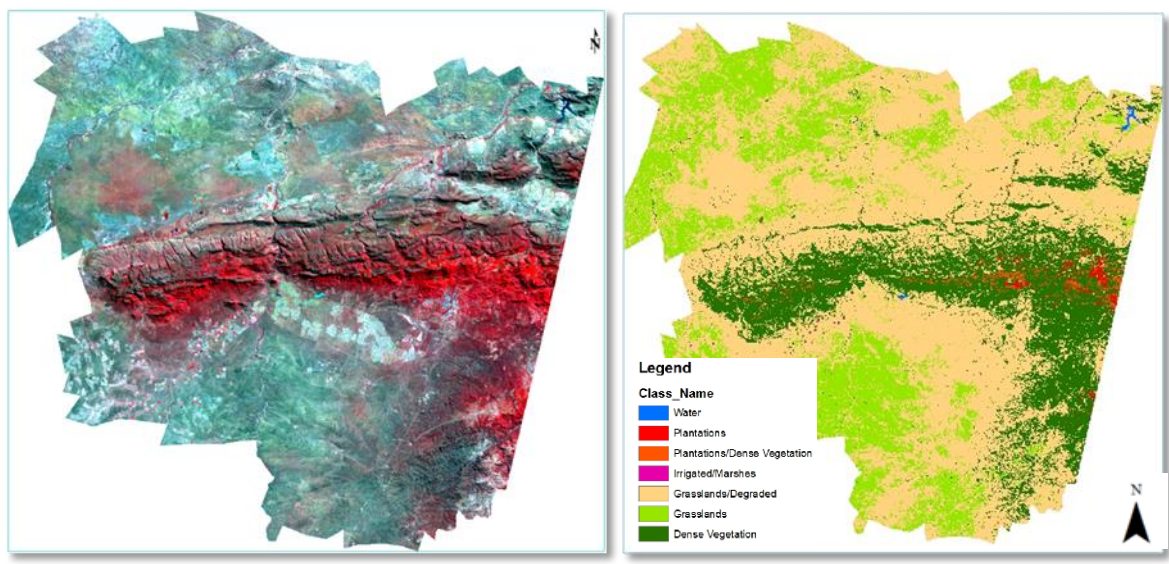


Figure 4.7-Classification map for Landsat 5 (May 2009) generated through the ML classifier

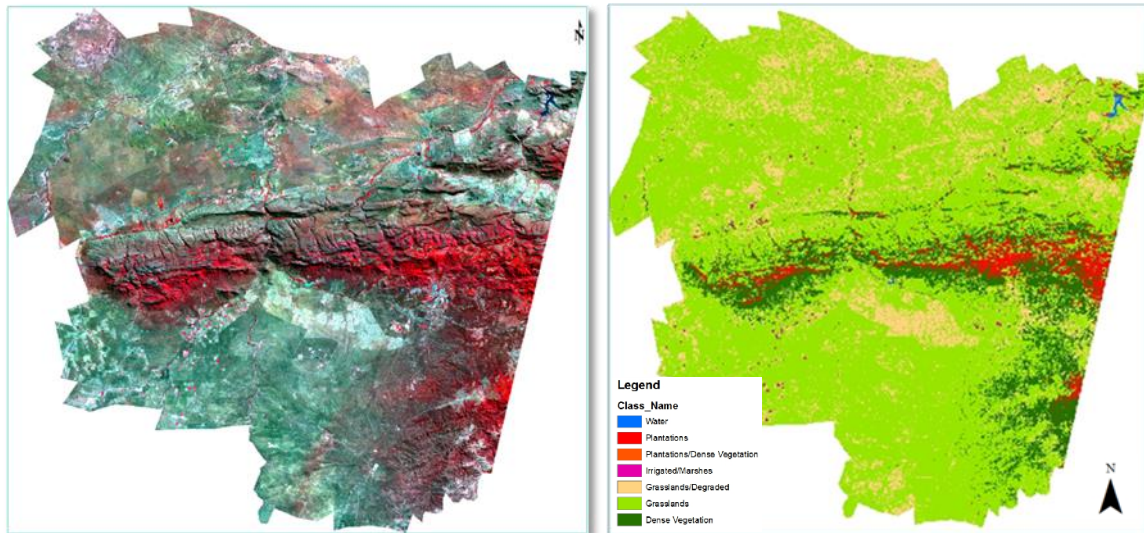


Figure 4.8 -Single-date classification map of Landsat 8 (May 2015) through the ML classifier

The classification map results were then assessed using reference points from the field, NLC 2013/2014, SPOT 6 satellite data. The accuracy results of the two images are distinct which, is expected considering the classification map results that were produced. The confusion matrix results (Table 4.1) of the 2009 classification map illustrate the overall accuracy, K_c , producer and user accuracy. The class that performed best was the water class, 100% accuracy. Classes such as irrigated/marshes, dense vegetation and plantations/dense vegetation had a PA that was above 80%. The lowest accuracy was that of grassland with producer's accuracy of 56.82%. The overall accuracy of the map was 78.1 % with a K_c value of 0.74. In the 2015 classification map the accuracy results (Table 4.2) were significantly low with the Plantations/Dense vegetation class consisting of 0 producer accuracy and user accuracy. The water class still remained as the accurate class classified. Grasslands and dense vegetation were two of the classes that had a PA higher than 75 %. Irrigated/Marshes class was slightly above 50% with the other two classes, grassland/degraded and plantations consisting of the lowest PA. On an overall basis, the classification performed at an accuracy of 54.3 % with a K_c of 0.46. The classes below are represented as GD: Grassland/Degraded, GR: Grasslands, PL: Plantations, PD: Plantations/Dense Vegetation, DV: Dense Vegetation, IM: Irrigated/Marshes and WA; Water.

Table 4.1- Confusion matrix of MLC, 2009 single-date classification map illustrating % of OA, PA and UA

		Classification Data									
Reference Data	CLASS/REFERENCE	GD	GR	PL	PD	DV	IM	WA	TOTALS	OMISSIONS	PA
	GD	14	4						18	4	77.78
	GR	14	25	1		4			44	19	56.82
	PL			25	9	2			36	11	69.44
	PD				18	3			21	3	85.71
	DV			2		26	4		32	6	81.25
	IM	1	2				26		29	3	89.66
	WA							30	30	0	100.00
	TOTALS	29	31	28	27	35	30	30	210		
COMMISSIONS	15	6	3	9	9	30	0				
USER'S ACCURACY	48.28	80.65	89.29	66.67	74.29	86.67	100.00				
% Cover	13.81	14.76	13.33	12.86	16.67	14.29	14.29				
Kappa	0.74										
Overall accuracy	78.1										

Table 4.1- Confusion matrix of MLC, 2015 single-date classification map illustrating % of OA,PA and UA

		Classification Data									
Reference Data	CLASS/REFERENCE	GD	PD	GR	PL	DV	IM	WA	TOTALS	OMISSIONS	PA
	GD	7	2	17		2	1		29	22	24.14
	PD			3	5	17	2		27	27	0.00
	GR		1	25		6	1		33	8	75.76
	PL			9	7	12			28	21	25.00
	DV	1		2		30	1		34	4	88.24
	IM					14	15		29	14	51.72
	WA							30	30	0	100.00
	TOTALS	8	3	56	12	81	20	30	210		
COMMISSIONS	1	3	31	5	51	20	0				
USER'S ACCURACY	87.50	0.00	44.64	58.33	37.04	75.00	100.00				
% Cover	3.81	1.48	26.67	5.71	38.57	9.52	14.29				
Kappa	0.46										
Overall accuracy	54.3										

The overall results of the single-date imagery approach correlate with the Landsat imagery used for the study. The visual observations were different from both images. Further analysis of what may have caused such distinction will be discussed in chapter 5. Also it is important to note the crispiness in the Landsat 8 images which contribute in accurately visually interpreting an image.

4.3.4 Multi-temporal classification maps and accuracy assessment

The multi-temporal classification map results are distinctive compared to the results of the single-date classification maps. There is no table visual difference after stacking the images of different dates. Within the 432 false colour composite the different features show a strong variety of different shades of different colours. As a result of this approach, it was easier to delineate features. The 2006-2009 multi-temporal imagery (Figure 4.8) shows redder as compared to the 2013-2015 multi-temporal imagery (Figure 4.9). However, the 2013-2015 multi-temporal imagery illustrates much deeper hues as compared to the 2006-2009 multi-temporal imagery. This as a result, the 2013-2015 classification map shows more dense vegetation, plantations and plantations/dense vegetation classes being mapped out compared to the 2006-2009 classification map. In the 2006-2009 classification map there are more grasslands than in the 2013-2015 classification map. The water areas seem to have remained unchanged for both these periods in this multi-temporal approach. The grasslands/degraded class in both periods were slightly similar. The overall classification of multi-temporal images shows quite a distinction when compared to the single-date images.

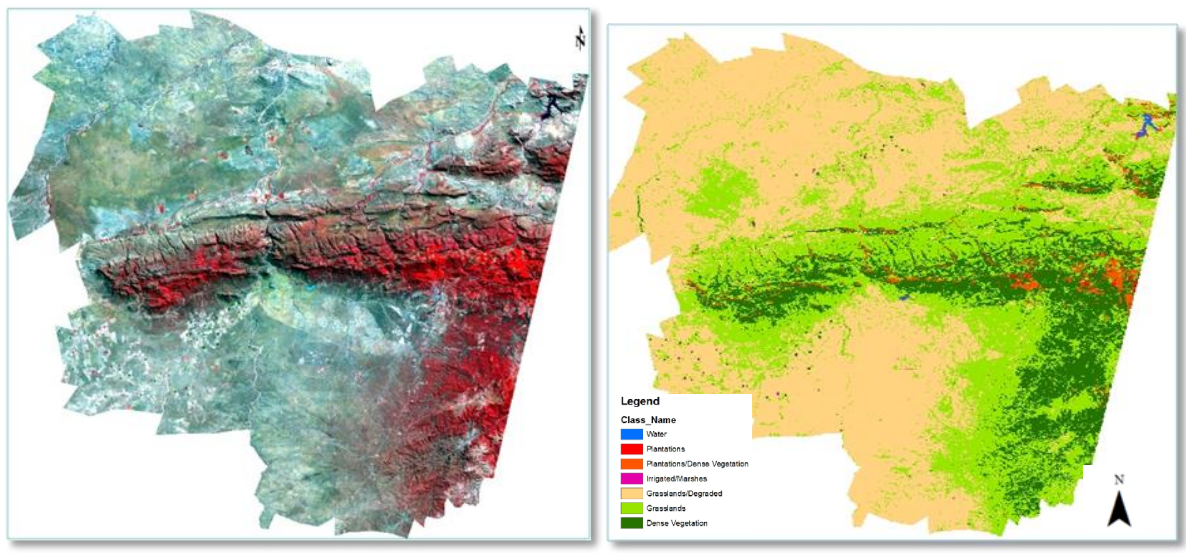


Figure 4.9- 2006-2009 Multi-temporal classification map generated by the ML classifier

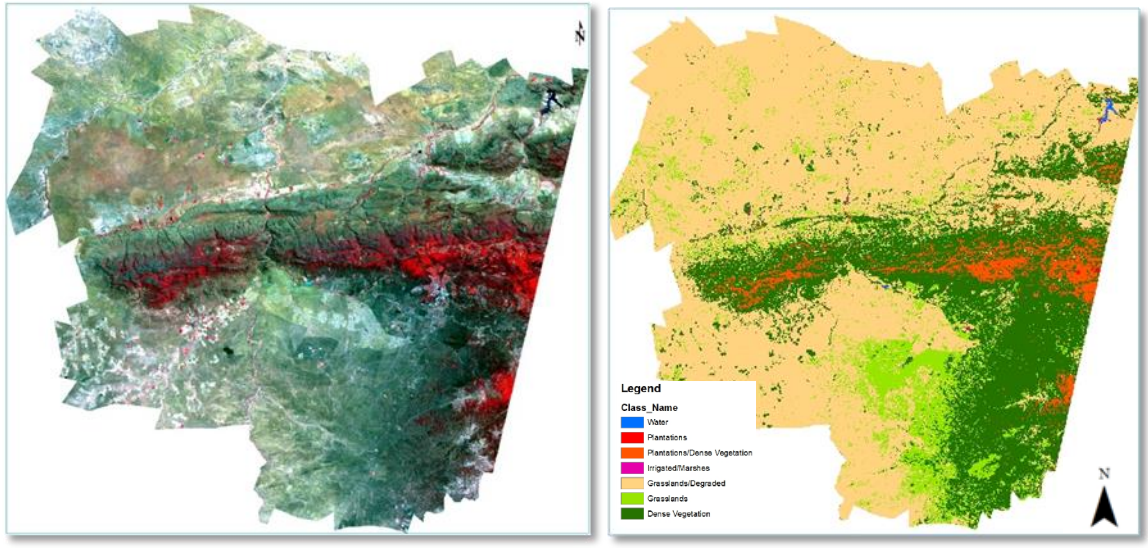


Figure 4.10- 2013-2015 multi-temporal classification map generated by the ML classifier

The accuracy results of these maps were compiled using a confusion matrix. The results of the assessment were better than the single-date classification assessments. Both periods had an overall accuracy that was above 70.0%. The 2006-2009 accuracy assessment results (Table 4.3) illustrated two classes, grassland/degraded and water with a PA that was above 95.0%. The dense vegetation class also had a higher % PA of 81.3%. Irrigated/Marshes class had the lowest PA, 32.1%. Plantations and grasslands class had a PA that was above 55.0%. The overall accuracy of the 2006-2009 classification map was 72.9% with a K_c of 0.68. On the other hand, the plantations class of the 2013-2015 map had the highest PA of 93.1% with three classes, plantations/dense vegetation, grasslands/degraded and dense vegetation having a PA that was more than 80.0% (Table 4.4). The water class had a PA of 80.0% and grasslands with a PA of 57.1%. The irrigated/marshes had a higher PA of 66.7% compared to the 32.1% from the 2006-2009 accuracy assessment. The overall accuracy of the 2013-2015 map was 79.0% with a K_c of 0.76.

Table 4.3- Confusion matrix of the 2006-2009 multi-temporal MLC classification map

		Classification Data									
Reference Data	CLASS/REFERENCE	GD	PD	PL	DV	GR	IM	WA	TOTALS	OMISSIONS	PA
	GD	29			1				30	1	96.67
	PD		20			9		1	30	10	66.67
	PL			20	4	3			27	7	74.07
	DV			2	26	2	2		32	6	81.25
	GR	2			10	17	1		30	13	56.67
	IM				9	3	9	7	28	19	32.14
	WA	1						32	33	1	96.97
	TOTALS	32	20	22	50	34	12	40	210		
COMMISSIONS	3	0	2	24	17	12	8				
USER'S ACCURACY	90.63	100.00	90.91	52.00	50.00	75.00	80.00				
% Cover	15.24	9.52	10.48	23.81	16.19	5.71	19.05				
Kappa	0.682										
Overall accuracy	72.9										

Table 4.4- Confusion matrix of 2013-2015 multi-temporal classification map

		Classification Data									
Reference Data	CLASS/REFERENCE	GR	PD	GD	PL	DV	IM	WA	TOTALS	OMISSIONS	PA
	GR	20		3		11	1		35	15	57.14
	PD		29	1		1	2		33	4	87.88
	GD	4		26					30	4	86.67
	PL		2		27				29	2	93.10
	DV	2				20	2		24	4	83.33
	IM			1	1	5	14		21	7	66.67
	WA						8	30	38	8	78.95
	TOTALS	26	31	31	28	37	27	30	210		
COMMISSIONS	6	2	5	1	17	19	0				
USER'S ACCURACY	76.92	93.55	83.87	96.43	54.05	51.85	100.00				
% Cover	12.38	14.76	14.76	13.33	17.62	12.86	14.29				
Kappa	0.756										
Overall accuracy	79.0										

4.3.4.1 Actively irrigated fields and their change over time

The approach was undertaken using a smaller area which consisted of more agricultural areas than any other parts of the whole area of the study. The area illustrated in a yellow box in figure 4.11 is the area of interest and all results shown in this section are of the area. The results are for both period 1, 26 May 2009 and period 2, 27 May 2015.

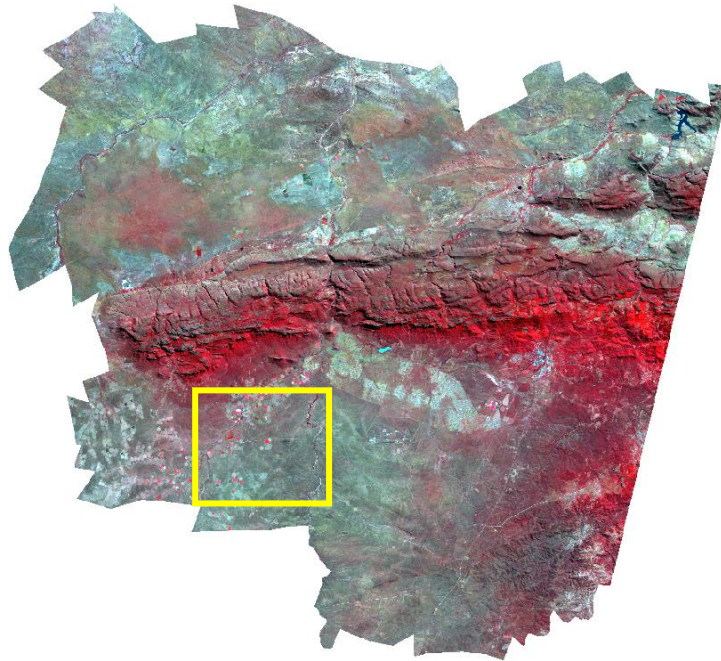


Figure 4.11: Processed Landsat image illustrating the area of study for the irrigation approach

In figure 4.12 are the results of all the actively irrigated fields of the chosen study area. These fields are represented in white and the black background is the non-irrigated areas. The thresholds that were suitable in each of this periods are as follows;

Period 1:

$LST \leq 21$ AND $NDWI \geq 0.1$

Period 2:

$LST \leq 24$ AND $NDWI \geq 0.05$

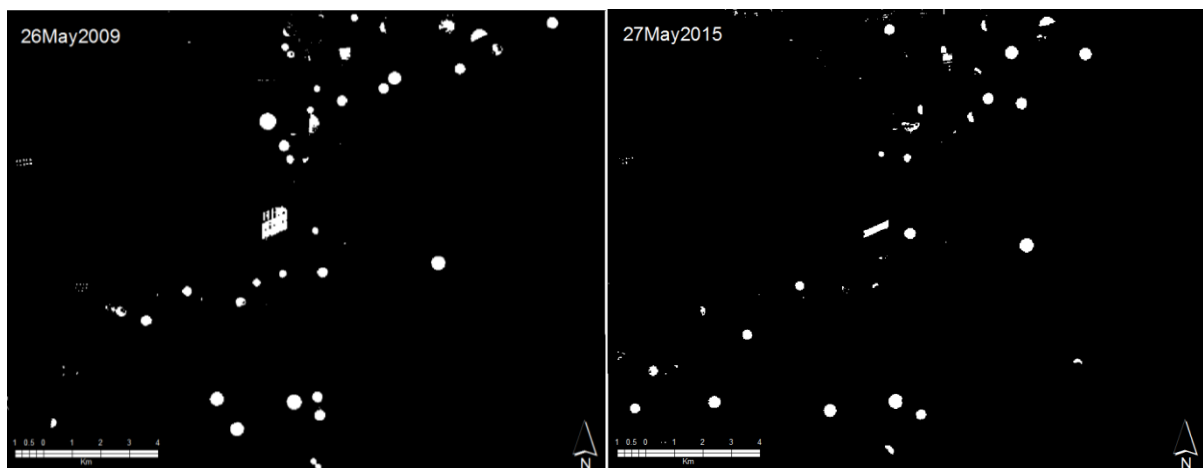


Figure 4.12: Illustrates the results for both 2009 and 2015 actively irrigated fields

The results of the approach show visually similar actively irrigated fields even though in period 1 there seem to be more white fields as compared to period 2. Also, the actively

irrigated fields in period 1 are slightly bigger compared to period 2. Quantitatively, the values of NDVI, NDWI, LST as well as the area size showed significant differences (see Table 4.5). From the table, the LST maximum values of period 1, 2015 were significantly higher than those of 2009. It is important to note that the two images were from different years but the same seasonal period. The NDWI values were also different from period 1 to those of period 2. In period 1 the maximum NDWI value was 0.14 and in period 2 was 0.12 and NDVI maximum values were 0.47 and 0.26 respectively. The area sizes of the actively irrigated fields were 558 Ha and 379 Ha respectively (see Figure 4.12).

Table 4.5: Illustrates the values of NDVI, NDWI, LST and area size for both periods

Parameters/Image Date	LST (°C)		NDWI		NDVI		Area (Ha)
	Min	Max	Min	Max	Min	Max	
20090526	-70.34	26.65	-0.39	0.14	0.06	0.47	558
20150527	-74.62	36.5	-0.13	0.12	0.10	0.26	379

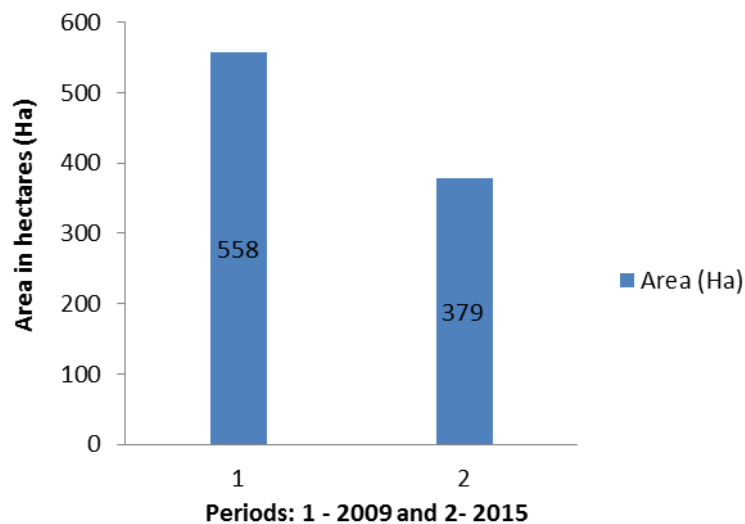


Figure 4.13: Area sizes in Ha for both 2009 and 2015 study periods

4.4 Post-classification change detection using multi-temporal classification maps

The change detection techniques were employed in this study using the multi-temporal classification maps of 2006-2009 and 2013-2015. The accuracy results of these maps had minimal errors when compared to the single-date classification maps (see Table 4.1 and 4.2). The post-classification change detection method was employed through the assistance of ArcMap.

Table 4.6- Classes area size in ha and percentages for both 2006-2009 and 2013-2015 periods.

Classes	2006-2009		2013-2015	
	Area (ha)	Area in %	Area (ha)	Area in %
Grasslands/Degraded	333250	51.4	390641	60.3
Plantations/Dense Vegetation	10082	1.6	22811	3.5
Plantations	425	0.07	172	0.03
Dense Vegetation	86003	13.3	169847	26.2
Grasslands	217284	33.5	64011	9.9
Irrigated/Marshes	828	0.13	468	0.07
Water	455	0.07	381	0.06

Further, using ArcMap 10.4.1 the detection of area changes were done using the attribute information. The area results were then plotted in a 2 D column graph which provided a better representation of the results. From the results, four classes decreased in area percentages viz. plantations, irrigated/marshes, water and grasslands. The other three remaining classes viz. grasslands, plantations/dense vegetation and dense vegetation experienced an area increase during the 2006-2009 and 2013- 2015 study period. Change map as well as the visual observations from the two classification maps.

The total size of the study area was 648351 hectares and the totals of the area of the maps that were classified and later converted to vector are 648327 ha and 648331 ha respectively. The slight difference could have been caused converting a pixelated raster layer to a vector layer.

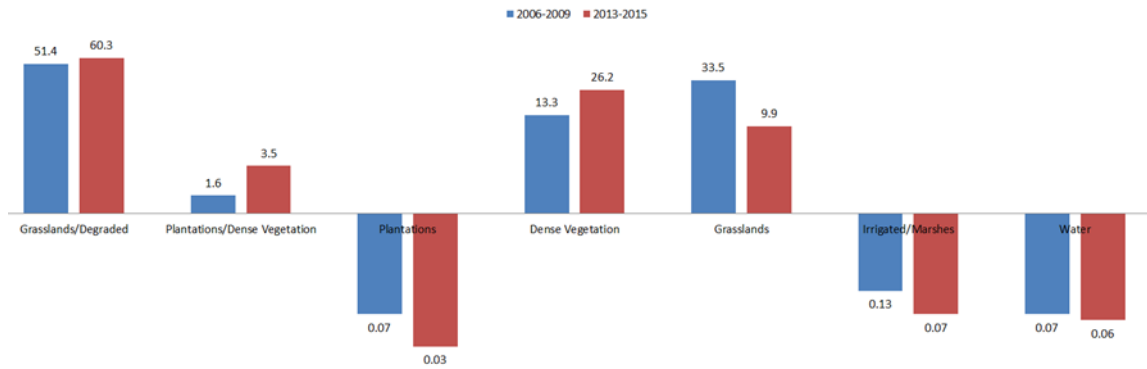


Figure 4.14- Area in percentage illustrated for 2006-2009 and 2013-2015 for all the classes of the study

Overall, the results of the different methods used to identify the changes in land cover classes of the study do correlate with each other. The visual observations of the classification maps for both periods and the area result support each other. The change detection results will be further explained in the discussion chapter.

CHAPTER 5: DISCUSSION

5.1 Introduction

In this chapter the focus will be on understanding what the findings of this study and how they are significant for the remote sensing research and also for people of Makhado. These results will highlight the importance of the use of remote sensing techniques to better understand natural resources in Makhado. The objectives of the study will, therefore, be discussed based on the results thereof. The discussion will further look into what could have been done to improve the results with regards to procedural methods that were employed. The overall focus will be on addressing the research questions, and if they have been answered throughout this study. Lastly, the results will assist in projecting the implications of any changes that may have occurred during the period of this study.

Limpopo is a naturally rich province in most natural resources of the country but also one of the least economically developed province. There always has to be a balanced in both developments in infrastructure and natural resources. Infrastructure developments to some extent do pose a threat in communities which are rich in natural resources that the locals depend on. Despite a greater need for such developments that uplifts the communities, a better understanding on how to successfully balance the needed growth both from the use of natural resources as well as in developments that will improve the economy of the province. Such instances illustrate the importance of putting in place successful environmental management strategies. These are a success when there is sufficient land cover information available. As a result, land cover mapping plays a tremendous role in most if not all parts of any society. This is one of the fundamental reasons of why this study is important for a community such as that of Makhado. The results of this study illustrate changes that pose a threat to the environment and the people living on it. Although, some of the changes are imperative and necessary e.g. urbanisation other changes are detrimental to the environment. Such changes can be studied and later avoided when appropriate planning and management of natural resources is implemented.

In remote sensing, there is a variety of applications used for land cover mapping and land cover change. These applications/methods commonly have merits and demerits which largely depend on a number of factors. Factors such as;

- *Location of study:* different areas consists of different surface features which contributes to the effectiveness of various methods

- *Satellite sensor*: different satellite sensors have different properties which improve the image processing
- *Software*: A number of good software are expensive and the ones which are open source, commonly do not have many applications. For example, there are a number of algorithms that are usually not incorporated in the software packages which usually leads to finding new ways of getting results.
- *Environmental factors*: these factors include temperature and precipitation which play a role in the conditions of the surface features.

These factors are dependent on each other and thus an application of a particular method in a specific area rarely has the similar response in a different area. This brings out the necessary need to continuously implement and explore different methods for specific areas. The results of such studies contribute greatly to the remote sensing research field of the country. In South Africa, land cover studies using different methods/techniques are yet to be widely explored especially the incorporation of different methods to produce a single land cover map. This study is imperative in that aspect.

5.2 The use of multiple techniques for image classification

The study implemented two pre-classification approaches for better comparisons of image classification results. The single-date image approach is the commonly used method for image classification but for this study, the stacking of images of multiple dates was also explored. Land cover maps were produced and analysed and their results were different when compared with each other. Single-date classification maps for both 2006-2009 and 2013-2015 period were distinctive as seen from the results chapter. The 2013-2015 single-date classification had confusion or major errors with the grassland and the grassland/degraded classes. The original Landsat 8 image shared similar spectral characteristics for both classes. This was observed when the values of the ROIs for the study were analysed for this image. There were slight differences in the low lying areas where these two classes were observed. This majorly contributed to the overall accuracy of the classified map of this period. The multi-temporal classification, on the other hand, consisted of less of misclassifications when compared to the single-date classification map. The same area that consists of misclassification in the single-date map had more classes classified correctly in the multi-temporal classification map. As a result the overall accuracy of the multi-temporal classification maps for both the periods was small. The grassland and grassland/degraded class in this multi-temporal image were easy to delineate as the

reflectance values of the same low lying area were separable. This may be due to stacking images of different seasons that highlight the growth of different vegetation.

5.3 Multi-temporal approach improved the accuracy of land cover mapping in this study

The results of the multi-temporal assessment approach improved the process of mapping the land cover of Makhado municipality. The results in chapter 4 illustrated how the accuracy of the two assessments differed in terms of appearance but most importantly in terms of accuracy. Generally, from the study, there was a clear distinction of how both the single and multi-date images visually appeared. Multi-temporal images for both the periods in a false colour combination Landsat 5 TM (432) and Landsat 8 OLI (543) had very distinctive hues of different colours. The deeper shades clearly illustrated the distinction of different classes. This was not the case with single-date images. Further, multi-seasonal images stacked together did improve and enhance the performance of the classifier. This is because of how stacking images of different seasons which incorporates different growing stages of vegetation significantly improve the results of the classifier. Also, stacking of Landsat images with the same phenological stages can consequently improve the spectral behaviour of vegetation. The spectral information is comparable.

Studies of the multi-temporal approach previously done showed good results. Most of them were done for change detection studies. In a study done by Guerschman *et al.* (2003), images of 1996-1997 were used to explore the multi-temporal approach. The study was motivated by the understanding that images of different dates but of the same growing season should illustrate low discrimination capability. Further, as previously mentioned by Tottrup (2004) the approach improves the spectral information through the recording of phenological stages and canopy roughness. This approach thus should be recommended for more accurate land cover mapping (Guerschman *et al.*, 2003). In the study, there was a highlight of multi-date studies done by Badhwar (1984), Turner and Congalton (1998), Pax-Lenney and Woodcock (1997) and Wolter *et al.* (1995) that produced good results in land cover classification. The study illustrated that multi-temporal approach majorly assists in accurately classifying different land cover types. Despite the use of band ratios, the approach still significantly performed well. Guerschman *et al.* (2003) further state that band ratios such as NDVI do not change the performance of the classifier because they are relatable to the seasonal dynamics that are already entailed in the multi-temporal image. Another study which compared single and multi-date approach was done by Meddens *et al.*

(2013). The classification differed between the single and multi-temporal approach. The accuracy results of the study were as follows; for the single-date approach the accuracy was 91.0% with a K_c of 0.88. The multi-date approach accuracy results were 89.6% with a K_c of 0.86. In this study, both approaches produced good results but in different environments. The multi-date worked well in the intermediate level of tree mortality and on the high mortality tree level the single-date approach worked better (Meddens *et al.* 2013). Multi-temporal approaches whereby multiple images are stacked into a layer before a classification process have not been fully explored.

5.4 Monitoring irrigated fields using LST, NDVI and NDWI

The study of finding an innovative approach to monitor actively irrigated fields has a great potential. The results of this study, illustrated that within the irrigated/marshes class land cover type, other fields were undergoing irrigation at the time the image was acquired. Despite having no accuracy done on the approach, the background study behind the approach was correct. The thresholds done on the areas of interests had low temperatures in the fields that had high NDVI and high NDWI values.

The NDWI, LST and NDVI also illustrated how there have been changes in the Makhado area from 2009 to 2015. The maximum temperature was highest in 2015 as compared to 2009. This could be evidence that in period 2, the conditions were much drier and hot and conditions that were associated with drought. The NDWI and NDVI values also had lower maximum values in 2015 which meant the vegetation had lesser biomass and lesser water content when compared to the year 2009. These are good indicators of what affected the changes in the land cover.

More field datasets can be collected to improve the confidence of this approach. Ideally, accuracy assessment can be done using field data of the same date as that of the Landsat image. Such studies greatly contribute to the work that most government departments do. In most cases, this information is majorly used for verification and validation projects. Further, monitoring actively irrigated areas assist in calculating the amount of water needed by crops per year for water allocation use, in government department such as Water and Sanitation. An improvement in this approach can only make the work of such departments easier.

5.5 Makhado District natural resources have changed over the 2006-2009 and 2013-2015 period

During the two study periods there was a change in the natural resources of Makhado. Some classes increased from the previous period and the others decreased. Classes such as plantations, water and irrigated/marshes experienced a slight decrease over the period of the study. These slight changes of plantations have been replaced by dense vegetation and in some areas grasslands/degraded. The grasslands, on the other hand, have experienced a significant decline during the study period. Most of the grasslands areas are now classified under the grasslands/degraded class which entails surface features such as urban built-up, cultivated subsistence (low), low shrubland, urban village, erosion, and bare non-vegetated. These results further illustrate that grasslands may have been turned into built-up areas, eroded and also experienced degradation.

Degradation might have been a major cause of grasslands decreasing. It is also evident in the climatic conditions of the Limpopo province during this study. The plantations, water and irrigated/marshes experienced a slight decrease over the same period of study. Most of the plantations are either degraded or are more dense bushes. The grasslands are becoming more degraded, whilst the grassland/degraded class increased during the same period. Limpopo, South Africa did experienced some drought in the year 2009 (Maponya and Mpandeleli, 2012) and was documented as the worst ever. Recently, the province experienced similar conditions which were declared as the worst drought since 1983. Due to this extreme disaster, many cattle died and communities suffered due to low water availability in the province. The Figure below illustrates the Nsami Dam which currently consists of mud cracks and muddy water and was previously full and functional.



Figure 5.1- Dried-up Nsami Dam and cattle drinking water from the dam

The significant decrease in grasslands poses a serious threat to the people of Makhado and largely to the environment. Majorly, anthropogenic activities are known to cause such changes in the productivity of grasslands. This results to major complexities between grasslands ecosystems and climate change (Iftikhar *et al.*, 2016). In this regard, the effect of drought might have played a significant role in the decrease in grasslands of the Makhado village. The possible climatic factors are discussed in the following discussion.

5.6 Major factors that affected the changes of natural resources in Makhado Municipality

The results of this study illustrated that there were changes in the natural resources of Makhado municipality. The common factors that affect natural resources are usually associated with climate. These factors affect the resources directly and/indirectly. Climatic factors such as rainfall and temperature greatly contribute to the growth or lack thereof of natural resources. In the year 2015, South Africa experienced the worst drought since 1933 with only 403 mm of rain. This natural phenomenon brought by the El Nino resulted in a disastrous impact majorly affecting the agricultural sector. This is a sector that plays a tremendous role in the economic growth of the country. A number of food suppliers hiked their prices due to the increased cost in food production. As a result, the economic growth of the country was greatly affected, with a number of people losing their jobs. Such a change detection study manages to bring context of what changed during and after such a

phenomenon. This then provides information that is needed in order to devise plans of how to control the damage and further monitor the resources. Priorities are then set, plans are put in place and as well as proper management structures can be made in order to properly manage the stressed and strained natural resources.

The rainfall and temperature data supplied by the South African Weather Services (SAWS) provides evidence of the changes in the natural resources of Makhado municipality. The 2009 rainfall data was collected at the Louis Trichardt station and the 2015 rainfall data was from Makhado Air Force Base. The maximum daily temperature data was collected from the Thohoyandou station. The temperature and rainfall graphs do correlate and also illustrate significant differences when the 2009 and 2015 are compared. In Figure 5.2, the temperatures recorded for both 2009 and 2015 show different patterns throughout the months of the different years. In 2009 the highest temperature recorded was in January and February with a temperature of 29.5 °C. In the same year, the lowest temperature was 21.1 °C, which was in July. The average temperature for the year 2009 was 26.9 °C. In 2015, the temperature recordings were a bit higher compared to those of 2009. Moreover, the highest temperature was 32.9 °C recorded in December and in June the temperature was the lowest recording at 24 °C. The average temperature recorded for that year was 28.6 °C. It is evident that the year 2015 had higher temperatures compared to the year 2009. Looking at the graphs, it is also evident that the temperatures in 2015 fluctuated drastically when compared to those of 2009.

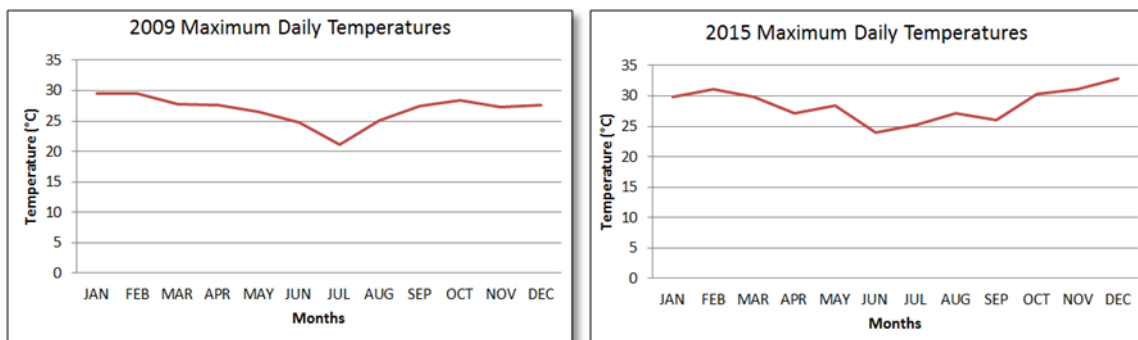


Figure 5.2: 2009 and 2015 maximum daily temperatures

The monthly rainfall data shown in Figure 5.3 correlates with the behaviour of the temperature graphs (Figure 5.2). In 2009 the highest rainfall recordings were 336.6mm in November with the lowest of 1.2 mm recorded in September. It is important to note that throughout the year, on a monthly basis there was rainfall recordings in Makhado Municipality. The total amount of rainfall received in the year 2009 was 1245.4 mm. Only

24% of the 2009 rainfall was received in 2015, the total rainfall received in 2015 was 299.6 mm for the Makhado area. In 2015, the Makhado area did not receive any rainfall for three months in the months of May, July and August and only 0.4 mm in June. The highest monthly rainfall recorded was 108.6 mm in February. This data proves that there were significantly low rainfall recordings for the year 2015 as compared to the year 2009.

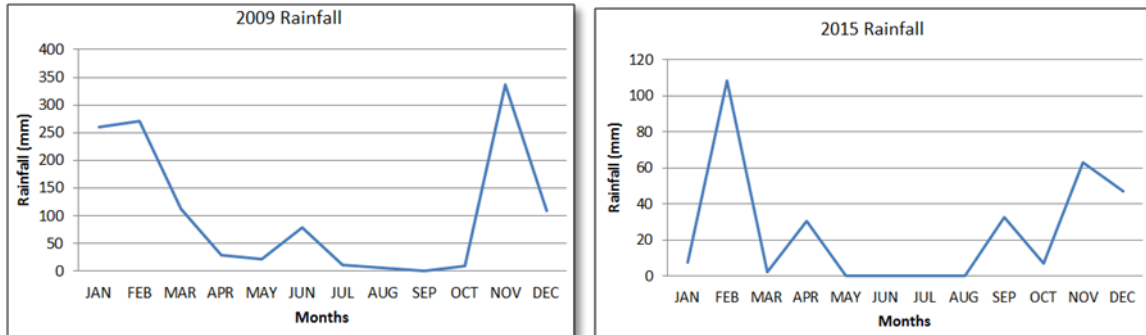


Figure 5.3: 2009 and 2015 monthly rainfall in mm.

The above temperature and rainfall graphs illustrate two distinctive periods with regards to the climate of the study area. The year 2006 experienced more rainfall as compared to the year 2015. This gives evidence to the changes that occurred in the area, shown through the change detection methods. There was a significant decrease in some natural resources in Makhado Municipality. These results thus show that the drastic changes in temperatures and rainfall of the area may have been the drivers of this significant change.

CHAPTER 6: CONCLUSION, CHALLENGES AND RECOMMENDATIONS

6.1 Conclusion

The study conducted in Makhado Municipality, in the northern part of Limpopo illustrated different aspects of remote sensing applications. The maximum-likelihood classification algorithm mapped different classes differently. The need of devising a new approach to improve the classification of the algorithm was explored and produced better results. This study proved that a combination of old and new methods can produce better classification results. The main focus was on determining which between the multi-date approach and the single-date approach produced better accuracy results. It also further focussed on the classes that were majorly misclassified during the process.

The land cover maps of the Makhado district study area were created for both single and multi-temporal imagery within the 2006-2009 and 2013-2015 periods. Multi-temporal classification maps were more accurate compared to single-date classification. The accuracy of the multi-date approach did improve the performance of the classifier. The innovative study of exploring multi-temporal approach together with the use of other useful input variables such as the DEM and band ratios yielded better results for this study. The multi-temporal classification maps were then utilised for detecting possible changes that occurred in the areas during the chosen study periods. The results of change detection methods illustrated changes in some of the major classes of the study area. One major change observed was the decrease in the grasslands of the area and an increase in the grassland/degraded class which consisted of urban built-up, cultivated subsistence (low), low shrubland, urban village, erosion, and bare non-vegetated. Through visual observations from Landsat images and classification maps, most areas were classified under the grassland/degraded class. This illustrated that most areas were in a less vegetated state. This could then be linked to the possibility that the area was receiving less water for the 2013-2015 period. This was expected as the area had undergone severe drought during the year 2015. The rainfall information and temperatures of the Makhado area illustrated the drastic changes that occurred between the year 2009 and 2015. The significantly low amount of rainfall and high temperatures in 2015 affected the natural resources of Makhado municipality majorly grasslands and agricultural areas.

The overall performance of maximum-likelihood produces good results when the innovative approach was employed and analysed accurately. Multi-temporal approach with the use of NDVI and NDWI to reclassify some classes proved to be useful for this study. The use of NDVI and NDWI band ratios has shown to be beneficial for improving the accuracy of the multi-temporal approach classification process. The use of band combination to enhance the surface features also contributed to improving the analytic process that led to image classification. The wide-variety of data and methods used during this land cover study produced good results. The results of the study were useful for change detection. Post-classification methods assisted in highlighting the changes of the classes.

The application of LST, NDWI and NDVI indicates a great possibility of successfully mapping actively irrigated fields. The relationship between LST and NDWI greatly assists in positively delineating actively irrigated fields. The use of these three variables illustrates a great possibility for institutions that require such information timeously. The results of this approach illustrated changes from 2009 to 2015. There were more actively irrigated fields in 2009 May than in 2015 May. These results also suggest that the area could have experienced low water intake. The temperature and rainfall data from South African Weather Services showed that the area received less rainfall in 2015 as compared to 2013. Using the few field data that were collected for this class, two of the three actively irrigated fields were correctly mapped.

The results of this study give an indication to the status of the natural resources of Makhado Municipality. This information can be used to further understand the dynamics that encapsulate the interaction that exists between the people of the village and their environment. They also provide information for decision makers in government and other institutions for water-use related projects. Further, the study provides information on how in an innovative way traditional classification methods can be used together with improved approach to accurately map the land cover of an area.

6.2 Challenges

In this study a number of challenges were encountered which had a significant impact in the whole study. There are majorly three challenges that were encountered during the course of this study viz. image resolution, area size and surface features.

- Spatial resolution

For this study, Landsat imagery was suitable for use as it is freely available on a continuous basis. Despite that, land cover mapping of larger areas using a satellite such as Landsat has its own limitations. The spatial resolution of the sensor is 30m. For larger areas, there is a variety of different classes that exist within an area. It then becomes a challenge to have as minimal classes as possible because from the image there is no clear distinction of all possible classes. Such does lead to class confusion when there are no clear boundaries within different features. It is therefore advisable to work with a smaller area for better accuracy results or use high-resolution satellite imagery which comes at a cost.

- Area size for the study

The initial stages of this study attempted to do a study of the whole of Vhembe district but the mosaicked image of four Landsat tiles became too big to be processed. The larger the area size, the bigger the image size. Bigger image size, need more powerful computers to process the images without encountering technical glitches. The more time and space it also requires. As a result of these challenges, a part of the Makhado area which consisted of one Landsat tile was utilised to perform this study.

- Spatial surface feature variation

Some other challenges that cannot be avoided were the spatial surface variation relating to the study area. The Makhado area consists of a mountain range which contributed in how well the classifier performed. In some other parts of the escarpment consisted of shadows. Other parts had areas with different types of vegetation. Highly elevated areas are commonly associated with shadows and cloud cover. These factors do affect the performance of a classifier in any image processes.

6.3 Recommendations

The study highlights the changes that occurred in Makhado Municipality. Moving forward, such studies should be done on a regular basis in order to assist government such as Department of Water affairs to monitor the water-use of farmers. We can only manage and monitor what we know. During the study, accessing areas of interest was a challenge for this study as most of the areas were not accessible. There should be plans in place to assist scientific researchers to be able to access any areas for the purpose of any scientific study.

This will better improve the findings of any studies which will ultimately contribute in improving the accuracy on image classification.

The results of this study should reach the villagers. Programs of teaching the rural people about their environment should be created. These programs will assist in bringing better understanding to the villagers of how the interactions that exist between people and the environment positively and negatively affect the whole ecosystem. This ultimately contributes in devising appropriate policies that can govern such environments. As a result of such initiatives, continuous monitoring in rural areas can easily be executed. It is important to monitor natural resources, especially in areas such as that of Makhado Municipality. A rural area which is rich in natural resources that greatly contributes to the economy of South Africa.

References

- Anderson, J. R., Hardy, E. E., Roach, J. T. and Witmer, R. E. (1978). A land Use and land cover classification system for use with remote sensor data. *Geological Survey Professional*. Vol. 38: 1. pp. 33-36.
- Arneth. A., Schurgers.G., Kulmala.M., Sorvari.S., Vesala. T., Harrison.S.P., Zaehle.S., Tsigaridis.K., Menon.S., Bartlein.P.J., Feichter.J., O'Donnell.D.D. and Korhola.A. (2010). *Terrestrial Biogeochemical Feedbacks in the Climate System. Nature Geoscience*, Vol 3: 8. pp. 525-532.
- Badhwar, G. D. (1984). Automatic corn-soybean classification using Landsat MSS data, I – Near-harvest crop proportion estimation. I - Early season crop proportion estimation. *Remote Sensing of Environment*. Vol. 14. pp. 15-29.
- Bhagat, V. S. and Sonawane, K. R. (2011). Use of Landsat ETM+ data for delineation of water bodies in hilly zones. *Journal of Hydroinformatics*. Vol. 13: 2. pp. 661-667
- Bhandari, A. K., Kumar, A. and Singh, G. K. (2014). Improved feature extraction scheme for satellite images using NDVI and NDWI technique based on DWT and SVD. *Arabian Journal of Geosciences*. Vol. 8: 9. pp. 6949-6966.
- Bodart, C., Eva, H., Beuchle, R., RaÅji, R., Simonetti, D., Stibig, H.J., Brink, A., Lindquist, E. & Achard, F. (2011). Pre-processing of a sample of multi-scene and multi-date Landsat imagery used to monitor forest cover changes over the tropics, *ISPRS Journal of Photogrammetry and Remote Sensing*. Vol. 66. pp. 555-563.
- Browning, D. M., Archer, S. R. and Byrne, A. T. (2009). Field validation of 1930s aerial photography: What are we missing?. *Journal of Arid Environments*. Vol. 73: 9. pp. 844-853.
- Bruzzone, L., Cossu, R., Vernazza, G. (2002). Combining Parametric and Non-Parametric Algorithms For A Partially Unsupervised Classification Of Multi-temporal Remote-Sensing Images. *Information Fusion*. Vol. 3. pp. 289-297.
- Butt, A., Shabbir, R., Ahmad.S. S. and Aziz, N. (2015). Land use change mapping and analysis using Remote Sensing and GIS: A case study of Simly watershed, Islamabad, Pakistan. *The Egyptian Journal of Remote Sensing and Space Sciences*. Vol. 18. pp. 251-259.
- Campbell, J. B. (2007). *Introduction to Remote Sensing*. 4th ed. The Guilford Press. New York, London.
- Campbell, J.B. (1996). *Introduction to Remote Sensing*. Taylor & Francis, London.
- Campbell, J. B. and Wynne, R. H. (2011). *Introduction to Remote Sensing*. 5th ed. The Guilford Press. New York, London.

- Canty, M. J. (2007). Image analysis, classification and change detection in remote sensing: with algorithms for ENVI/IDL. Boca Raton. Florida.
- Cho, M.A, Naidoo, L, Mathieu, R, Asner, G.P and Ramoelo, A. (2012). Comparing parametric and non-parametric classifiers for remote sensing of tree species across a land use gradient in a savannah landscape. In: 9th International Conference of the African Association of Remote Sensing and the Environment, El Jadida Morocco October 29 to November 2, 2012.
- Chuvieco, E. and Huete, A. (2010). Fundamentals of satellite remote sensing. CRC Press.
- Clark, M. L. and Kilham, N. E. (2016). Mapping of land cover in northern California with simulated hyperspectral satellite imagery. *Journal of Photogrammetry and Remote Sensing*. Vol. 119. pp. 228-245.
- Conese, C and Maselli, F. (1991). Use of multi-temporal information to improve classification performance of TM scenes in complex terrain. *Journal of Photogrammetry and Remote Sensing*. Vol. 46: 4. pp. 187-197.
- Department of Environmental Affairs (DEA). (2015). GeoTerralmage: 2013-2014 South African National Land-Cover Dataset. A commercial data product prepared for Department of Environmental Affairs. Report.
- Dickinson, G.C. and Shaw, M.G. (1977). What is 'Land use'?. *Area*, published by Blackwell Publishing on behalf of The Royal Geographical Society with the Institute of British Geographers. Vol. 9: 1. pp. 38-42.
- Dimiyati, M., Mizuno, K., Kitamura, T., 1996. An analysis of land use/cover change using the combination of MSS Landsat and land use map: a case study in Yogyakarta, Indonesia. *International Journal of Remote Sensing*. Vol. 17. pp. 931-944.
- Driese, K. L., Reiners, W. A., Lovett, G. M. and Simkin, S. M. (2004). A vegetation map for the Catskill Park, derived from Multi-temporal Landsat imagery and GIS data. *North eastern Naturalist Journal*. Vol. 11: 4. pp. 421-442.
- Dupigny, G., Lesley, A. & Lewis, J. E. (1999). A moisture index for surface characterization over a semi arid area. *Photogrammetric Engineering and Remote Sensing*. Vol. 65: 8. pp. 937-945.
- El-Hattab, M. M. (2016). Applying post classification change detection technique to monitor an Egyptian coastal zone (Abu Qir Bay). *The Egyptian Journal of Remote Sensing and Space Science*. Vol 19: 1. pp. 23-36.
- Fairbanks, D. H. K., Thompson, M. W., Vink, D. E., Newby, T. S., Van den Berg, H. M. and Everard, D. A. (2000). The South African land –cover characteristics database: A synopsis of the landscape. *South African Journal of Sciences*. Vol. 96: 2. pp. 69-82.

- Falko, T.B., Marinda, F.A., Esterhuysen, S., Marthie, E.K., Fred, J.K., Olusola, O.O., Maitland, T.S., A, T.V. and Watson, M. (2016). Producing the next generation of water resource experts in South Africa. *South African Journal of Science*. Vol. 112: 3. pp. 1-4.
- Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*. Vol. 80. pp. 185-201.
- Friedl, M. A. and Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*. Vol. 61. pp. 399-409.
- Gao, B. (1996). NDWI – A Normalized difference water index for remote sensing of vegetation liquid Water from space. *Remote Sensing of Environment*. Vol. 58. pp. 257-266.
- Gibson, P. J. and Power, C. H. (2000). Introductory remote sensing: Digital image processing and applications. Routledge. London.
- Gregorio, A. D and Jansen, L. J. M. (2000). Land cover classification system: classification concepts and user manual. Food and Agriculture Organization. Viewed 14 August 2016. From: <http://www.fao.org/docrep/003/x0596e/x0596e01e.htm>.
- Gregory, K. J. (2010). The Earth's Land Surface: landforms and processes in geomorphology, Recognising the Land Surface. SAGE Publications. London. From: <http://dx.doi.org/10.4135/9781446251621.n1>.
- Guerra, F., Puig H. and Chaune R. (1998). The forest savannah dynamics from multi-data Landsat TM data in Sierra Parima, Venezuela. *International Journal of Remote Sensing*. Vol. 19:11. pp. 2061–2075.
- Guerschman, J. P., Paruelo, C. D., Bella, M. C., Giallorenzi and Pacin, F. (2003). Land cover classification in the Argentine Pampas using multi-temporal Landsat TM data. *International Journal of Remote Sensing*. Vol. 24: 17. pp. 3381-3402.
- Gwet, K. (2002). Kappa statistic is not satisfactory for assessing the extent of agreement between raters. *Statistical Methods for Inter-Rater Reliability Assessment*. Vol. 76. pp. 378-382.
- Haines, A., Kovats, R. S., Campbell-Lendrum, D. and Corvalan, C. (2006). Climate change and human health: Impacts, vulnerability and public health. *Public Health*. Vol. 120: 7. pp. 585-596.
- Hansen, M. C. and Loveland, T. R. (2012). A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment*. Vol. 122:1. pp. 66-74. From: 10.1016/j.rse.2011.08.024.
- Hedden, S. & Cilliers, J. (2014). Parched prospects - the emerging water crisis in South Africa. *African Futures Paper*. Vol. 11. pp. 1-16.

- Horning, N. (2004). Land cover classification methods. American Museum of Natural History, Centre for Biodiversity and Conservation. From: <http://biodiversityinformatics.amnh.org>. [accessed on: 21 July 2016].
- Huang, S. Bartlett, P. and Arain, M. A. (2016). Assessing nitrogen controls on carbon, water and energy exchanges in major plant functional types across North America using a carbon and nitrogen coupled ecosystem model. *Ecological Modelling*. Vol. 323. pp. 12-27.
- Hunter, L. M., Nawrotzki, R., Leyk, S., Maclaurin, G. J., Twine, W., Collinson, M. and Erasmus, B. (2014). Rural outmigration, natural capital, and livelihoods in South Africa. *Population of Space and Place*. Vol. 20. pp. 402-420.
- Iftikhar, A., Cawkwell, F., Dwyer, E., Barrett, B., and Green, S. (2016). Satellite remote sensing of grasslands: from observation to management. *Journal of Plant Ecology*. Vol. 9:6. pp. 649-671.
- Jarman, C. (2016). Satellite imagery for estimating water use by irrigation. EE Publishers. From: <http://www.ee.co.za/article/satellite-imagery-estimating-water-use-irrigation.html>. [Accessed on: 25 January 2017].
- Jeeves, A. (1998). Land, Labour and Livelihoods in Rural South Africa. *Canadian Journal of African Studies*. Vol. 32: 1. pp. 146-152.
- Jewitt, D., Goodman, P.S., Erasmus, B.F.N., O'Connor, T., G. and Witkowski, E.T.F. (2015). Systematic land-cover change in KwaZulu-Natal, South Africa: Implications for biodiversity. *South African Journal of Science*. Vol. 111: 9. pp. 1-9.
- Jie, L., Zhang, L. and Wylie, B. (2009). Analysis of dynamic thresholds for normalized difference water index. *Photogrammetric Engineering and Remote Sensing*. Vol. 75: 11. Pp. 1307-1317.
- Juana, J. S., Mangadi, K. T. & Strzepek, K. M. (2012). The socioeconomic impacts of climate change on water resources in South Africa. *Water International*. Vol. 37:3. pp. 265-278.
- Kleynhans, W., Salmon, B. P. and Olivier, J. C. (2015). Detecting settlement expansion in South Africa using a hyper-temporal SAR change detection approach. *International Journal of Applied Earth Observation and Geoinformation*. Vol. 42. pp. 142-149.
- Kloer, B. R. (1994). Hybrid parametric/non-parametric image classification. *ERDAS Inc. Atlanta, Georgia*. pp. 308-316.
- Kumar, M. and Singh, R. K. (2013). Digital image processing of remotely sensed satellite images for information. Conference on Advances in Communication and Control Systems 2013 (CAC2S 2013). From: www.atlantis-press.com.
- Kumar, Y. and Sahoo, G. (2012). Analysis of parametric and non-parametric classifiers for classification technique using WEKA. *Information Technology and Computer Science*. Vol. 7. pp. 43-49.

- Kumbu, P. M., Mathivha, F. I. and Nkuna, T. R. (2015). The use of GIS and remote sensing techniques to evaluate the impact of land use and land cover change on the hydrology of Luvuvhu river catchment in Limpopo Province. Water Research Commission. Report number: 2246/1/15.
- Kyei, K. A. (2011). Some Socio – Economic indicators from Vhembe district in Limpopo province in South Africa. *Journal of emerging Trends in Economics and Management Sciences*. Vol. 2: 5. pp. 364-371.
- Lankhankar, T., Ghedira, H., Temini, M., Sengupta, M., Khanbilvardi, R., and Blake, R. (2009). Non-parametric methods for soil moisture retrieval from satellite remote sensing data. *International Journal of Remote Sensing*. Vol.1. pp. 3-21.
- Lillesand, T.M. and Kiefer, R. (1993). Remote Sensing and image interpretation. 3rd ed. John Wiley, New York.
- Lillesand, T.M. and Kiefer, R. (1999). Remote Sensing and Image Interpretation. John Wiley, New York.
- Lilliesand, T. M., Keifer, R. W. and Chioman, J. W. (2004). Remote sensing and image interpretation. John Wiley and Sons. New York.
- Li, Z., Tang, B., Wu, H., Ren, H., Yan, G., Wan, Z., Trigo, I. F. and Sobrino, J. A. (2013). Satellite-derived land surface temperature: Current status and perspectives. *Remote Sensing of Environment*. Vol. 131. pp. 14-37.
- Liu, Y., Huang, X., Yang, H. and Zhong, T. (2014). Environmental effects of land use/cover change caused by urbanization and policies in Southwest China, Karstarea – A case study of Guiyang. *Habitat International*. Vol. 44. pp. 339-348.
- Loveland, T. R. and Dwyer, J. L. (2012). Landsat: Building a strong future. *Remote Sensing of Environment*. Vol. 122. pp. 22-29.
- Lu, D. and Weng, Q. (2006). Use of impervious surface in urban land use classification. *Remote sensing and the environment*. Vol. 102. pp. 146- 160.
- Lynn, N. A. (2003). Effects of recreational use of impacts on hiking experiences in natural areas. *Land and Urban Planning*. Vol. 64. pp. 77-87.
- Maponya, P. and Mpandeli, S. (2012). Impact of drought on food scarcity in Limpopo province, South Africa. *African Journal of Agricultural Research*. Vol. 7: 37. pp. 5270-5277.
- Mas, J. F. (1999). Monitoring land-cover changes: a comparison of change detection techniques. *International Journal Remote Sensing*. Vol. 20: 1. pp. 139-152
- McCafferty, J. R., Elender, B. R., Weyl, O. L. F. and Britz, P. J. (2012). The use of water resources for inland fisheries in South Africa. *Water SA*. Vol. 38: 2. pp. 327-344.

- McFeeters, S. K., (1996). The use of normalized difference water index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*. Vol.17. pp. 1425-1432.
- Meddens, A.J.H., Hicke, J.A., Vierling, L.A. and Hudak, A.T. (2013). Evaluating Methods to Detect Bark Beetle-Caused Tree Mortality Using Single-Date and Multi-Date Landsat Imagery. *Remote Sensing of Environment*. Vol. 132. pp.49–58.
- Moeletsi, M. E., Mellaart, E. A. R., Mpandeli, N. S. & Hamandawana, H. (2013). The Use Rainfall Forecasts as a Decision Guide for Small-scale Farming in Limpopo Province, South Africa. *The Journal of Agricultural Education and Extension*. Vol. 19: 2. pp. 133-145.
- Mpandeli, N. S. & Maponya, P. I. (2013). Coping with Climate Variability in Limpopo Province, South Africa. *Journal of Agricultural Sciences*. Vol. 1: 4. pp. 54-64.
- Mpandeleli, S., Nesamvumi, E. and Mamponya, P. (2015). Adapting to the impacts of draught by smallholder farmers in Sekhukhune District in Limpopo Province, South Africa. *Journal of Agricultural Science*. Vol. 7: 2. pp. 1916-9760.
- Muriithi, F. K. (2015). Land use and land cover change (LULC) in semi-arid sub-watershed of Laikipia and Athi River basins, Kenya, as influenced by expanding intensive commercial horticulture. *Remote Sensing Applications: Society and Environment*. Vol. 3. pp.73-88.
- National Water Resource Strategy. (2013). National Strategic Imperatives. Department of Water Affairs. pp. 9. From: <http://www.dwa.gov.za/documents/Other/Strategic%20Plan/NWRS2-Final-email-version.pdf>. [Accessed: August 2016].
- Nel, G. P. & Nel, E. J. (2009). Biodiversity Impact Assessment of the Planned Vele Colliery. Invirodel – Dubel Association (Coal of Africa). From: <http://www.coalofafrica.com>. [Accessed: 12 June 2016].
- Ngcofe, L. and Thompson, M. (2015). The status of land cover mapping in South Africa: 1994-2015. From: <http://www.ee.co.za/article/status-land-cover-mapping-south-africa-1994-2015.html>. [Accessed: 10 August 2016].
- Oberhauser, A.M. (2015). (Re)constructing rural–urban spaces: gendered livelihoods, migration, and natural resources in South Africa. *Geography Journal*. Vol. 81: 3. pp. 489-502.
- Odindi, J. Mhangara, P. and Kakembo, V. (2012). Remote sensing land cover change in Port Elizabeth during South Africa's democratic transition. *South African Journal of Science*. Vol. 108. pp. 1-7.
- Paumgarten, F and Shackleton, C. M. (2011). The role of non-timber forest products in household coping strategies in South Africa: the influence of household wealth and gender. *Population and Environment*. Vol. 33. pp. 108-113.

- Pax-Lenney, M. and Woodcock, C. E. (1997). The effect of spatial resolution on the ability to monitor the status of agricultural lands. *Remote Sensing of Environment*. Vol. 61: 2. pp. 210-220.
- Pervez, M., Budde, M and Rowland, J. (2014). Mapping irrigated areas in Afghanistan over the past decade using MODIS NDVI. *Remote Sensing of Environment*. Vol. 149. pp. 155-165.
- Petropoulos, G. P., Kalaitzidis, C. and Prasad, V. K. (2012). Support vector machines and object-based classification for obtaining land-use/cover cartography from Hyperion hyper spectral imagery. *Computers and Geosciences*. Vol. 41. pp. 99-107.
- Prenzel, B. (2004). Remote Sensing-based quantification of land-cover and land-use change for planning. *Progress in Planning Journal*. Vol. 61. pp. 281-299.
- Ramoelo, A., Majozi, N., Mathieu, R., Jovanovic, N., Nickless, A. and Dzikiti, S. (2014). Validation of Global Evapotranspiration Product (MOD16) using Flux Tower Data in the African Savanna, South Africa. *Remote Sensing Journal*. Vol. 6. pp. 7406-7423.
- Ramoelo, A., Munyati, C., Vogel, M., Le Maitre, D. and van Aardt, J. (2007). Land degradation mapping for modelling of ecosystem benefit flows in the Inkomati Catchment using Remote Sensing. From: <http://hdl.handle.net/10204/3827>. [Accessed on: 03 April, 2017].
- Rasethe. M. T., Semanya, S. S., Potgieter, M. J. and Maroyi, A. (2013). The utilization and management of plant resources in rural areas of the Limpopo Province, South Africa. *Journal of Ethnobiology and Ethnomedicine*. Vol. 9:27. pp. 1-8.
- Rawat, J.S. and Kumar, M. (2015). Monitoring Land Use/cover Change Using Remote Sensing and Gis Techniques: A Case Study of Hawalbagh Block, District Almora, Uttarakhand, India. *The Egyptian Journal of Remote Sensing and Space Sciences*. Vol. 18:1. pp. 77-84.
- Reddy, S. J. (1985). Suggested farming systems and associated risks over southern Mozambique. Report no. 24. Terra and Water Series, INIA. Maputo.
- Reis, S. (2008). Analyzing Land Use/Land Cover Changes Using Remote Sensing and GIS in Rize, North-East Turkey. *Sensors*. Vol. 8. pp. 6188-6202.
- Rickie, H. (2011). The Carbon Cycle. Available on: <https://earthobservatory.nasa.gov>. [Accessed: 28 October 2015].
- Schoeman, F., Newby, T. S., Thompson, M. W. and Van den Berg, E. C. (2013). South African national land-cover change map. *South African Journal of Geomorphology*. Vol. 2: 2. pp. 94-105.
- Senzanje, A., Boelee, E. and Rusere, S. (2008). Multiple uses of water and water productivity of communal small dams in Limpopo Basin, Zimbabwe. *Irrigation Drainage Systems*. Vol. 22: 3. pp. 225-237.

- Shackleton. S., Campbell, B., Wollenberg, E., and Edmunds D. (2002). Devolution and community-based natural resource management: Creating space for local people to participate and benefit. *Natural Resources Perspect.* Vol. 76. pp. 1-4.
- Shackleton, C and Shackleton, S. (2004). The importance of non-timber forest products in rural livelihood security and as safety nets: A review of evidence from South Africa. *South African Journal of Science.* Vol. 100. pp. 658-664.
- Shafri, H. Z. M., Suhaili, A. and Mansor, S. (2007). The performance of maximum-likelihood, spectral angle mapper, neural network and decision tree classifier in hyperspectral image analysis. *Journal of computer science.* Vol. 3: 6. pp. 419-423.
- Singh, A. (1989). Review Article Digital change detection techniques using remotely-sensed data, *International Journal of Remote Sensing.* Vol. 10:6. pp. 989-1003.
- Singh, K.V., Sahoo, R. S. S., Prasad, A. & B. Pateriya. (2015). Evaluation of NDWI and MNDWI for assessment of waterlogging by integrating digital elevation model and groundwater level. *Geocarto International.* Vol. 30: 6. pp. 650-661.
- Sobrino, J. A & Raissouni, N. (2000). Toward remote sensing methods for land cover dynamic monitoring: Application to Morocco. *International Journal of Remote Sensing.* Vol. 21: 2. pp. 353-366.
- Son, N. T., Chen, C. F., Chen, C. R., Chang, L. Y. and Minh, V. Q. (2012). Monitoring agricultural drought in the lower Mekong Basin using MODIS NDVI and land surface temperature data. *International Journal of Applied Earth Observation and Geoinformation.* Vol. 14: 1. pp. 417-427.
- South African Weather Services. (2017). Makhado Air Force Base and Thohoyondou Rainfall and Temperature data.
- Spurr, S. H. (1948). Forest resources of the world: Aerial Photography. *Unasylva.* Vol. 2: 4. From: <http://www.fao.org/docrep/x5345e/x5345e04.htm>. [Accessed: 9 June 2016].
- StatsSA (Statistics South Africa) (2006). Limpopo Province Profile. Report - 00–91-09, Pretoria.
- Statistics South Africa. (2011). South African National Census of 2011 – Limpopo, Vhembe. From: <http://www.statssa.gov.za>. [Accessed: 03 July 2015].
- Swift, J. (Editorial). (2008). Land use or Land cover. *Journal of Land use Science.* Vol. 3: 4. pp. 199-201.
- Tlou, C. S., Mashiloane, M. L., Norris, D., Ng'ami, J. W. and Brown, D. (2015). Morphological differentiation of indigenous goats in different agro-ecological zones of Vhembe District, Limpopo, South Africa. *Indian Journal of Animal Research.* Vol. 49: 4. pp. 527-531.

- Tottrup, C. (2004). Improving tropical forest mapping using multi-date Landsat TM Data and pre-classification image smoothing. *International Journal of Remote Sensing*. Vol. 25: 4. pp.717–730.
- Turner, M. D. and Congalton, R. G. (1998). Classification of multispectral SPOT XS satellite data for mapping rice field on a West Africa. *International Journal of Remote Sensing*. Vol. 19. pp. 21-41.
- Twine, W., Moshe, D., Netshiluvhi, T. and Siphugu, V. (2003). Consumption and direct-use values of savanna bio-resources used by rural households in Mametja, a semi-arid area of Limpopo province, South Africa. *South African Journal of Science*. Vol. 99. pp. 467-473.
- United States of Geological Survey. (2009). SLC-off Products: Background. United States Government. From: <https://landsat.usgs.gov/slc-products-background>. [Accessed: 19 September 2016].
- United States of Geological Survey. (2016). Transpiration - The Water Cycle. From: <http://water.usgs.gov/edu/watercycletranspiration.html>. [Accessed: 15 August 2016].
- United States Geological Surveys. (2016). Landsat- Earth Observation Satellites. United States Government. Available from http://landsat.usgs.gov/CDR_LSR.php . [Accessed: 05 May 2016].
- Van den Berg, E.C., Plarre, C., Van den Berg, H. M & Thompson, M.W. (2008). The South African National Land-Cover 2000. Agricultural Research Council-Institute for Soil, Climate and Water. Unpublished Report No. GW/A/2008/86.
- Van Riet, W. (2015). *Nzhelele Catchment Basin – Ecosystem Services and Land Use*. From: <http://www.profwillemvanriet.com>. [Accessed: 10 September 2015].
- Wessels, K. J., Prince, S. D., Frost, P. E., and van Zyl. (2004). Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1km AVHRR NDVI time-series. *Remote Sensing of Environment*. Vol. 91. pp. 47-67.
- Wilson, E., H. and Sader, S. A. (2002). Detection of the forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*. Vol. 80: 3. pp. 385-396.
- Wolter, P. T., Mladenoff, D. J., Host, G. E. and Crow, T. R. (1995). Improved forest classification in the northern lake states using multi-temporal Landsat imagery. *Photogrammetric Engineering and Remote Sensing*. Vol: 61: 11. pp. 1129-1143.

- Xian, G., Homer, C. And Fry, J. (2009). Updating the 2001 National Land Cover Database land cover classification to 2006 by using Landsat imagery change detection methods. *Remote Sensing of Environment*. Vol. 113:6. pp. 1133-1147.
- Xie, Y., Sha, Z. and Yu, M. (2008). Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology*. Vol. 1:1. pp. 9-23.
- Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing*. Vol. 27:14. pp. 3025-3033.
- Yang, X., Chen, L. Li, Y., Xi, W. and Chen, L. (2015). Rule-based land use/land cover classification in coastal areas using seasonal remote sensing imagery: a case study from Lianyungang City, China. *Environmental Monitoring and Assessment*. Vol. 187:7.
- Zhang, C., Li, C.F., Chen, X., Luo, G.P., Li, L.H., Li, X.Y., Yan, Y. and Shao, H. (2013). A Spatial-Explicit Dynamic Vegetation Model That Couples Carbon, Water, and Nitrogen Processes for Arid and Semi-arid Ecosystems. *Journal of Arid Land*. Vol. 5. pp.102-117.
- Ziervogel, G., Bharwani, S. and Downing, T. E. (2006). Adapting to climate variability: Pumpkins, people and policy. *Natural Resources Forum*. Vol. 30. pp. 294–305.