Assessing the impacts of flooding on vegetation cover in the Shashe-Limpopo confluence area using earth observation data.

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A research report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science (Geography and Environmental Studies) at the School of Geography, Archaeology & Environmental Studies

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DECLARATION

I Andani Gangashe hereby declare that the research project titled "Assessing the impacts of flooding on vegetation cover in the Shashe-Limpopo confluence area using earth observation data." is my own work and has not previously been submitted for assessment in any University or for any other qualification.

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Student Signature

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Abstract

The extensive and frequent flood events in the Shashe-Limpopo confluence area provide an opportunity to investigate the impacts of such an extreme event in terms of vegetation cover. Extreme flooding events are expected to occur more frequently as a consequence of climate change. Understanding the impacts of flood events on vegetation dynamic would be very useful to develop a dynamic simulation model that can predict the woody species composition of water retention areas or restored floodplains on the basis of flooding characteristics and therefore proposed riverine forest and landscape planning and management.

This study used Landsat 7 data to quantify the response of vegetation to flood events in the Shashe-Limpopo confluence area. Two flood events that occurred in 2000 and 2013 respectively were analysed to evaluate the patterns of vegetation response in the area of study. Different indices such as NDVI, NDWI and Modified NDWI (MNDWI) were tested in mapping vegetation patterns and the flood extent. The MNDWI was shown to be more effective in extracting water information than the NDWI. NDVI results and change detection statistical change showed efficiency in indicating vegetation response to floods. The results show that using MNDWI and a 0.2 threshold value, water delineation is possible. Vegetation shows that it flourishes after the floods however; there is some degree of change. The results derived from this can be able to help with landscape planning and management.

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Contents

DECLARATION i

Abstract ii

ACKNOWLEDGEMENTS iii

List of figures vi

List of Tables vii

ABBREVIATIONS AND ACRONYMS viii

1. Introduction 1

1.1. Background 1

1.2. Problem Statement 3

1.3. Research Aim and objectives 4

1.3.1. Research Aim 4

1.3.2. Research Objectives 4

1.4. Research Questions 4

1.5. Description of the study area 5

1.5.1. Climate 6

1.5.2. Vegetation 9

1.5.3. Geology and Soils 10

1.5.4. Hydrology 10

1.6. Outline of the dissertation 11

1.6.1. Chapter 1: Introduction 11

1.6.2. Chapter 2: Literature Review 11

1.6.3. Chapter 3: Methodology 11

1.6.4. Chapter 4: Results 11

1.6.5. Chapter 5: Discussions 11

1.6.6. Chapter 6: Conclusions and recommendations 12

Literature review 13

Introduction 13

2.1. General Impacts of floods 14

2.2. Vegetation cover change 15

2.3. Impacts of floods on vegetation 16

2.4. Remote Sensing for flood disturbances monitoring 17

2.5. Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI) 19

2.6. Remote sensing for Vegetation Monitoring 20

2.6.1. Normalized Difference Vegetation Index 20
2.6.2. Image classification 22
2.7. Change Detection 22
2.8. Summary 23
Methodology 24
3.1. Data Sources 24
3.1.1. Satellite data 24
3.1.2. Field data 26
3.2. Methods 27
3.2.1. Pre-Processing 27
3.2.2. Mapping vegetation species using WV2 imagery 28
3.2.4. Mapping flood extent using Water Indices 31
Results 33
4. Vegetation Species classification 33
4.1. Flood extent mapping for the Shashe-Limpopo Confluence area 35
4.2. Vegetation analysis using NDVI 42
4.3. Change detection using Classification 49
Discussion 58
5. Introduction 58
5.1. Mapping vegetation species 58
5.2. Flood extent Mapping 59
5.4. Vegetation cover change due to flood events 60
5.5. Vegetation species adaptation to floods 62
6. Conclusions 63
6.1. Recommendation 64
References 65

List of figures

Figure 1: Map of the Shashe-Limpopo Confluence Area 6
Figure 2: River monthly discharge data in Cubic Meters (m3) for the Beit Bridge Station ..... **Error! Bookmark not defined.**
Figure 3: River monthly discharge data in Cubic Meters (m3) for the Point Drift Station 8
Figure 4: a) *Stuhlmanni Terminalia,* b) Acacia Tortilis, c) *Ficus*; d) Mopane leaves; e) *Croton Megalobtrys*; f) Mopane trees (Photos taken by A. Gangashe, 11 February 2016) 10
Figure 5: Map showing sites where GPS points were collected in the field 27
Figure 6: Vegetation classification of the Shashe-Limpopo Confluence area using WV2 and Maximum Likelihood Classification Algorithm 33
Figure 7: Water extent for the 2000 floods using Modified Normalized Difference Water Index. Note: a-b (before floods; c-d (After floods) 38
Figure 8: Water extent for the 2013 floods using Modified Normalized Difference Water Index. Note: a-b (before floods; c-d (After floods) 41
Figure 9: Maps showing NDVI for before and after the 2000 floods NDVI 43
Figure 10: Maps showing NDVI for before and after the 2013 floods NDVI 45
Figure 11: NDVI Change Detection for the 2000 flood event 47
Figure 12: Change Detection for the 2013 flood event 48
Figure 13: MLC results for the image after the 2000 floods. a) Image before floods, b) Image after floods. 50
Figure 14: MLC results for the image after the 2013 floods. a) Image before floods, b) Image after floods. 52

List of Tables

Table 1: Worldview-2 designated bands.....24
Table 2: Selected images for the study 25
Table 3: Landsat 7 ETM+ designated bands.....25
Table 4: Tree species as well as the number of GPS points taken for each tree species 26
Table 5: Maximum Likelihood Classification data 28
Table 6: Confusion Matrix for validation of the tree species classification. Note: W=Water, AS= Acacia Senegalia, AT= Acacia Tortilis, CM= *Croton Megalobotrys,* FS= *Ficus Sycomorus,* AE= Acacia Erubescens, M= Mopane, ST= *Stuhlmanni Terminalia,* BS/BU= Bare Soil/Built-up, CL= Cultivated Land, OVT= Other Vegetation Types. 34
Table 7: NDWI (a) and MNDWI (b) water and non-water features indicated using before and after images. 35
Table 8: Change detection statistics results in percentages for the 2000 floods.....53
Table 9: Change detection statistics results in percentages for the 2013 floods. 54
Table 10: Change Detection Statistics results in Percentages between the two images captured before the two flood events. 55
Table 11: Change Detection Statistics results in Percentages between the two images captured after the two flood events. 56

ABBREVIATIONS AND ACRONYMS

ETM+ Enhanced Thematic Mapper Plus

- ETM+ is a fixed ‘whisk-broom’ 8-band multispectral scanning radiometer that provides high resolution imagery

GPS Global Positioning System

- A system that is designed to determine location anywhere in the World

MLC Maximum Likelihood Classifier

- MLC classifier is a pixel based classification that classifies according to the likelihood that a pixel fits within a particular class and takes variability of classes into account by using covariance matrix.

MNDWI Modified Normalized Difference Water Index

- MNDWI is a water extraction Index from multi-spectral images.

NDVI Normalized Difference Vegetation Index

- NDVI is a numerical indicator that uses the visible and the near-infrared bands of the electromagnetic spectrum to show vegetation health.

NDWI Normalized Difference Water Index

NIR Near Infrared

ROI Region of Interest

- ROIs are selected samples of different features within a raster that are identified for the purpose of supervised classification.

SLCA Shashe-Limpopo Confluence Area

TM Thematic Mapper

- TM is an advanced multi-spectral scanning designed to achieve higher resolution images.

USGS	United States Geological Survey

CHAPTER 1

1. Introduction

1.1.Background

The Shashe-Limpopo Confluence area has a history of severe floods. These events are mostly recorded during the rainy season(s) when excess rainfall is experienced in this area. The severe floods that are recorded in this area tend to transform the surrounding landscapes including vegetation patterns and cover. In a study conducted by O'Connor (2010) on the transformation of riparian forest to woodland, the author noted that the 2000 flood event was accountable for 20% of the recorded losses in vegetation in the Shashe-Limpopo confluence area. With that being noted, it is important to consider rainfall as an important factor that contributes to change in vegetation.

Rainfall is an important hydro-climatic variable (Love *et al.* 2010) that can be classified as average or extreme leading to flash floods or river floods depending on the duration and the intensity (Balica, 2012). Worldwide, an increased population as well as changes in land-use patterns have rapidly increased human vulnerability to floods (He *et al.* 2015). The most dangerous impacts of flood include death, damages to crops, infrastructure and property (Dewan, 2015). Heavy rainfall events may also have some major effects on the lower reaches of the river basin (Jena *et al*.2015). Extreme flood events transport sediments from upstream to downstream; this transportation of sediments may lead to extreme changes of river morphology such as river bed slope, channel roughness, and flood routing process (He *et al.* 2015). Jena *et al.* (2015) also noted that floods are natural occurrences that can be an important source of sediment and nutrients to a variety of downstream riverine; however they may cause serious changes in the surrounding vegetation.

Floods occur in many different parts of the world and with them, they bring negative as well as positive impacts (Kuenzer *et al.* 2013). In most cases, natural events like floods may cause changes in land-cover depending on the intensity and their frequency. The increasing death tolls and economic losses have led to the conclusion that, this event is to be considered in the list of the most dangerous natural events (Zhang *et al.* 2008). The importance of assessing and studying flood events has been shown over the past years by different authors who

indicated that flood assessment is an ongoing study as different parts of the world are affected by heavy flooding each year (Popovska & Ivanoski, 2009; Apel *et al.* 2004; Gautam & Van der Hoek, 2003). Most studies show that there is a great damage that results from flood events, which includes physical, social and economic (Yande, 2009). Studies have shown that globally, riverine flood plains are among the most threatened ecosystems. It is evident that there are a lot of changes within these ecosystems. These changes include changes in the vegetation cover (Tockner & Stanford, 2002).

Vegetation cover is a very important useful aspect for evaluation of environmental conditions. Changes in the patterns of vegetation may also change the structure and functions of the landscapes in that way causing disturbance in ecological processes (Wang, 2015). Heavy rainfall that results in flooding of the surface may lead to vegetation cover destruction which is a negative impact, since vegetation cover may prevent soil erosion, landslides, surface roughness and sediments transportation into the river. Flood events in rivers not only affect the river channels but they also create disturbances in the riparian habitats. These disturbances that are being caused include washing away of herbs and trees and dispersing their propagules. Therefore, floods play a significant role in influencing and maintaining the intricate mosaic of vegetation that is normally present in the riparian habitats. It is therefore evident that whenever there is flood during heavy rainfall season the vegetation cover is also affected (Asaeda *et al*.2012). While heavy flooding has an impact on the riparian habitat, it may also in most cases have a negative impact on the downstream areas of the river. Asaeda et al (2012) noted that while flooding can cause desiccation on the riparian vegetation, the transported downstream sediments and nutrients may result in growth of vegetation. However, this type of vegetation growing in these areas may not be similar to the vegetation that grows when there is normal run-off of the river. This may cause disturbances on the river morphology as well as the ecosystem as a whole. The transported sediments and nutrients not only have negative impacts whenever it is flooding, they are also helpful in agricultural practices. Vegetation in the area understudy is very diverse and it mostly includes mopane as well as the acacia trees. However, the area around the confluence has different types of vegetation that includes the Ficus trees and the Croton Megalobotrys. The study therefore considers these different types of tree species within the study area, alongside grass and cultivated areas.

This study focuses on monitoring the dynamics of the two most recent important flood events that have occurred in the Shashe-Limpopo confluence area in the years 2000 and 2013 and

how they have impacted the distribution of the surrounding vegetation. The study used remote sensing techniques to quantify the results.

From a methodological perspective, monitoring floods and assessing their impacts on vegetation can be achieved by a variety of methods including remote sensing. Remote sensing is being widely used in studies involving floods to improve general understanding of hydrology and ecology of river floodplains (Chignell *et al*. 2015; Klemas, 2014; Ward *et at*. 2014; Smith, 1997). Remote sensing as defined by most scholars is the science of obtaining information about objects or areas on the Earth's surface without direct contact to that specific object (Aggarwal, 2004). The information is acquired through satellite images. Satellite images have been successfully employed to monitor and quantify water and vegetation cover changes (Makinde, 2013; Ahmad, 2012; Nemani, 1996). Haq *et al.* (2012) noted that remote sensing has made a significant contribution in monitoring floods as well as assessing the damages, which leads to disaster management authorities being able to organise prompt responses to flood hazards.

The choice of using remote sensing in this study is based on its ability to provide historical data and to study large areas. This is an advantage that is not offered by exclusively field based studies. Vegetation can be quantified using remote sensing techniques and algorithms such as Vegetation Indices (VI), the most common being the Normalized Difference Vegetation Index (NDVI). NDVI as well as supervised classification are used in this study to monitor change in vegetation cover with reference to the flood events under study.

1.2. Problem Statement

Distortion in the natural balance of the vegetation cover is of serious concern within the environment. Shashe-Limpopo confluence area is one of the areas where great amount of vegetation has been lost throughout the years. The South African National Biodiversity Institute (SANBI; 2011) released a list of the most threatened biodiversity in South Africa and the vegetation that is found within and around the Shashe-Limpopo Confluence area is said to be amongst the most threatened.

Although various factors such as drought and animals have contributed on the loss of vegetation, flood activities that have been occurring throughout the years have also had a great contribution on the loss of vegetation in the SLCA. Losses in vegetation through floods within this area have been highlighted by Kotze (2015) & O'Connor (2010) who noted that,

although drought is accountable for more changes in the vegetation cover, the 2000 floods accounted for almost a quarter of the vegetation losses with about 20% in losses.

Limited knowledge on how floods impact vegetation has been highlighted in this area. Thus, studying the dynamics of the vegetation cover with reference to flood events will enable insight on the impacts of these flood events on the surrounding vegetation and how to avoid the ecosystem imbalance that these changes cause. It is then against this background that the changes in the vegetation cover in this area are studied with reference to the 2000 and the 2013 flood events.

1.3. Research Aim and objectives

1.3.1. Research Aim

The aim of the study is to establish how two specific historical flood events (2000 and 2013), which can be monitored through the use of remote sensing, have had an impact on the vegetation cover in the Shashe-Limpopo Confluence area. The aim is to determine the impacts of floods on vegetation cover.

1.3.2. Research Objectives

To answer the proposed research questions, the following research objectives were formulated:

- To map the common vegetation species in the area in 2015, using remotely sensed data and classification. This is be used as a baseline for the current distribution of vegetation in the area.
- To map the two distinct flood events using remotely sensed data (Landsat Imagery). This is be done to determine the extent of the two floods.

To determine changes in cover of the different vegetation species due to flood events using remotely sensed data (Landsat Imagery) and change detection techniques.

1.4. Research Questions

The research questions for the proposed study are as follows:

- What are the common vegetation types in the Shashe-Limpopo Confluence area?
- What was the extent of the 2000 and 2013 flood events?
- What are the changes in vegetation cover with reference to the flood events understudy (2000 and 2013)?

1.5. Description of the study area

Located approximately 22°11'44"S and 29°22'31"E is the Shashe-Limpopo confluence area. This is the area where these two great rivers meet, the Shashe and the Limpopo River. The Shashe and Limpopo rivers are the marks of the boundaries between South Africa, Botswana and Zimbabwe as well as the boundary of the Mapungubwe National park (Sinthumule, 2014). The Shashe River is a main left-bank tributary of the Limpopo River in the Zimbabwe side. It rises northwest of Francistown in Botswana and flows into the Limpopo River. The Shashe-Limpopo confluence area is part of the Vhembe district in the Limpopo province, South Africa.

The Shashe-Limpopo confluence area is considered to be highly vulnerable to flooding events. It comprises of a very complex landscape of Caroo sandstone ridges, riverine forest and mopane bushveld (Spaliviero *et al.* 2014). The study area was selected because of the occurrence of flood events throughout the years as well as its variation in vegetation cover types. Figure 1 below shows the location of the Shashe-Limpopo Confluence area. The figure below also shows the Elevation in a form of a DEM, rivers as well as the river discharge data.

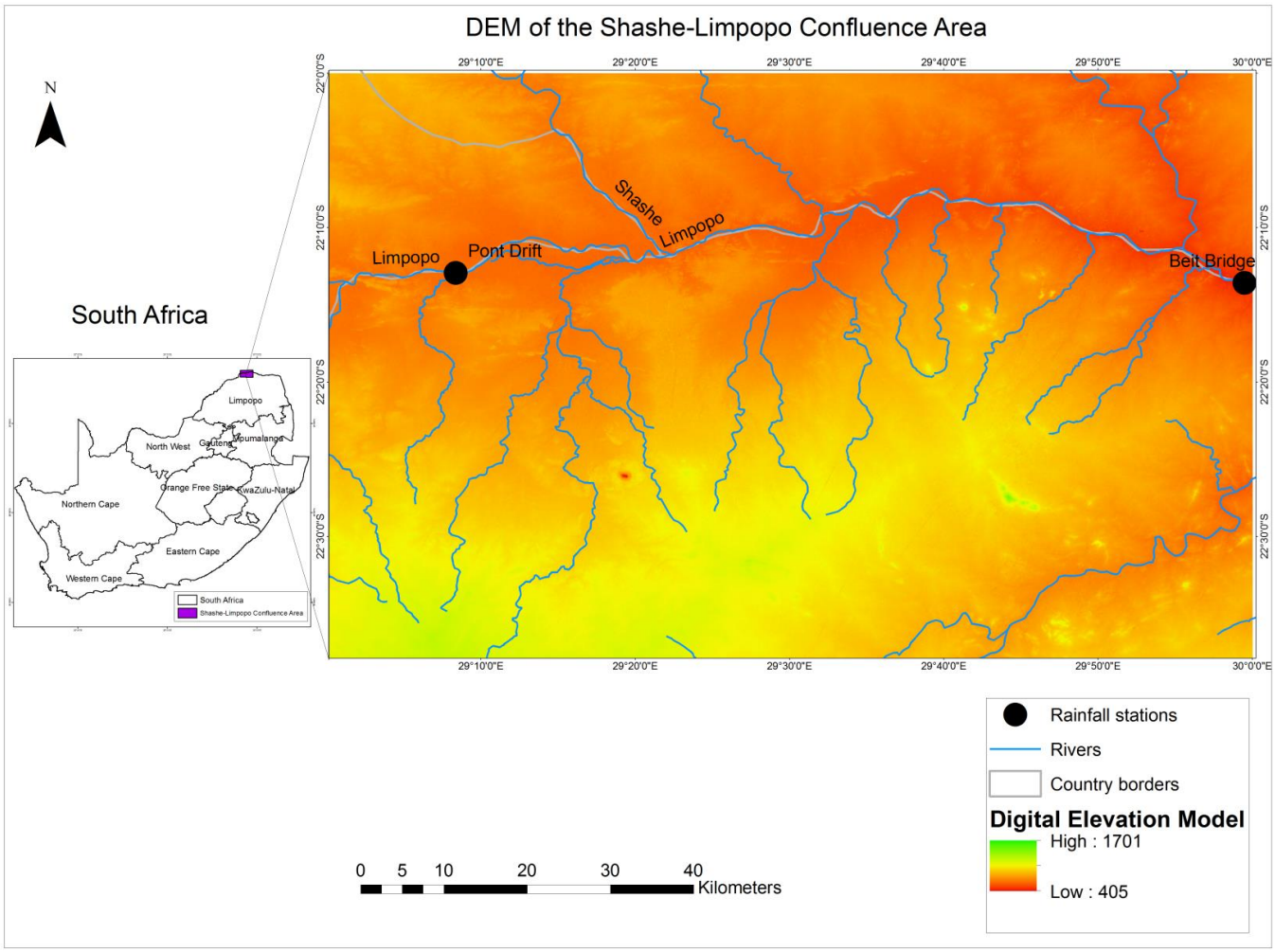


Figure 1: Map of the Shashe-Limpopo Confluence Area

1.5.1. Climate

The climate in the Shashe-Limpopo Confluence area varies from being arid to semi-arid. The climate in this area is influenced by the three wind systems, the tropical cyclones from the Indian Ocean, the south-easterly wind systems that leads to rainfalls from the Indian Ocean as well as the Inter-Tropical Convergence Zone (ITCZ) which at times moves southwards to influence rainfall. The climate of this area is semi-arid, with the mean annual rainfall ranges from 350-400mm (Sinthumule, 2014). However this range usually decreases during the summer months. The temperature in this area rises up to 45ºC in summers whereas in winter, it is usually mild and frost may occur at times (Götze *et al.* 2003).

Rainfall plays a very important role in within the area of the study with regards to the distribution of vegetation. The graphs (Figure 2 & 3) show the monthly discharge data for the period 1998 to 2017.

The monthly discharge data for the period of interest is shown in figures 2 and 3, below. The data are collected at the weather stations of Beit Bridge near Mussina, on the Limpopo River as well as Pont Drift another Limpopo River crossing into Botswana. The data below shows when the river had more water discharge during the presented years. The year 2013 which is one of the years the study is focused on shows that there was high volume of discharge during that year around January as well as February. This indicates that during those mentioned months there was high rainfall as compared to other years. The year 2000 has missing data within the Beit Bridge rainfall station. This is one of the limitations that were encountered when searching for rainfall data. This missing data problem is also seen within most stations where the data for that year was missing. However, the graph that is shown by figure 3 which is the representation of the Pont Drift station has some of the data that is missing from the other station which works in our advantage because it also presents the missing 2000 data from the other station. Presenting both the graphs gives a clear indication of when the river had high volume in discharge. The Pont Drift station also has most of the data missing including some of the 2013 data. The data presented below does not represent rainfall data, this is a representation of water discharge hence the first station which is Pont Drift has lesser discharge volume. This is because; compared to the Beit bridge station the point drift comes first. Therefore, Beit Bridge shows high volume of discharge on those years that has available data.

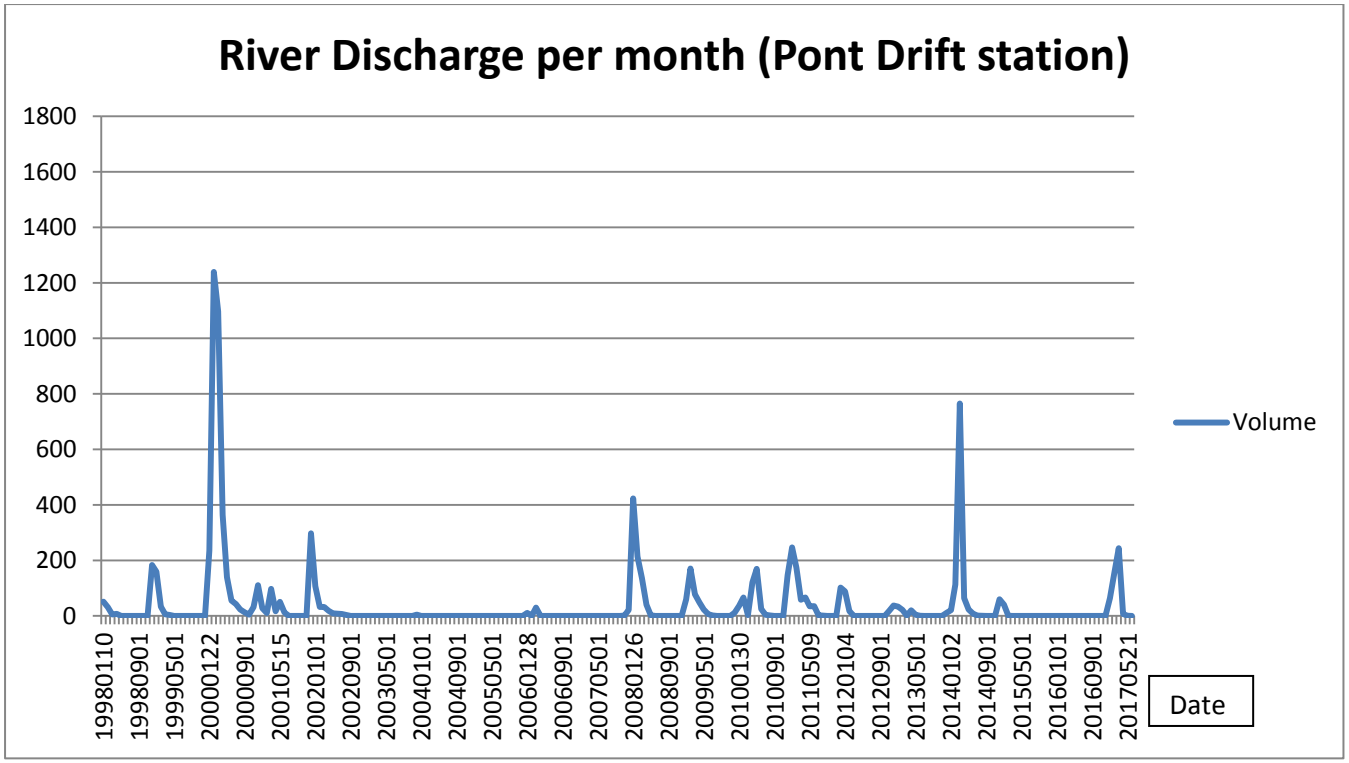


Figure 2: River monthly discharge data in Cubic Meters ($\mathbf{m^3}$) for the Pont Drift station

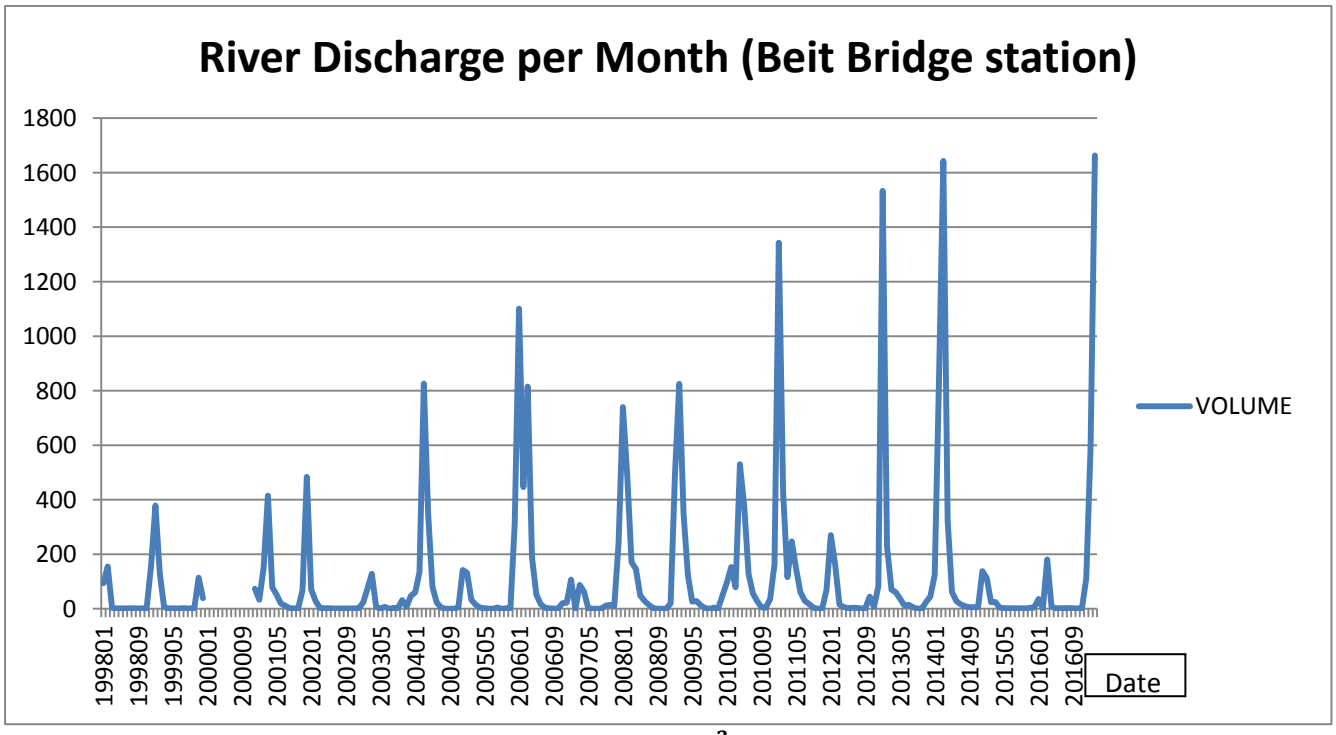


Figure 3: River monthly discharge data in Cubic Meters ($\mathbf{m^3}$) for the Pont Drift Station.

1.5.2. Vegetation

The Shashe-Limpopo Confluence area consists of different types of vegetation. The land type in this area includes riverine and non-perennial wetland vegetation with deep to moderate soils with a high amount of silt and clay content (Götze *et al.* 2003). The main recognised types of vegetation include tree species such as three types of acacia (*acacia tortilis, acacia erubescens and acacia senegalia*), *Colophospermum Mopane, Stuhlmanni Terminalia,* as well as the *Ficus* trees and the *Croton Megalobotrys* along the river. Other types of vegetation found in this area are shrub species that are *Abutilon grandiflorum, Ochna inermis* and grass species such as *Trichoneura, Schmidtia pappophoroides, Aristida scabrivalvis subsp. scabrivalvis* and *Brachiaria nigropedata* (Götze *et al* 2008). The area is also characterised by the baobab trees which are not as dominant as other tree species. Another part of the study area adjacent to the Limpopo River has completely been changed through agricultural practices. Parts of the floodplains in this study area are cultivated for agricultural produce such as crushed maize, ground nuts, millet as well as sorghum. The community around this area produces great amount of these crops in order to generate surpluses (Huffman, 2009). Pictures below are showing images of some of the tree species that were noticed during field work.

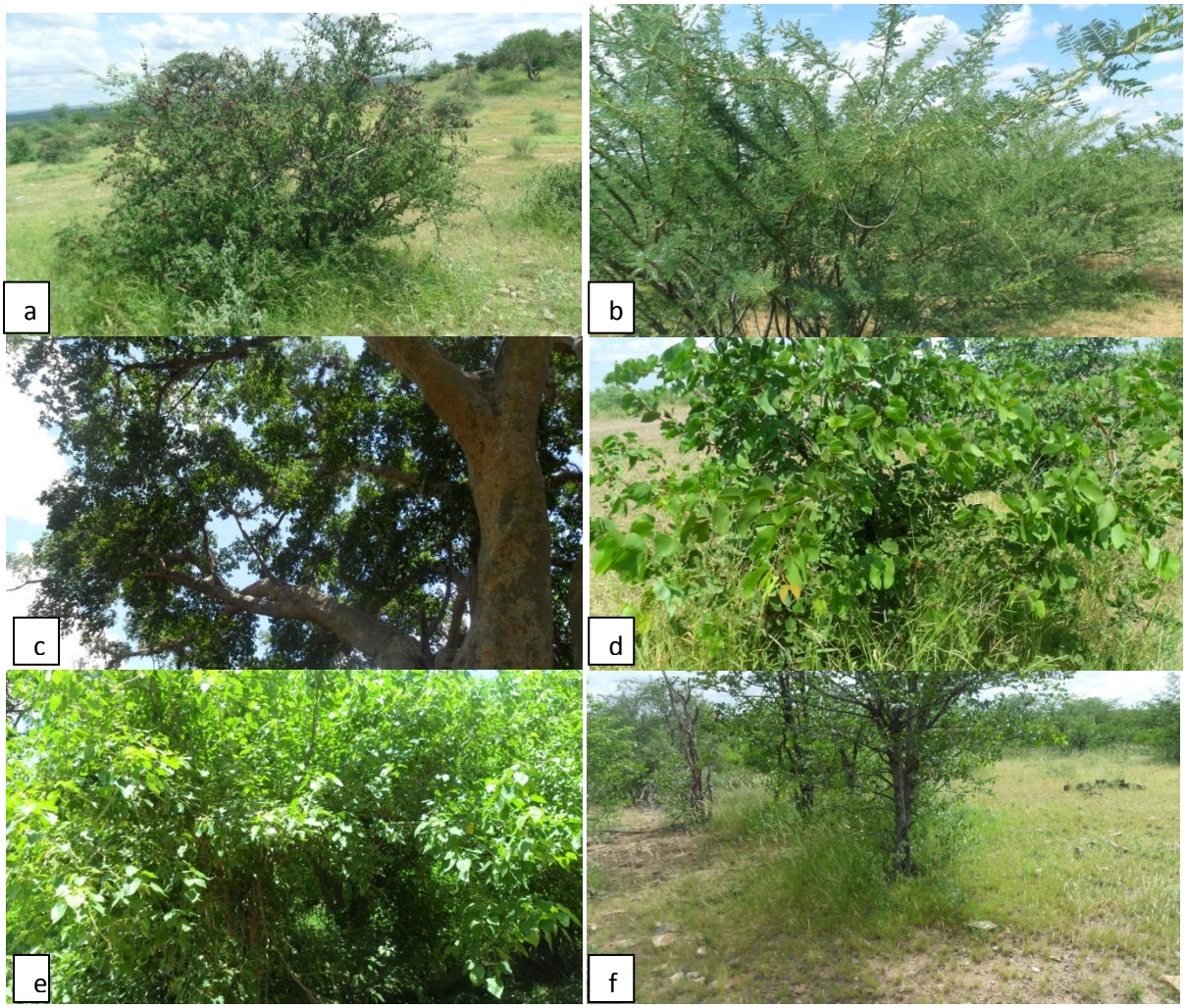


Figure 4: a) *Stuhlmanni Terminalia*, b) Acacia Tortilis, c) *Ficus*; d) Mopane leaves; e) *Croton Megalobtrys*; f) Mopane trees (Photos taken by A. Gangashe, 11 February 2016)

1.5.3. Geology and Soils

The geology of the Shashe-Limpopo Confluence area comprises of the sand and alluvium from the quaternary system. The soils of the Shashe-Limpopo confluence area are resultant from the rocks of the Archaean granite in the south and more commonly from the Karoo system. The soils differ from red-brown sandy loam to dark brown clays with high amount of silt content. Large areas are characterized by sand, lime-rich soils (Götze *et al.* 2003, O'Connor, 2010). There are Kimberlites that are more than 100 years old which are found in this area (Götze *et al.* 2003). There is also a large diamond mine in Venetia (Götze *et al.* 2003).

1.5.4. Hydrology

The confluence of the seasonally-flowing Shashe and Limpopo rivers is classified as dominant hydrological feature. This area's ground water supplies are usually poor except

along the fault lines (Mapungubwe National Park and World Heritage Site Management plan, 2013-2018). The irrigation withdrawals upstream as well as downstream around the confluence area are large relative to water supplies. There are also dolerite features close to the confluence that are crucial to the function of the floodplain. Springs associated to these dolerite intrusions are also found by the area.

1.6. Outline of the dissertation

This dissertation comprises of six chapters. The chapters are divided into background and introduction, literature review, methodology, results, discussion and conclusions. The chapters are outlined as follows:

1.6.1. Chapter 1: Introduction

This chapter gives a general background of the study and provides a general overview of the problems that are related to floods and ecosystem vulnerability to these flooding events. This chapter includes aims and objectives as well as the description of the study area.

1.6.2. Chapter 2: Literature Review

In this chapter the review of literature relating to floods and their disturbance to ecosystems is outlined. The concept of flood hazards is explained in details according to the findings of the studies that were conducted in the past. The impacts of floods on vegetation according to past studies are also documented in detail. The methods that were utilised in these studies are also briefly explained. These methods are explained according to the studies that were done in the past and actually achieved the results with these methods. The advantages and disadvantages of using these methods is also reviewed. Relevant literature on remote sensing as main part of the study is also explained in detail as well as the pass papers that used remote sensing techniques for water extent mapping and vegetation mapping.

1.6.3. Chapter 3: Methodology

In this chapter a description of data and their sources as well as the methods that are used to carry out this study is outlined.

1.6.4. Chapter 4: Results

In this chapter the results that were obtained using the data, methods and techniques that were briefly explained in chapter 3 are presented in detail. The results answer the research questions and achieve the research aim and objectives.

1.6.5. Chapter 5: Discussions

In this chapter the research finding are discussed in relation to relevant literature.

1.6.6. Chapter 6: Conclusions and recommendations

This chapter concludes the study. It covers the conclusions that are made based on the results findings. Recommendations of the study are also documented in this chapter.

CHAPTER 2

Literature review

Introduction

Intense rainfall during a short period of time maybe caused by extreme conditions as results of climate change, as a result flood events are experienced. Floods are events that occur when there is excessive water flow. It is an inundation of dry regions in the surface caused by rising water in the existing waterway such as river, stream or drainage (Musyoki *et al.* 2016). Lo *et al.* (2015) noted that when a great volume of water cannot be drained in time within the rainfall area, the area face overflow in results causing a large number of casualties and a severe loss of property. Floods are natural hazards that occur as a result of heavy rainfall and excess run-off. Floods are amongst the most severe disasters that are great risk to human life (Leigh et al. 2014) and it has been noted that they are amongst the most dangerous 15 kinds of natural disasters (Zhou et al., 2002). Many people around the world are affected by this natural phenomenon, with over one-third of the world's land being prone to flooding (Sharma et.al, 2011) and this is mostly due to the increase in population which leads to an increase of human vulnerability to these events. These events bring positive but they may also bring negative effects, their effects may depend on their severity and their frequency. Thus depending of these two factors, impacts of these disturbances may vary.

Throughout the whole world, people have lived and died because floods of since the beginning of time (O'Connor & Costa, 2004). Normal flooding is greatly expected in many parts of the world for the reason that they bring rich soil for cultivation and provision with water as well. However the past decades, the pattern of the floods have been changing and they have become more intense, frequent and also unpredictable. In addition to the world population rapidly increasing, people are forced to live in areas that a more prone and more vulnerable to flooding events (Alam *et al.* 2008). With growth in population and more developments in all the areas of the world, floods are more likely to occur. Hence, the increase in the frequency and the intensity of the floods within the past decades. Most authors have recorded floods and their impacts in different parts of the world (Eni *et al.* 2011; Hölzel, & Otte, 2001) from food security, economy, social aspects and the environments. Flood

events are said to be very costly for countries worldwide. They are disasters that are not only costly to the developing and the underdeveloped but also costly to developed countries.

In this study, the area of interest is situated in South Africa in one of the areas that are most vulnerable to floods (Spaliviero *et al.* 2014; Jesse & Swemmer, 2013). South Africa has an interesting history of severe floods in many of its provinces. In the past years (1995-2015), South Africa has experienced many flood events with most of them being devastating. The most valid example would be an example of the most recent winter floods in the Kwa-Zulu Natal province, not only did it leave millions of damages but it also claimed lives. In South Africa, the annual risk of flood events is said to be at 83.3%, this could be explained by the population being high and also geographical location (Zuma *et al.* 2012). The most memorable events include Kwa-Zulu Natal in 1995/1996, the Limpopo February 2000 as well as other events that hit Mpumalanga and Eastern Cape Provinces (Van Bladeren *et al.* 2007). According to Zuma *et al.* (2012), the areas that are more vulnerable to floods are Limpopo, KwaZulu-Natal (KZN), Eastern Cape and North-West. Flood events in South Africa has been recorded by many authors such as Spaliviero *et al.* (2014) who noted the Limpopo river basin floods in 2000 and 2013. The authors analyse the past flood events with the aim of explaining the evolution of the river. The study also noted that human race tend to settle closer to the river due to semi-arid and sub-humid conditions in the basins, hence their vulnerability to these events.

2.1.General Impacts of floods

The most dangerous impacts of flood include direct mortality, damage of crops, infrastructure and property (Dewan, 2015). The impacts of these floods events may be classified as primary and secondary. Primary damages being those that include the damages on infrastructures in general whilst the secondary includes the impacts on people, agriculture and water (Efobi & Anierobi, 2013). With the secondary impacts of these disturbances, one may refer to the affected area's economy. The Economy of the country is one of the portions that are affected negatively when these events occur. These floods may affect the economic sector in terms of supply chain, for example in the events of flood disasters the entire supply chain may suffer disruption and break down (Haraguchi & Lall, 2015). The impacts may also be in terms of damages to infrastructures and other entities. Haddad & Teixeira (2015) noted that floods not only contribute to domestic economic growth but also international growth. Not only do they reduce the economic growth of the flood affected area, but also the international economic

growth. The economy being the most important asset in the world, then suffers. Floods not only have impact on the economy but also the environment and its characteristics.

Flood events have also been noted to play a massive role in the change in environmental impacts more importantly the shaping of the ecosystem. (Michener & Houhoulis, 1997) noted that floods play the most important role in regulating the ecosystem structure as well as its functions, more importantly the plant communities and animal population. Mostly, the impacts on the ecosystem are more on the morphological changes along the river. The river pattern is mostly determined by the disastrous natural events like floods than normal activities (Gautam & Van Der Hoek, 2003). Jena *et al*.(2015) noted that flood events may have some major effects on the lower reaches of the river basin considering the transportation of sediments from upstream to downstream; this transportation of sediments may lead to extreme changes of river morphology such as river bed slope, channel roughness, and flood routing processes (He *et al.* 2015).

The impacts of these events depend on their intensity and the frequency as well. How much of floodwater is present may be a very reasonable explanation on the severity of the damage or the positive impacts.

2.2.Vegetation cover change

Vegetation differs in each and every area of study whether it is mountainous or plain regions (Liang *et al*. 2015). Although it varies with location and climatic conditions, vegetation cover change is a very significant indication of the ecological environment change (Sun *et al.* 2008). Climate change and mostly human activity have led to an increase in vegetation change (Wei *et al.* 2016). As one of the most important and sensitive factor in the ecosystem, vegetation change does not only reflect general state of the environment but also has an influence on other environmental factors (Liu, 2016). It has been noted that vegetation strengthens the biogeochemical and ecological functioning of most environments on earth and often provides the foundation for the classification of the ecosystem. Vegetation species composition and structure are particularly sensitive and also vulnerable to climate change. Jeyaseelan (2003) noted that vegetation condition reflects the overall effect of rainfall, soil moisture, weather and agricultural practices. According to Li *et al* (2016) changes in vegetation directly or indirectly shapes the biosphere-atmosphere interactions including the hydrological cycle. With regards to vegetation growth, Li *et al.* (2016) noted that the growth cools local land surface temperature. Research has shown that increased vegetation coverage

results in changes in water resources, which is a major element of the most ecological regions. This leads to a conclusion that vegetation maybe good as well as bad for most of the delicate ecosystems (Li *et al.* 2016). Rose *et al* (2016) note that response to conditions in the area, changes in population and reduction in nitrogen availability may also contribute to the overall changes in vegetation more especially if the area is in the uplands. Quantification of the important drivers of vegetation change is vital for the informed management of vulnerable habits (Rose *et al.* 2016 & Liu *et at.* 2016).

A number of studies in recent years have been interested in examination of widespread vegetation changes (Chen *et al*. 2014; Elliott *et al*. 1998). Many of these authors noted that changes in temperature, soil moisture and water in the area could alter the vegetation cover characteristics (Stow *et al*. 2004).

2.3.Impacts of floods on vegetation

Vegetation plays a vital role during extreme events like floods, such as dissipating flows and stabilising banks by preventing erosive forces of overland flowing (Hickey & Salas, 1995). However in most cases vegetation cannot withstand the forces of these overflows. Most studies have highlighted the importance of studying vegetation patterns prior and after flood events (Meer & Ahmad, 2014; Shoopala, 2008). Flood disturbances are one of the important factors that have an impact on the riparian vegetation on river flood plains (Dzubakova *et al*. 2015). The results of floods on the vegetation cover may be both positive and negative. The amount of rainfall determines how much water is kept in the soil at different depth and how vegetation responds in terms of germination and growth (Tietjen, 2015). In most extreme events, vegetation cannot withstand the power of floodwater and it is broken or uprooted (Hickey, 1995). In the study of floods and their effects on forest trees, Basak et al. (2015) noted that the increasing trend of climate induced floods have had such impacts as, millions of trees dying due to increased floods and water-logging. The study further more noted that these severe long period floods and also water-logging caused root rotting, defoliation of the trees and also there was absence of air in the root system, hence the dying of trees in numbers. Uneven distribution of precipitation has an effect on soil erosion, land degradation and vegetation covers. Vegetation conditions are positively associated with precipitation in most of the dry areas. However it also has a negative correlation with heavy rainfall in humid areas (Wang, 2015). In a study where the author was analysing institutional mechanisms that support community response to impacts of flood, one of the impacts of floods noted in this study was that, households (74%) in this area cultivated on the flood plain, they practiced

dowe, which is the stream bank cultivation, and this was because of the rich nutrients and wetter land on the flood plain (Muhonda et al. 2014). However these crops that were grown on the floodplain were shown to be vulnerable to destruction during floods (Muhonda *et al*. 2014). Moats (2007) also in the study assessing the impacts of flood inundation noted that, the two land cover types that were mostly affected by floods were cultivated crops and the deciduous forest. These authors showed that during flood events, cultivated crops experience a great loss. On the study that was conducted to show the floodplain inundation and the vegetation dynamics, Ward *et al* (2014) noted that there is a need for baseline information on inundation driven dynamics of the region to support the growth of natural resource management. The study made use of remote sensing to quantify the results of the study.

2.4.Remote Sensing for flood disturbances monitoring

Flood mapping during and after floods is essential. Nowadays, flood extent is succesfully mapped using technologies such as remote sensing and Geographical Information Systems (GIS) (Ward *et al* 2014; Ho *et al*. 2010; Samarasinghea et al. 2010). A number of authors have emphasised the usefulness of satellite data that it is important in determining, detecting and estimating the flood extent, damage and its impacts on the environment (Hussaina et al. 2011; Khanna *et al*. 2006).

Remote sensing also referred to as Earth Observation System (EOS) and GIS are amongst several tools available for disaster management (Simonovic & Eng, 2002). Remote sensing based flood mapping basically records what land has actually been flooded or non-flooded based on topography, hydrological data and hydraulic modelling (Brakenridge *et al.* 2003). Mapping of these events as they occur in years can provide information with regards to flood hazard evaluation as well as the damages that the floods had on the surrounding environment as well as land use changes. Brakenridge *et al* (2003) noted that satellite observation allows extent of flooding to be preserved and local flood histories to be defined. The ability of a satellite to provide a complete, synoptic and multi-temporal coverage of very large areas within a short period time have been very valuable in monitoring and managing flood events (Khanna *et al.* 2005). Flood maps that are derived from the satellite imagery play a vital role in the improvement of flood modelling and flood forecasting (Barneveld *et al.* 2008) as well as future planning and management strategies. According to Jeyaseelan (2003), using remote sensing to monitor floods depends on factors such as topography, climate as well as some environmental factors such as vegetation and population.

There are different techniques that are used in mapping the floods. The techniques include using DEMs, Satellite images and flood records. Other authors use an integration of all these techniques. Remote sensing images and GIS data which cover very large areas of the earth surface can be acquired at regular time intervals and also at a very low cost. Zhang *et al* (2002) noted that when the Remote sensing data is integrated with the non-Remote sensing data it is easy and also sufficient to monitor the floods as natural disasters. Many remote sensing satellite sensors maybe used to observe water which may be useful with flood extent mapping. It is of great advantage that remote sensing allows one to explore ideas and come up with new ways of mapping water extent/features. Sensors may also be used in combination in practical applications. However, satellite sensors have their own disadvantages. Because satellite measurements are in the visible and near-infrared wavelengths, useful data is obtained during daylight under cloud-free conditions. That becomes a disadvantage when there is no useful data because of the conditions that the data is being obtained (Zhang *et al.* 2002). Zhang et al (2002) also noted that the satellite becomes more advantageous when the flood is over. According to the authors (Zhang *et al.* 2002), the satellite images can actually be used to calculate the actual losses in different administrative areas. Such information allows the determination of damage control strategies to be used. These data also provides comprehensive spatial information and it is documented that it actually gives support when it comes to planning damage control such as rebuilding, planning water conservation facilities as well as selecting locations for new towns for relocations.

On a study that was conducted to determine the extent of flooding, Chormanski *et al* (2011) the use of satellite imagery (Landsat) was shown by the authors. The authors combined the collected GPS with the imagery for mapping inundated areas. In this study, Landsat ETM images were used for classification where the resultant classification was grouped to wet and dry classes. The study noted that the classification method that was used to re-classify the images gave satisfactory results. The results were also verified using the collected GCPs. However, collecting GCPs may be problematic while dealing with historic floods in a sense that, the GCPs may not be reliable. Authors have highlighted the use of optical remote sensing and its success in terms of mapping flood extents. Jung *et al* (2014) suggested an approach to obtain flood extent boundaries using Landsat imagery and DEMs. The author's approach is very similar to the approach that Chormanski *et al* (2011) and other author's (Klemas, 2014; Schnebele & Cervone, 2013; Qi *et al.* 2009) used. The Approach extracts the

flooded area by using the ISODATA image processing algorithm, and then the DEMs are used to extract the ground elevation in order to match them with the classified results.

With new technologies and approaches for water features discrimination being developed, it may seem oblivious not to explore them further and observe if they work in similar ways with the other techniques that are used in previous studies. The developing techniques that are mentioned above make use of water indices to classify water features. There have been studies recently on the use of water indices in delineating water features. These studies make use of multi-temporal data to develop these indices that can be used in the delineation of water features. The indices that are mostly documented by different scholars include the Normalised Difference Water Index (NDWI), the Normalised Difference Moisture Index (NDMI) as well as the Modified Normalised Difference Water Index (MNDWI). The history of the development of these indices was recorded by Mcfeeters (1996). The author developed a methodology that uses the NDWI as an index to delineate open water features and enhance their presence in the remotely sensed data. The indices normally use the fraction of green and Near Infrared as well as Red and Shortwave Infrared depending on the index (Memon *et al.* 2015). These types of water feature delineation indices have been used by number of authors (Li *et al.* 2013; Ji *et al.* 2009 ;) in different studies.

2.5.Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI)

According to Rokni *et al.* (2014) the NDWI was developed for water features extraction from multi-spectral images while the MNDWI extract water features while suppressing errors that may be derived from built up land as well as vegetation and soil. The NDWI was recorded by Gao (1996) where the author noted that the NDWI proposed that it uses two near-infrared channels. The author introduced this method as a method of extracting vegetation liquid water. Rogers & Kearney (2004) also worked with NDWI using the red and Short Wave Infra-red (SWIR) bands for the Landsat TM. Quite a number of authors have used this water index to delineate water and map surface water (Rodgers & Kearney, 2004; Gao, 1996; Mcfeeters, 1996).

The Modified Normalized Difference Water Index (MNDWI) can be calculated as follows:

$$NMDWI= (Green-MIR)/ (Green+MIR)$$

The MNDWI has been noted as the best index in mapping water features as compared to the NDWI. The NDWI is said to confuse different class pixels as water however, the MNDWI

eliminates this problem. Xu (2006) noted that the application of NDWI in water regions where there are built-up areas does not fully achieve the purpose of mapping water only. Meaning that, other built-up areas have positive values in the NDWI results. The author (Xu, 2006) noted that with detail examination of signatures, it was concluded that the average digital number of a band representing MIR radiation is much greater that of the green band. Therefore if MIR band is used instead of the NIR band the built up areas should have negative values. Hence the NDWI is modified by substituting the MIR band for the NIR band.

2.6.Remote sensing for Vegetation Monitoring

Remote sensing tools can be used in vegetation monitoring. Satellite base vegetation monitoring plays an important role in defining the impacts of floods and their severity. Because of technology advancements, analysis of plant physiology and biometrical properties using electromagnetic spectrum is possible (Jarocinska & Zagajewski, 2006). Studies have shown the relationships of red and near-infrared (NIR) to the amount of vegetation present at a certain area on the ground (Jeyaseelan, 2003). The decrease in the reflected red goes along with the development of plant due to chlorophyll absorption in the photosynthetic leaves. On the other hand, reflected NIR will increase with plant development through scattering processes such as reflection and transmission in healthy turgid leaves. A large number of methods are being used to quantify vegetation cover and many of these methods are dependent on remote sensing technologies and analyses. The use of satellite imagery has enabled measurements in the changes of vegetation cover and its health. Zhang *et al* (2003) noted that a number of methods have been developed to determine the vegetation changes using time series of Normalised Difference Vegetation Index (NDVI).

2.6.1. Normalized Difference Vegetation Index

Normalised Difference Vegetation Index (NDVI) is a numerical indicator that uses the visible and the near-infrared bands of the electromagnetic spectrum. This indicator was adopted to work with remote sensing measurements and assess if whether the target being observed contains live green vegetation or not (Ryan, 1997). According to (Govaerts & Verhulst, 2010) Satellite based NDVI are influenced by many factors that are not vegetation, factors such as atmospheric conditions, satellite geometry as well as soil backgrounds and crop canopy. Ryan (1997) noted that NDVI calculations are based on the principle that suggests that actively growing plants absorb radiation in the visible region of the spectrum; on the other hand they

strongly reflect radiation in the Near-Infrared region. The satellite based NDVI is calculated using the formula,

$$NDVI = (NIR-Red)/(NIR+Red).$$

This formula yields the values that range from -1 to +1. -1 usually representing water and the positive values representing strongest vegetation growth. This formula also allows the understanding of the fact that two identical covers of vegetation could have different values.

NDVI has a variety of applications in vegetation related studies as it can be used for estimation of crop yields, pasture performances and many other applications (Panda *et al*. 2010). NDVI is mostly associated to the other ground parameters such as percent of ground cover, photosynthetic activity of the plant, surface water, leaf area index and the amount of biomass (Ceccato *et al*.2001). Overall healthy vegetation will absorb most of the visible and reflects in the near-infrared light. The unhealthy vegetation reflects more in the visible spectrum and less in the near-infrared. Numerous researchers have extensively employed the NDVI to analyse the various factors regarding vegetation and vegetation cover response to climate change and population change (Bhalli *et al.* 2013; Ceccato *et al*.2001; Lenney *et al*. 1996).

NDVI has been used by a massive number of author's for different applications as well. One application would be to show the relationship between built environment characteristics and NDVI as a indicator of surrounding greenness. In a related study, Gascon *et al* (2016) noted that it is important to understand what the NDVI means in a particular area of study. The authors made use of NDVI maps as well as the land use and land cover maps to define factors of built environment that explains NDVI. The results for this study showed that NDVI can be a very useful greenness metric depending on the hypothesis of the study.

This vegetation measurement has also been used in calculating or mapping vegetation dynamics using time series analysis of certain study areas (Detsch *et al.* 2016; Tian *et al.* 2016; Martínez & Gilabert, 2009). The studies that have been conducted included drylands as well. Tian *et al.* (2016) evaluated vegetation optical depth (VOD) using AVHRR NDVI and in situ green biomass over West African Sahel for vegetation dynamics. The authors noted that the VOD has proven to be efficient for green biomass in all types of vegetation, which included herbaceous vegetation and woody vegetation (Tian *et al.* 2016). Detsch *et al.* (2016) also conducted a study on vegetation dynamics using time series analysis where images from

1982 to 2011 were used. The results showed that the NDVI record that was used proved to be capable of capturing long-term and seasonal vegetation patterns.

NDVI has also shown usefulness in measuring precipitation (Birtwistle *et al.* 2016). Birtwistle *et al* (2016) used Normalized Difference vegetation index from Landsat imagery to estimate precipitation. The author used NDVI values for 26 years of before and after rainfall season to determine the change. The study noted that the change in NDVI from pre to post-rainfall season image explained high percentage of variance in annual monsoonal precipitation totals from a nearby rain-gauge. It was also noted that NDVISs are also useful in determining when and where the flow events happen. With all the uses of NDVI, it becomes significant to utilize NDVI as a vegetation indicator and as a method for change detection calculations.

2.6.2. Image classification

Remote sensing imagery offers a unique opportunity in determining land use and land cover change information through the process of image interpretation and classification (Li et al. 2014). Classification is a process of assigning pixels into different classes depending on the reflectance of the object being classified. Classifications are based on the statistical methods such as Minimum Distance-to-Mean (MDM), Maximum likelihood classification (MLC) and Linear Discrimination Analysis (LDA) (Paradhan et al. 2010). Ayhan (2010) noted that major steps in image classification may include determining the most suitable classification methods, Training samples, feature extraction, image processing, and selection of suitable classification approaches as well as post classification processing. How well a classification works maybe is determined by the accuracy assessment.

2.7.Change Detection

Change detection in remote sensing can be defined as a measure of changes associated with land use as well as land cover (Lu *et al*. 2004; Ramachandra & Kumar, 2004). Change detection is a method used in identifying change between two or more dates that is uncharacterised of normal variation. This method of identifying change is useful in many applications including environmental changes.

NDVI is being used widely for change detection. NDVI change detection technique uses the initial and the final state image to produce a change detection difference map. This technique is referred to as NDVI differencing. This technique is more like any other technique of

change detection, however this methods minuses the old NDVI image from the newest image. The subtraction is based on the pixel values. NDVI Differencing is formulated as:

$$\text{NDVI Differencing} = \text{NDVI}_{new} - \text{NDVI}_{Old}$$

NDVInew refers to the NDVI results for the image acquired after the floods and NDVIOld refers to the NDVI results that were generated using the image acquired before floods.

Gandhi *et al* (2015) used the NDVI to present an improved change detection method for analysis. The authors used NDVI Differencing as a method of analysis. The results showed that NDVI is very useful in detecting changes within the surface features of a visible area. The study noted that the NDVI method gives greater results for vegetation changing in densities and also for scattered vegetation using multi-spectral remote sensing. Ahmad (2012) also noted on the change detection using NDVI that, advantages of NDVI based change detection it gives robust results and that it covers large areas as well.

2.8. Summary

This chapter comprises of the detailed definition of floods as well as their impacts on vegetation cover. It comprises of detailed literature on how remote sensing is used to tackle the objectives at hand. From the literature, it is evident that the methods presented are efficient in achieving the objectives that are mapped out for this study. This includes the use of indices and well as classification methods.

The following chapter (Chapter 3) will include the detailed specific methods that were used for the successful results of this study. The chapter includes the data used and the sources of the specific data as well as the methods of analysis for the acquired data and how each method was used to attain the results.

Chapter 3

Methodology

3.1.Data Sources

Sources of data refer to the origin of the data that were utilized in this study in order to fulfil the objectives of this study. Sources of data in this case include Satellite data as well as field data. A detailed description for each data acquired is provided in the sections outlined below. This study has utilized two data sources which are the satellite data as well as collected field data.

3.1.1. Satellite data

Remote sensing satellite data has become a very important technique in monitoring and evaluating land cover changes at low cost (Rawat & Kumar, 2015). To fulfil the main aim of this research, satellite data was obtained from different providers. World View-2 as well as Landsat 7 ETM+ images were used.

3.1.1.1.Worldview 2 (WV2)

World View 2 (WV2) imagery was used for this study to map the common vegetation species in the study area. WV2 was launched in 2009 and it has very high resolution with panchromatic resolution at 50cm as well as the multispectral resolution of 2m. WV2 was used for this study for the reason that it has remarkable improved resolution which for this study can be used for better vegetation species identification. The image that was used for this study was acquired on the 5th of August 2014. This image was provided by digital globe with no charges. The following table (Table 1) shows general designated bands for this satellite imagery.

Table 1: Worldview-2 designated bands

Spectral Bands	**Wavelength min - max (µm)**
Panchromatic	450 - 800 nm
Costal blue	400 - 450 nm
Blue	450 - 510 nm
Green	510 - 580 nm
Yellow	585 - 625 nm
Red	630 -690 nm
Red edge	705 - 745 nm

NIR 1	770 - 895 nm
NIR 2	860 - 1040 nm

3.1.1.2. Landsat Data

To map flood extent Landsat ETM+ imagery was acquired. These data was downloaded from the USGS website (https://earthexplorer.usgs.gov/) at no cost. Landsat data was chosen for the reason that it supports a range of applications in areas such as global change research, environmental monitoring, land cover mapping, resource management, water, as well as coastal studies over a long period and with a forthright frequency. Landsat 7 ETM+ that was launched in 1999 was used for the 2000 flood event. The Landsat 7 ETM+ SLC-off was used for the 2013 flood event and the Landsat 7 ETM+ was used for the 2000 flood event. The images that were selected are listed in table 2.

Table 2: Selected images for the study

Flood events	**Before Floods**		**After floods**	
	Acquisition date	Sensor type	Acquisition date	Sensor type
February 2000	17 September 1999	ETM+	23 April 2000	ETM+
January 2013	04 December 2012	ETM+	27 April 2013	ETM+

The Landsat 7 ETM+ has 8 designated spectral bands with a spatial resolution of 30m and panchromatic band with 15m spatial resolution. The band specification for the Landsat 7 ETM+ imagery is outlined in table 3 below.

Table 3: Landsat 7 ETM+ designated bands

Spectral bands	**Wavelength min - max (µm)**
Band 1 - blue	0.45 - 0.52
Band 2 - green	0.52 - 0.60
Band 3 - red	0.63 - 0.69
Band 4 - Near Infrared	0.77 - 0.90
Band 5 - Short-wave Infrared	1.55 - 1.75
Band 6 - Thermal Infrared	10.40 - 12.50

Band 7 - Short-wave Infrared	2.09 - 2.35
Band 8 – Panchromatic	0.52 - 0.90

3.1.2. Field data

Field data collection was carried out within the study area. The field data include the vegetation species identification and acquiring ground truthing points using GPS coordinates. The fieldwork was carried out from the 10th to the 13th of February 2017. A purposive site selection method was used to acquire the mentioned GPS points as well as the identification of the common tree species. A handheld Garmin GPS was used to collect a number of points to use as reference when classifying the vegetation species using the Worldview2 image. From the field observation, the study area has a number of vegetation species that are common. With each species observation, a GPS point was taken. The points collected with the GPS were used to identify/classify the common vegetation species within the study area along with the satellite imagery data (WV2 image) that is mentioned in this chapter. The main vegetation species types identified in the field were 7, including three different types of acacia trees and the mopane, which are the most common woody species in the area. The GPS points were collected along the river as well as in the Venetia Reserve, to the South east. The map below (Figuere 5) is showing sites where the GPS points were collected. A total number of 79 GPS points were taken for all the tree species. The table (Table 4) below shows the number of points taken for each tree species.

Table 4: Tree species as well as the number of GPS points taken for each tree species

Tree species	**GPS points**
Acacia Erubescens	13
Acacia Senegalia	13
Acacia Tortilis	7
Colophospermum Mopane	23
Stuhlmanni Terminalia	8
Ficus Sycomorus	6
Croton Megalobotrys	9

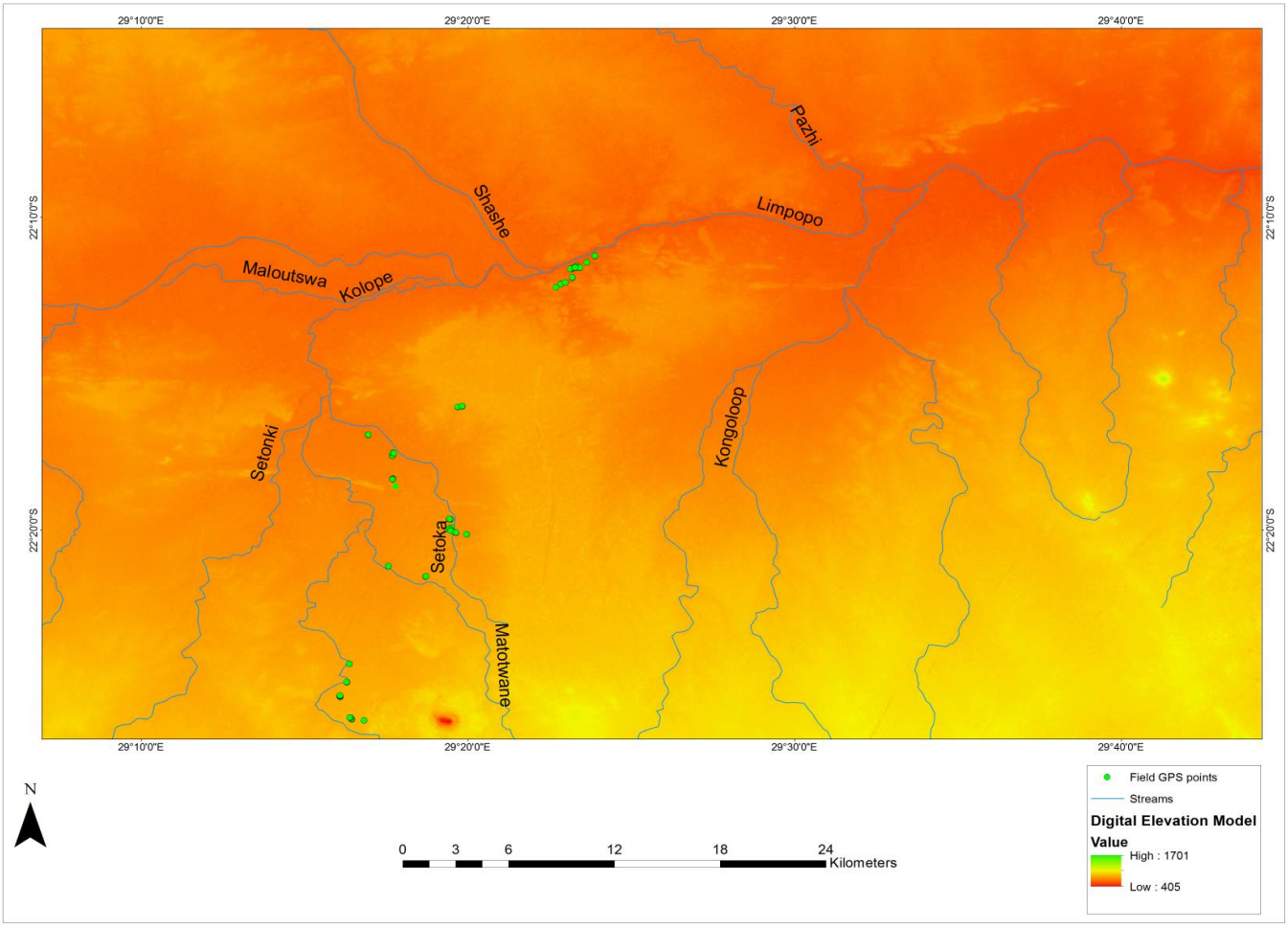


Figure 5: Map showing the location of GPS points collected in the field

3.2.Methods

3.2.1. Pre-Processing

Pre-processing was carried out for the correction of any possible distortions within the imagery data as well as for the preparation of the image analysis. The images for before and after the flood events were all subset in order to give the study a specific focus on the confluence area as well as the small portion of the surrounding areas.

Radiometric calibration was carried out to remove atmospheric noise in order to present data that accurately presents ground conditions (Montanaro *et al.*2014). This process was carried out using the function 'Radiometric Calibration' on ENVI Software. Atmospheric corrections were also carried out using the ENVI FLAASH atmospheric correction method. The FLAASH is an atmospheric correction method that modifies the wavelengths in the visible through near-infrared as well as the shortwave infrared regions (Berk *et al*. 2002). These processes were performed for all the Landsat 7 images as well as the WV2 image.

3.2.2. Mapping vegetation species using WV2 imagery

To map vegetation species, WV2 image was classified using Maximum Likelihood classification algorithm. The Maximum Likelihood classification algorithm is a classification algorithm that is pixel based. The classifier classifies according to the likelihood that a pixel fits within a particular class and takes variability of classes into account by using covariance matrix (Asmala, 2012). The training sites are used to provide spectral cluster of different vegetation species. The following table (Table 5) shows training sites that were generated as well as the test data used for accuracy assessment. The table below also shows the number of classes that were used as well as tree species that were classified for this study. Two independent data sets were used one for training and one for testing. For the testing data, the field ground truth data was used.

Table 5: Maximum Likelihood Classification data

Class name	**Independent Training sites**	**Independent Test sites**
Water	179	30
Acacia Senegalia	25	20
Acacia Tortilis	35	20
Croton Megalobotrys	30	15
Ficus Sycomorus	35	23
Acacia Erubescens	30	26
Mopane	106	30
Stuhlmanni Terminalia	29	22
Bare Soil/Built-up	134	20
Cultivated land	147	28
Other Vegetation types	131	41

3.2.3. Mapping Land cover types using Landsat 7 ETM+

Supervised classification in this study was used to determine change in vegetation within the study area in the periods before and after the two flood events. The Maximum Likelihood

classifier was used for the Landsat 7 to classify the image into five classes that include water, bare soil, cultivated land, dense vegetation as well as light vegetation. The training and the test sites were created for both the supervised classification as well as the accuracy assessment. For both training and test data, onscreen digitizing of classes was used. Change detection statistics method was used to monitor change in vegetation between the initial state capture and the final state capture. This method was only utilised for the images classified using the supervised classification indicated above. NDVI was also used to monitor change in vegetation before and after floods.

3.2.3.1.Normalized Difference Vegetation Index (NDVI)

NDVI was used in this study to monitor vegetation cover change using the above mentioned Landsat data that was downloaded. Mapping and classification of vegetation is an essential task as vegetation plays a significant role in defining most of the landscapes (Ahmad, 2012). The Normalized Difference Vegetation Index (NDVI) is a remote sensing measure for vegetation greenness and it is related to the structural properties of plants. Variety of vegetation changes can be analysed using NDVI time series (Forkel *et al.* 2013). The NDVI uses the visible and the Near Infrared bands on the electromagnetic spectrum. The NDVI values are calculated by the formula:

$$NDVI= (NIR-RED/NIR+RED)$$

The NDVI values are presented as a ration ranging from -1 to +1, though most (–) values represent water and the other values that are within the negatives represent soil/built up. The difference between the NDVI values for before and after floods determined the positive as well as the negative changes.

3.2.3.2.Accuracy Assessment

Accuracy assessment was performed after the classification of different vegetation species using the satellite data as well as the test sites data that were digitized. The test data that was used is shown in the table above (table 5) along with the training sites. Accuracy assessment is considered to be the degree of closeness of the acquired results to the accepted values as true (Zăvoianu *et al.* 2004). Accuracy assessment of a classified satellite images is an important step in image classification. The quality of a produced map is determined by its accuracy (Forkuo & Frimpong, 2012). Accuracy assessment of the resulting classification image can be described by using both the procedures and user's accuracy. When it comes to the procedures followed accuracy may be described by the amount of landscape categories

correctly classified on the image. On the other hand user's accuracy describes the probability that the class will be correct when correlated to the ground. The user accuracy and the procedure accuracy maybe represented using the error matrix. The sources of error may arise from remotely sensed data quality, training and test dataset, Algorithms and Atmospheric conditions (Busch, 2002). Accuracy assessment was performed from the resulting supervised classification images for both the World View2 classification as well as the Landsat images classification. This was done to observe the quality of the classifications and to determine the error from the classified images. The techniques that are developed for accuracy assessment take in to consideration the sources of errors in the images. Accuracy was performed using the test data that was created for all the classified images including the Worldview2 image. The confusion matrix using test Regions of Interest (ROIs) on ENVI Software was used in this case and the overall accuracy was represented on the following chapter.

3.2.3.3.Change detection

Change detection is an important application of remote sensing technology for understanding the relationships and interactions between humans and natural phenomenon in order for decision making to be possible (Xu *et al.* 2009). Digital change detection essentially comprises of the quantification of temporal phenomena from multi-date imagery. On change detection methods, Coppin & Bauer (1996) noted that the selection of the appropriate methods is of significant importance. Most digital change detections are based on per-pixel classifiers and change information contained in the spectral-radiometric domain of the images. (Lu *et al* (2004) on a study that explores all change detection techniques noted that, despite factors affecting the selection of the change detection techniques, image differencing, Principal Component Analysis and post-classification are the most commonly used. Landsat data has also been widely used for the change detection techniques. In a study of the analysis of land use change and human impacts, Zhou *et al* (2011) investigated two categories for land cover change which were, categorical change using image classification and quantitative change using vegetation index. Both the results of these change detection techniques worked out successfully.

In this study Change Detection Statistics method was used for all the images before and after floods. This was done in order to detect changes in vegetation within this area after the floods. The main purpose for this was to determine areas where there has been an increase in vegetation (positive change), decrease (negative change) as well as the areas of no change.

The results were presented in a map that is shown within the results chapter. The images that were used were the classified images from before and after floods.

3.2.3.3.1. Change Detection Statistics Method

Change detection statistics tool is a post classification statistical technique that is done using images of different times to determined changes in classes within the two images. Change detection is performed not only to detect changes within the classes understudy but also to identify the nature of those changes as well as to determine the extent and the spatial pattern of those changes (Kafi *et al*.2014). The two images for each flood event were independently classified. The classification was done using 5 classes that are; Water, Light Vegetation, Dense Vegetation, Cultivated land as well as cultivated land. The change detection statistics method was performed as post classification process to determine changes within the area under study. By using the change detection statistics method, the matrix table showing the initial state to the final state change was obtained. The change detection statistics tool that was used was performed on the ENVI software. The results are shown on the next chapter and they are presented on the matrix table in percentages.

3.2.3.3.2. NDVI Differencing Method

Change detection was for before and after images was also done using the NDVI Differencing method. First, NDVI was calculated for all the images then the resulting images were then used for change detection. The NDVI Differencing method is calculated using the equation:

$$\text{NDVI Differencing} = \text{NDVI}new - \text{NDVI}Old$$

The resulting NDVI images were subtracted to determine the positive as well as the negative change. The NDVI Differencing resulting image was then reclassified into 5 classes using a threshold method. The classes were classified as more increase, less increase, no change, less decrease as well as more decrease.

3.2.4. Mapping flood extent using Water Indices

3.2.4.1. Normalised Difference Water Index (NDWI) and the Modified Normalised Difference Water Index (MNDWI)

For flood extent delineation, NDWI as well as MNDWI water indices were used. Images that were used to achieve this were the same images that were used for vegetation change detection for this study. The images for the period of floods were not available and others had

cloud cover therefore, the results are presented using the same images. The NDWI and the MNDWI were tested to determine which index captures water the best between the two. The NDWI water index uses the equation, NDWI= (Green-NIR)/ (Green+NIR) whereas the MNDWI uses MNDWI= (Green-MIR)/ (Green+MIR). The indication of water for these indices is considered to be positive as its calculation like the NDVI is also represented by negative to positive values ranging from -1 to +1. NDWI was developed primarily to delineate water bodies and enhance its presence in remote sensing data, while simultaneously eliminating soil and vegetation features (Hui, 2008). The MNDWI extract water features while suppressing errors that may be derived from built up land as well as vegetation and soil. MNDWI was used to present the results as it presents better results than the NDWI. The thresholding method was used to delineate areas with water and areas that do not represent water. Threshold value of 0.2 was used for all the MNDWI resulting images. The threshold values can be adjusted depending on different studies (McFeeters, 1996).

Chapter 4

Results

4. Vegetation Species classification

The vegetation in the study area was classified using the WV2 image as well as the field data to acquire better results. The results for the classification using the Maximum Likelihood classification are presented in figure 6 below as well as the confusion matrix results (Table 6) in order to determine its accuracy.

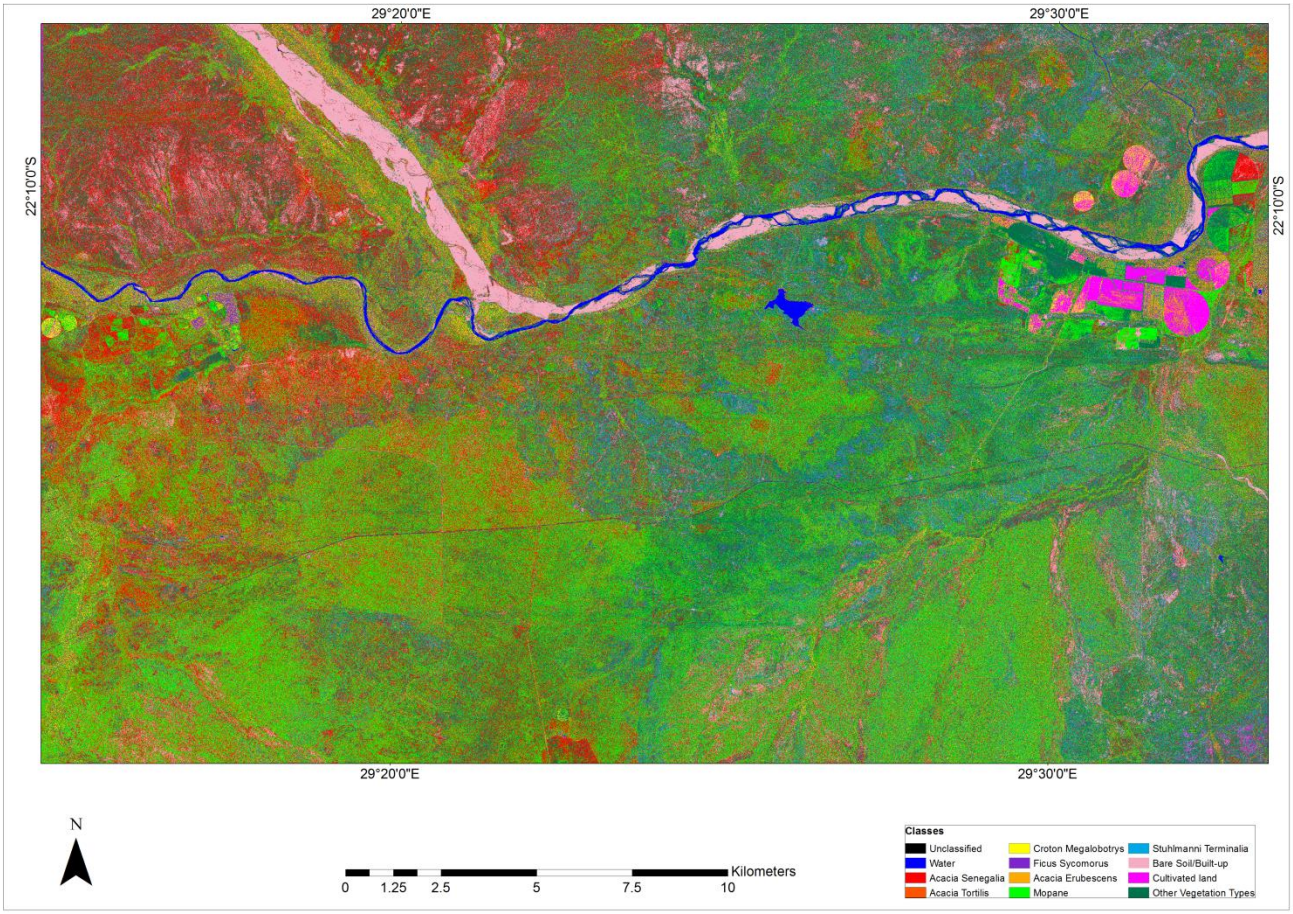


Figure 6: Vegetation classification of the Shashe-Limpopo Confluence area using WV2 and Maximum Likelihood Classification Algorithm

During the field visit, most common tree species were identified and notes were made of the other vegetation types present in the area (cultivated trees, grassland, etc.). The classification was based on 7 tree species plus a general 'other vegetation' class and cultivated land. The

results show that the most dominant species in this area includes three types of Acacia trees (acacia tortilis, acacia *erubescens* and acacia *senegalia*), *colophospermum mopane*, *Stuhlmanni Terminalia*, as well as the *Ficus* trees and the *Croton Megalobotrys* along the river/confluence edges. However, approaching the riverside more of the acacia trees, the *Ficus* as well as the *Croton Megalobotrys* trees are more visible than the Mopane trees.

The results also show a clear distribution of the acacia trees. The distribution of the acacia tree species is all over the study area; however more acacia trees are recognised more on the Northern side of the confluence which is the Zimbabwe side as well as in Botswana. The acacia trees are also widely distributed in areas where the mopane trees are dominant. The floodplains are also characterised by some agricultural activities which are presented above and are mostly found along the river.

Table 6: Confusion Matrix for validation of the tree species classification. Note: W=Water, AS= Acacia Senegalia, AT= Acacia Tortilis, CM= *Croton Megalobotrys*, FS= *Ficus Sycomorus*, AE= Acacia Erubescens, M= Mopane, ST= *Stuhlmanni Terminalia*, BS/BU= Bare Soil/Built-up, CL= Cultivated Land, OVT= Other Vegetation Types.

Overall Accuracy = 78.8942%												
Kappa Coefficient = 0.6814												
Class	W	AS	AT	CM	FS	AE	M	ST	BS/BU	CL	OVT	Total
Unclassified	0	0	0	0	0	0	0	0	0	0	0	0
W	6869	0	0	0	0	0	0	0	0	0	0	6869
AS	5	51	5	0	0	12	5	6	22	32	52	190
AT	12	0	31	3	9	0	15	7	0	68	115	260
CM	5	0	0	81	26	1	15	5	0	446	309	888
FS	0	0	0	5	90	0	3	17	0	353	171	639
AE	1	5	4	5	4	19	16	1	1	33	72	161
M	1	3	13	3	1	8	97	3	4	230	88	451
ST	27	0	3	5	4	4	2	25	2	17	33	122
BS/BU	1	2	0	0	0	0	0	0	1948	0	0	1951
CL	0	0	0	2	3	0	0	1	0	573	10	589
OVT	118	4	5	24	5	10	18	3	2	151	219	559
Total	7039	65	61	128	142	54	171	68	1979	1903	1069	12679

The accuracy for the classified WV-2 image is shown in the table above (table 6). The overall accuracy obtained using the test data set is 78.8942% with a Kappa Coefficient of 0.6814. The accuracy above shows the number of sampled pixel for each class as well as the number of pixels that were classified correctly and those that were classified incorrectly. In the above table, it can be noted that the classes that have the highest accuracy are water as well as the

Bare Soil/Built-up classes. The numbers of pixels that are incorrectly classified the most are that of the classes that represent vegetation. Most of the classified vegetation shows misclassification to 'cultivated land' as well as other types of vegetation classes. The class 'other vegetation types' represent a lot of different types of vegetation which may have similar spectral signatures as the identified tree species hence the misclassification of most of the tree species to this class. The overall accuracy that is presented for all the classes is shown as high (78.8942%) which is part of positive results in terms of Accuracy assessment.

4.1.Flood extent mapping for the Shashe-Limpopo Confluence area

To evaluate the extent of the flooding events under study, available Landsat images were used to develop MNDWI index which is used to identify open water. The results below show the MNDWI before floods as well as after floods. The threshold value that was used to generate water extent for this study is 0.2. Most studies that have presented the above mention index have used values ranging from 0.2 or 0.25 with maximum values ranging from 0.5 to 0.6 (Li *et al*. 2013). Determining threshold values is essential for every study; however the threshold values need to be adjusted for every case in order to obtain better results (McFeeters, 1996; Li *et al*. 2013). Using the MNDWI threshold of 0.2 for all the images, a map which is classified by areas with water and non-water was derived in different times (before and after the floods for both the events). Comparison between the NDWI and the MNDWI were done using the threshold value of 0.2. Using the pixels that were derived from the images, the tables below (Table 7a and 7b) shows the differences in results between two indices when it comes to mapping water and non-water features.

Table 7: NDWI (a) and MNDWI (b) water and non-water features indicated using before and after images.

NDWI Index	**(12 September 1999)**	**(23 April 2000)**	**(04 December 2012)**	**(27 April 2013)**
Water features	3372	24914	3423	6410
Non-Water features	3734565	3713023	3734514	3731527
Total	3737937	3737937	3737937	3737937

a)

MNDWI Index	(12 September 1999)	(23 April 2000)	(04 December 2012)	(27 April 2013)
Water features	3859	35326	3667	8820
Non-water features	3734078	3702611	3734270	3729117
Total	3737937	3737937	3737937	3737937

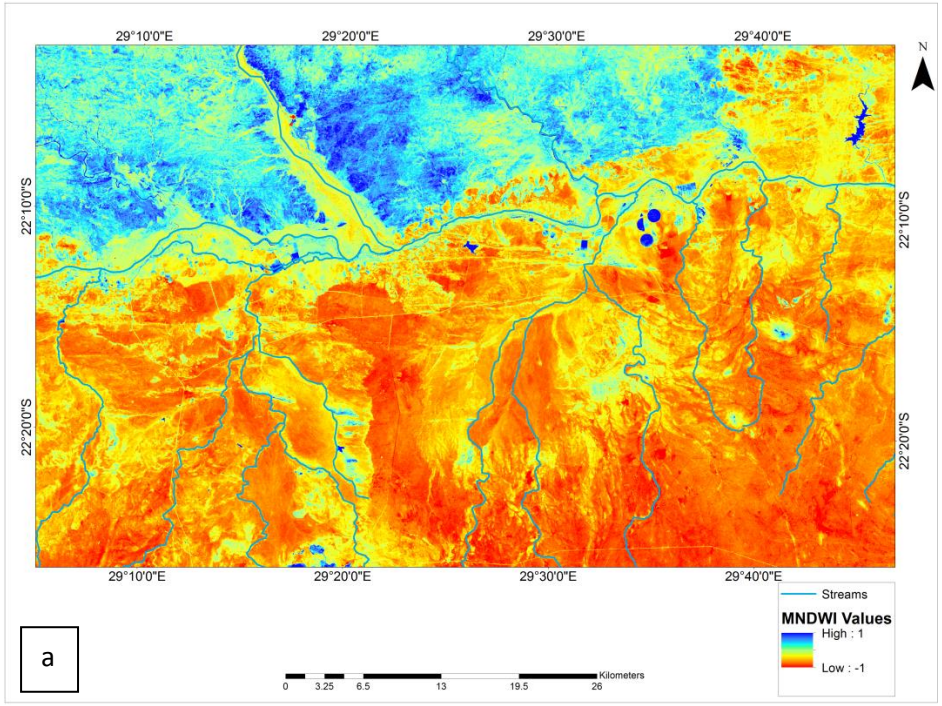
b)

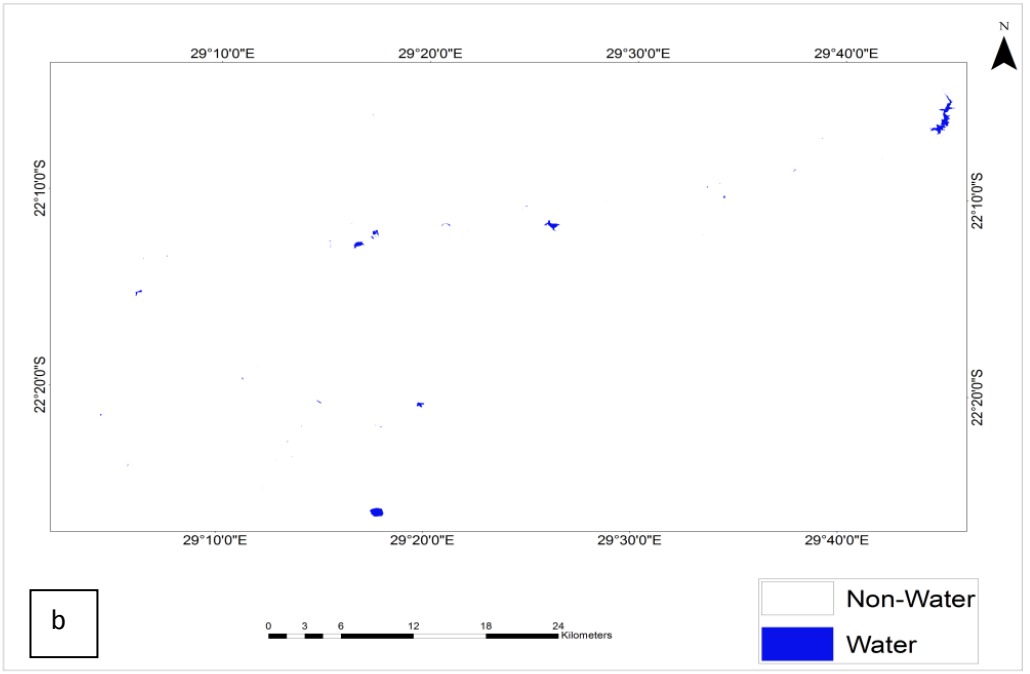
From the tables presented above the MNDWI index has shown more pixels as water compared to the NDWI. Evidently, MNDWI's accuracy in mapping water features correctly is higher than that of NDWI. The reason for this is that MNDWI maps water features while suppressing spectral interferences from built-up areas, vegetation as well as soil as compared to NDWI (Xu, 2006). With NDWI the water that this index extracts is either overestimated or underestimated because of the mixture of water areas with built-up and other classes, hence the use of MNDWI to map the flood extent. MNDWI from the results presented has shown that it has a great efficiency in mapping water as compared to the NDWI.

With evidence that the MNDWI is best suitable in showing water features, the results in this study are represented using the MNDWI index. Table (7b) above is showing the number of pixels available as water and non-water features for each durationtion (before and after floods for both the events). To achieve these results, the binary thresholding theory was used to discriminate between water and Non-water features. The table above was generated using pixel count that is possibly showing water according the threshold value of 0.2 in all the dates of image capture. The results from the index as well as the binary threshold are represented with the maps below.

4.1.1. Mapping the flood extent using MNDWI Index

4.1.1.1. The 2000 flood event


29°10'0"E
29°20'0"E
29°30'0"E
29°40'0"E
22°10'0"S
22°20'0"S
N
a
Streams
MNDWI Values
High : 1
Low : -1
0 3.25 6.5 13 19.5 26
Kilometers


29°10'0"E
29°20'0"E
29°30'0"E
29°40'0"E
22°10'0"S
22°20'0"S
N
b
0 3 6 12 18 24
Kilometers
Non-Water
Water

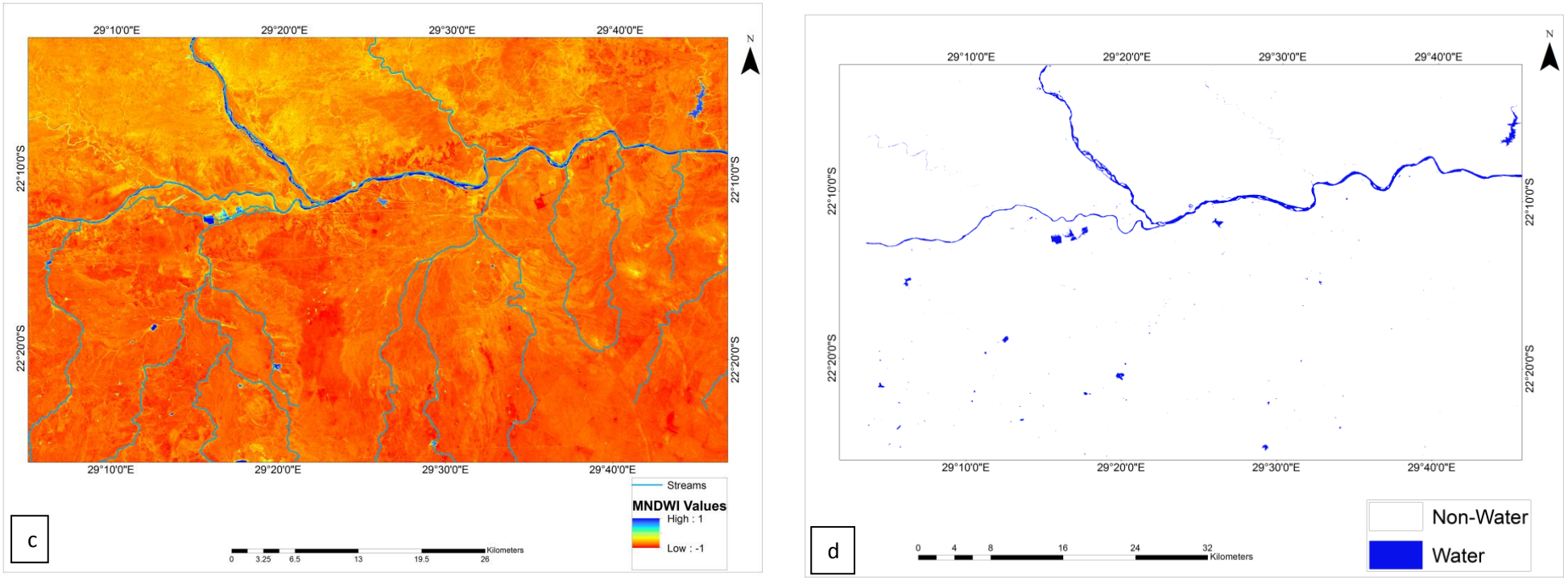


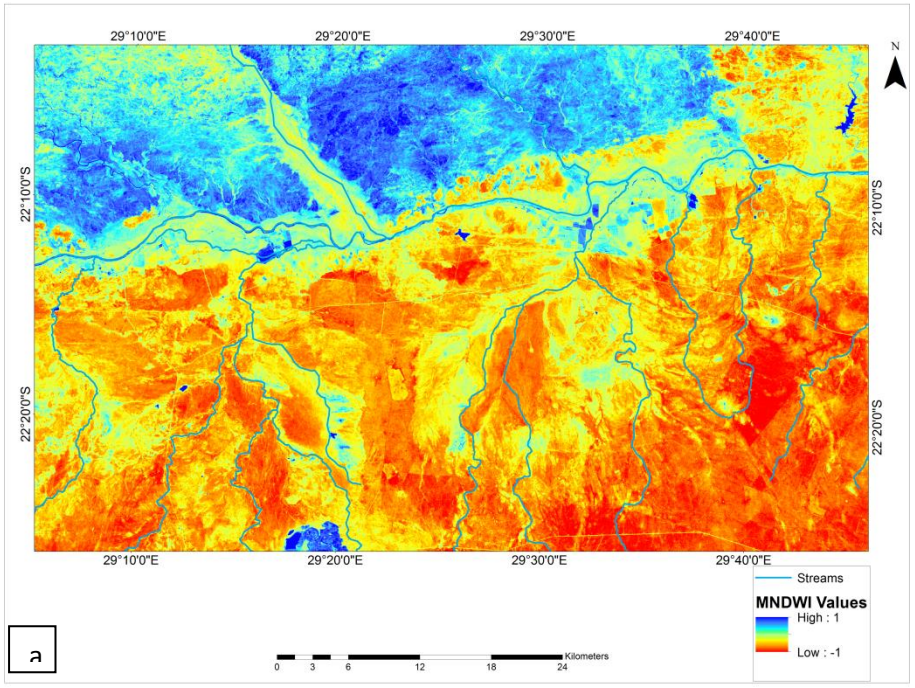
Figure 7: Water extent for the 2000 floods using Modified Normalized Difference Water Index. Note: a-b (before floods; c-d (After floods)

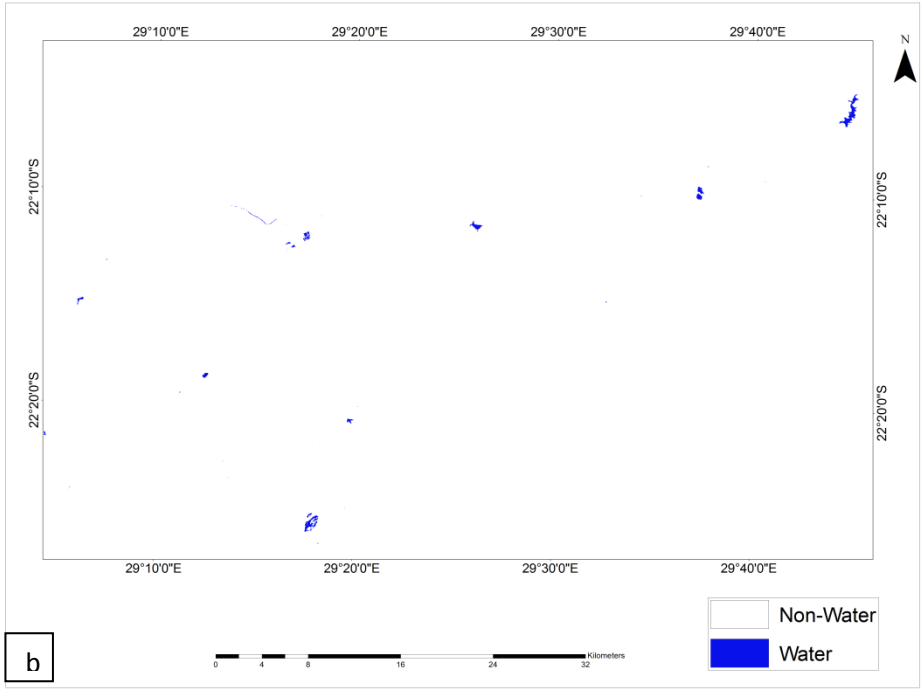
The MNDWI index was used to obtain the results presented. This index like most indices also represents the threshold values from -1 to +1. With regards to the above (Figure 7), the maps derived from the MNDWI results are showing that the time before the flood affected this area; the area was very dry with reference to the amount of area covered by water features. The maps are showing that at the time the image was taken, there were fewer water features. The pixels were derived by using the Binary thresholding method using the value 0.2 as a representation of water.

With reference to the above results figure (Figure 7) there is a clear indication that between the first image capture which was captured on the 12th of September 1999 and the image captured a month after floods, the areas indicated as water features have increased. From the results acquired, it is evident that the index mapped a few areas with visible water features. The areas that are mapped are marked in the generated binary maps above as water features. However using this index, accurate flood extent mapping cannot be expected. This is because, most of the water indices mostly map open water features. From the results, the index presented has shown efficiency in mapping water features instead of the expected flood extent.

Figure 7(a), the index is showing classification of most non-water features with high values. From the results, the non-water features are shown as the colour that is meant to represent water features classification. However, the threshold for these non-water features is show to be on the negative threshold. This shows that this index had a mix when classifying the water and non-water features. Comparing the results shown above (Figure 7a) with that of the NDWI, the MNDWI showed a lot of improvement when it comes to better classification of water and non-water features.. The reason why this index showed this pattern is that of a mix up in spectral reflectance where non-water features are mixed with water features. However in this case, non-water features have negative values. The only mix up was with their reflectance. This can be fixed by examining the features to remove the noise that is causing this mix up.

4.1.1.2. The 2013 flood event


29°10'0"E
29°20'0"E
29°30'0"E
29°40'0"E
22°10'0"S
22°20'0"S
N
Streams
MNDWI Values
High : 1
Low : -1
Kilometers
0 3 6 12 18 24
a


29°10'0"E
29°20'0"E
29°30'0"E
29°40'0"E
22°10'0"S
22°20'0"S
N
Non-Water
Water
Kilometers
0 4 8 16 24 32
b

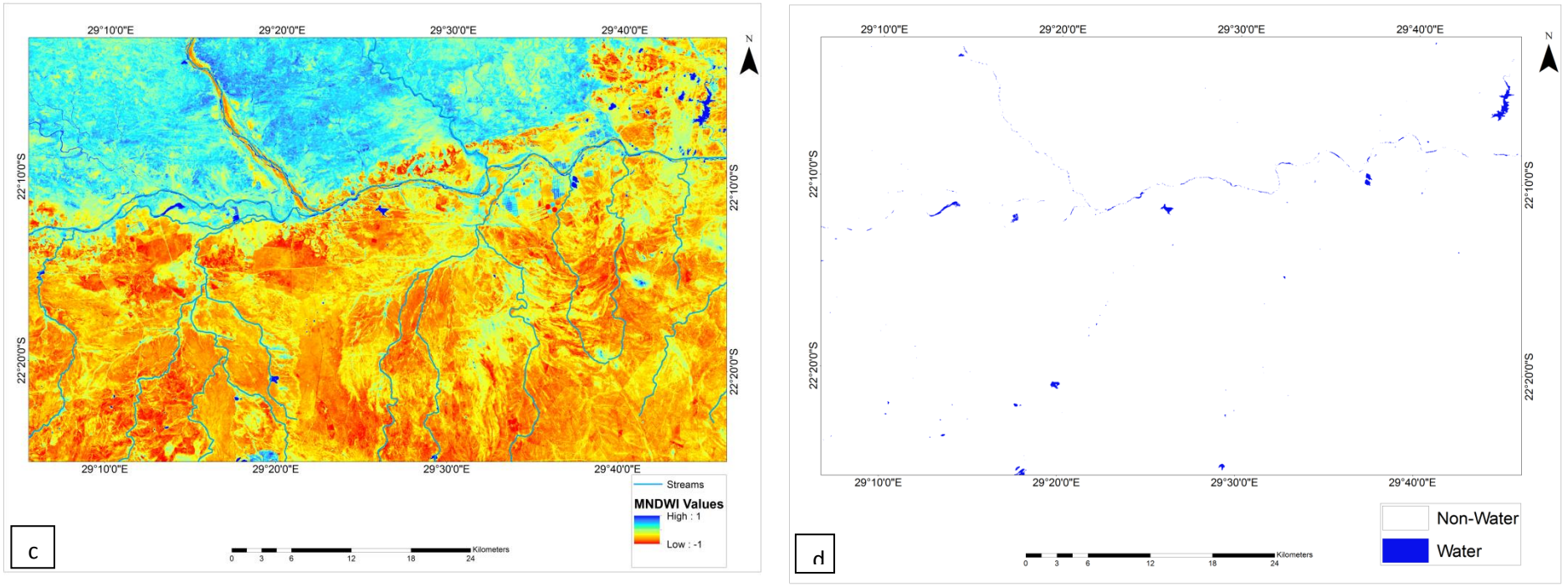


Figure 8: Water extent for the 2013 floods using Modified Normalized Difference Water Index. Note: a-b (before floods; c-d (After floods)

The results that are represented above show a representation of the 2013 floods. The results were acquired using MNDWI index as well. The water and non-water features results were also derived from using the threshold value of 0.2. The image captured before the floods, shows that the area had less water features as compared to the image captured more than a month after (27 April 2013) the area had been affected by the floods. The threshold method as well as the MNDWI maps shows a clear indication of water and non-water features. The MNDWI index shows the results with values ranging from +1 to -1. The water features are represented with the higher values ranging from 0.2.

The image before the floods shows more areas with lower values or dry areas whereas the image after the flood shows more moist areas. Though the index does not necessarily map the extent of the floods, it is evident that between the time of first image capture and the last image capture there has been an increase in water features.

The MNDWI shows areas that have water features for both the flood events even though it has limitations in terms of correctly delineating the flood extents. With the limitations that this index has, the difference between the 2000 flood event and the 2013 event is very visible looking at the amount of water that occupies the areas within both the events. The 2000 flood event visibly shows more water features than the 2013 flood event. With this kind of information a conclusion can be drawn without any form of quantification that the 2000 flood event has been shown to be more intense than the 2013 flood event.

4.2.Vegetation analysis using NDVI

Vegetation changes results are represented in this section. To determine the changes before and after the floods, the NDVI calculations were obtained for all the dates before and after floods. The NDVI Differencing technique is also presented as a technique for change detection for the NDVI results. The results are clearly indicated using NDVI maps below for all the images (before and after). The lowest as well as the negative NDVI values from the results are found to represent sand/bare soil, built up, water as well as dry vegetation. Figure 9 as well as Figure 10 which are a representation of vegetation using NDVI calculations before and after the two floods, show variation in NDVI values for each image. The vegetation change detection results are also presented in this section using Maximum Likelihood Classification as well as the Statistical change detection method for both flood events understudy.

4.2.1. 2000 flood event NDVI

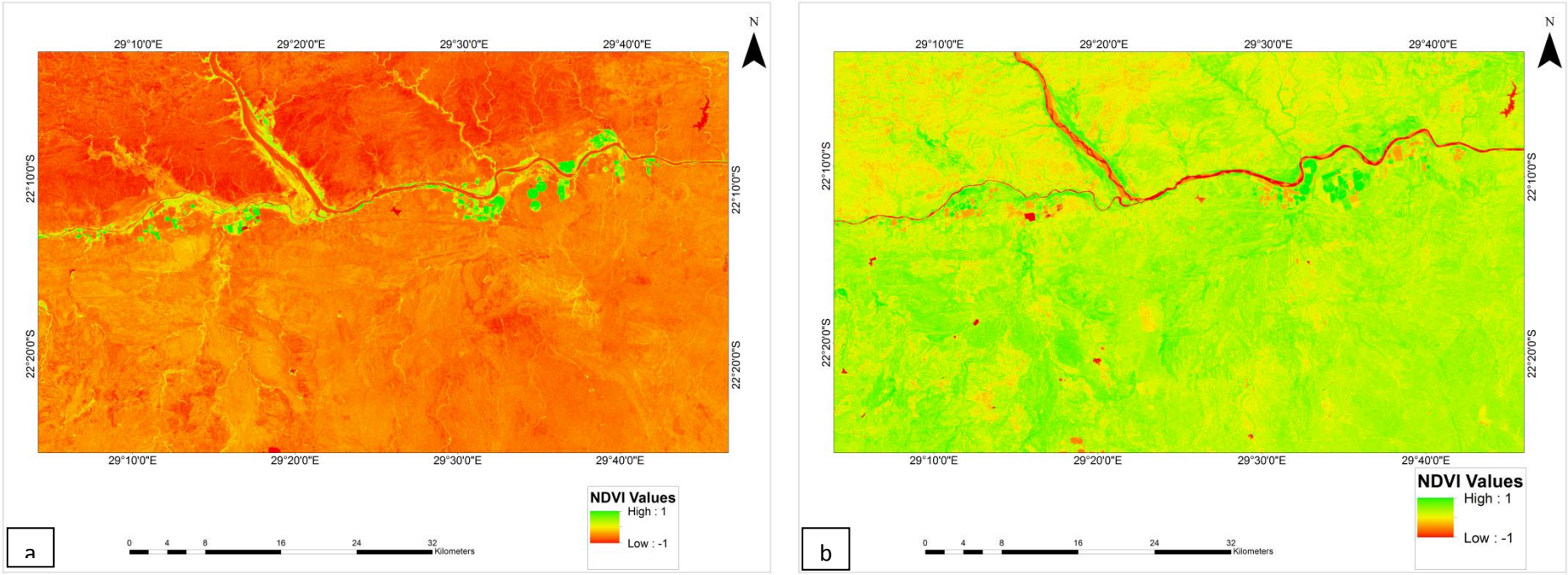


Figure 9: Maps showing NDVI for before and after the 2000 floods NDVI

Normalized Difference Vegetation Indices (NDVIs) for the 2000 floods were computed. The figures above (Figures 9a, 9b) show the NDVI values represented in a map form for the images that were acquired before and after the floods. From the results shown above, the NDVI for the image taken before the floods (12 September 1999) shows clear indication of vegetation values ranging from the lowest value of 0.2. Values that are represented by the NDVI as starting from 0.2 and 0.3 are shown to be the representation of what may be dry or woody vegetation as well as grassland with values greater than 0.4 representing very high dense vegetation. The indication of vegetation is shown in green and it shows that for the first flood event, the initial state which is the image captured before the heavy rain started (12 September 1999), vegetation was not healthy. In the map showing the initial state of the 2000 floods there is low reflectance of green and more orange (non-vegetated/unhealthy vegetation) which mostly is an indicator of high reflectance of soil.

The image after the 2000 flood event was captured a month after the event occurred and the resulting vegetation map is also presented above (9b) as the image captured on the 23rd of April 2000. The results show that vegetation at this time was much healthier as compared to the initial state which is the image captured before floods. The results evidently show that there are more areas with much higher NVDI threshold as compared to the image before floods.

4.2.2. 2013 flood event NDVI

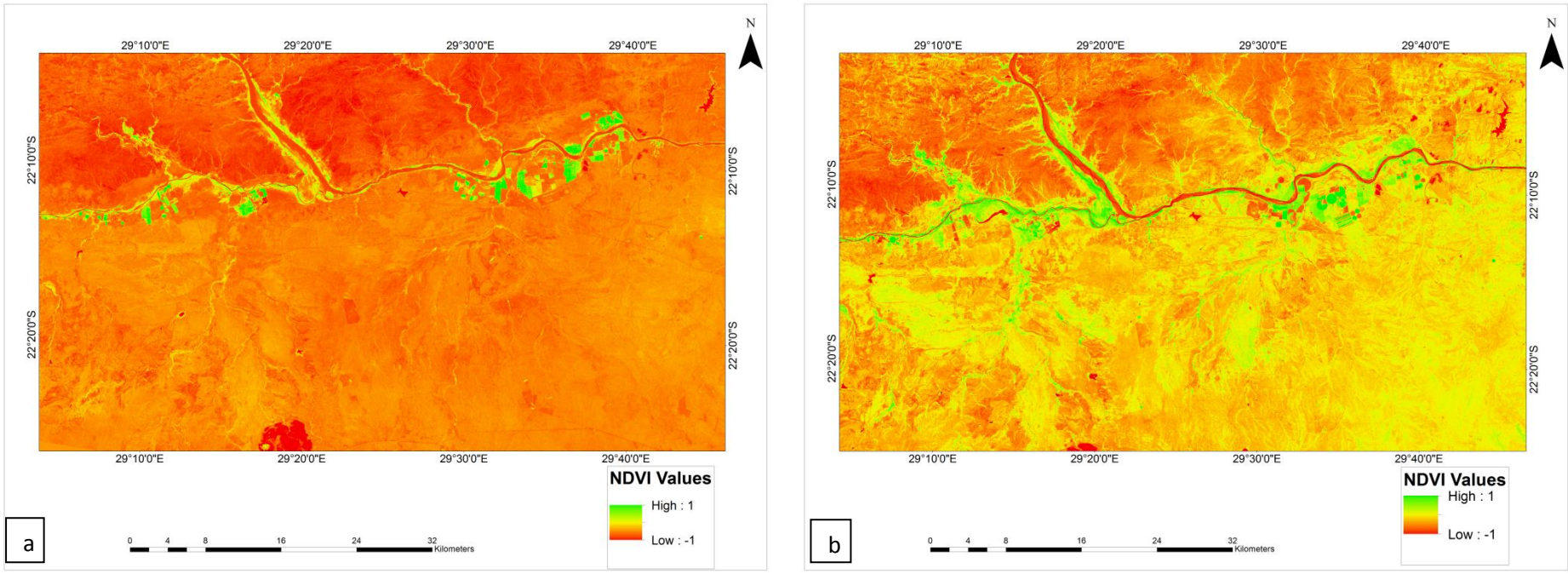


Figure 10: Maps showing NDVI for before and after the 2013 floods NDVI

The results shown above (Figure 10a, 10b) are also showing the NDVI representation for the reported 2013 floods. The image for before the floods was captured on the 04th of December 2012, less than a month before the floods. The image after the floods was captured on the 27th of April 2013. It has been recorded that when there is a decrease in soil water, the green in vegetation tend to decrease and the values of NDVI decreases as well. This may explain the results above, more especially the NDVI results for the image captured before the floods. From the maps presented above, it is evident that before carrying out any change detection techniques that the vegetation has increased greatly immediately after the floods.

It is evident that there is an increase in positive NDVI values between the initial and the final state of capture. The increase in NDVI values is a representation of healthier vegetation. However, some of the areas that were reflecting green before are reflecting orange. The areas that are mostly showing a great decrease on the amount of green are the cultivated areas or farming areas. This however does not give clear indication of the cause of the decrease within these areas.

4.2.3. NDVI Differencing

The change detection calculation results for the 2000 as well as the 2013 flood events are presented in figures 11 and 12 below.

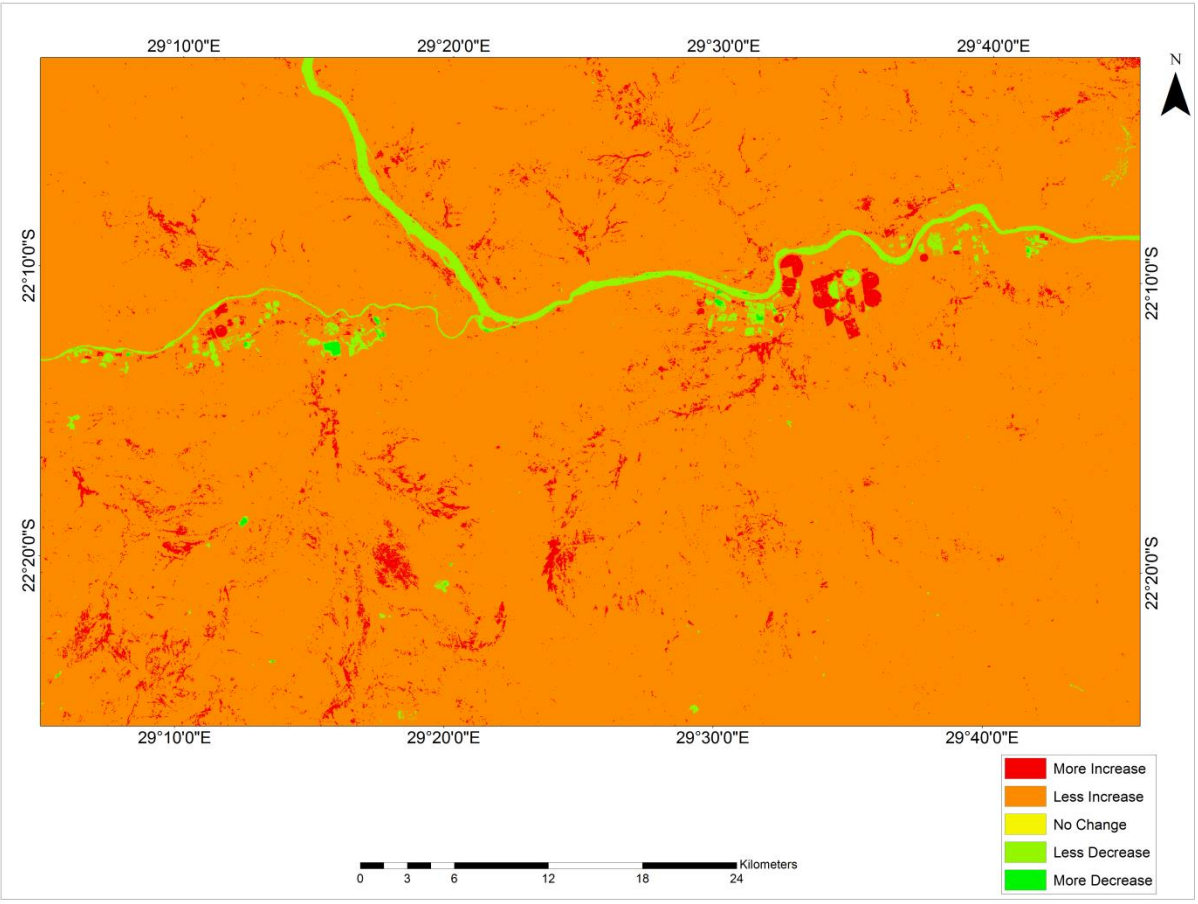


Figure 11: NDVI Change Detection for the 2000 flood event

The image above (figure 11), Shows the NDVI change detection results for the images between the 12th of September and after the floods which is the 23rd of April. The findings show that during the period from the first date to the second date of capture, the area has experience some increase in vegetation compared to the initial state of image capture. The meaning of this is that, there were very few vegetated areas before floods as compared to vegetation cover captured right after floods in April. The above NDVI Differencing results are represented using 5 classes which are, more increase, less increase, no change, less decrease as well as more decrease. The results show that there are more areas with vegetation that has slightly increased as presented by the 'less increase' class. The areas with more decrease especially in vegetation are shown as cultivated or agricultural areas.

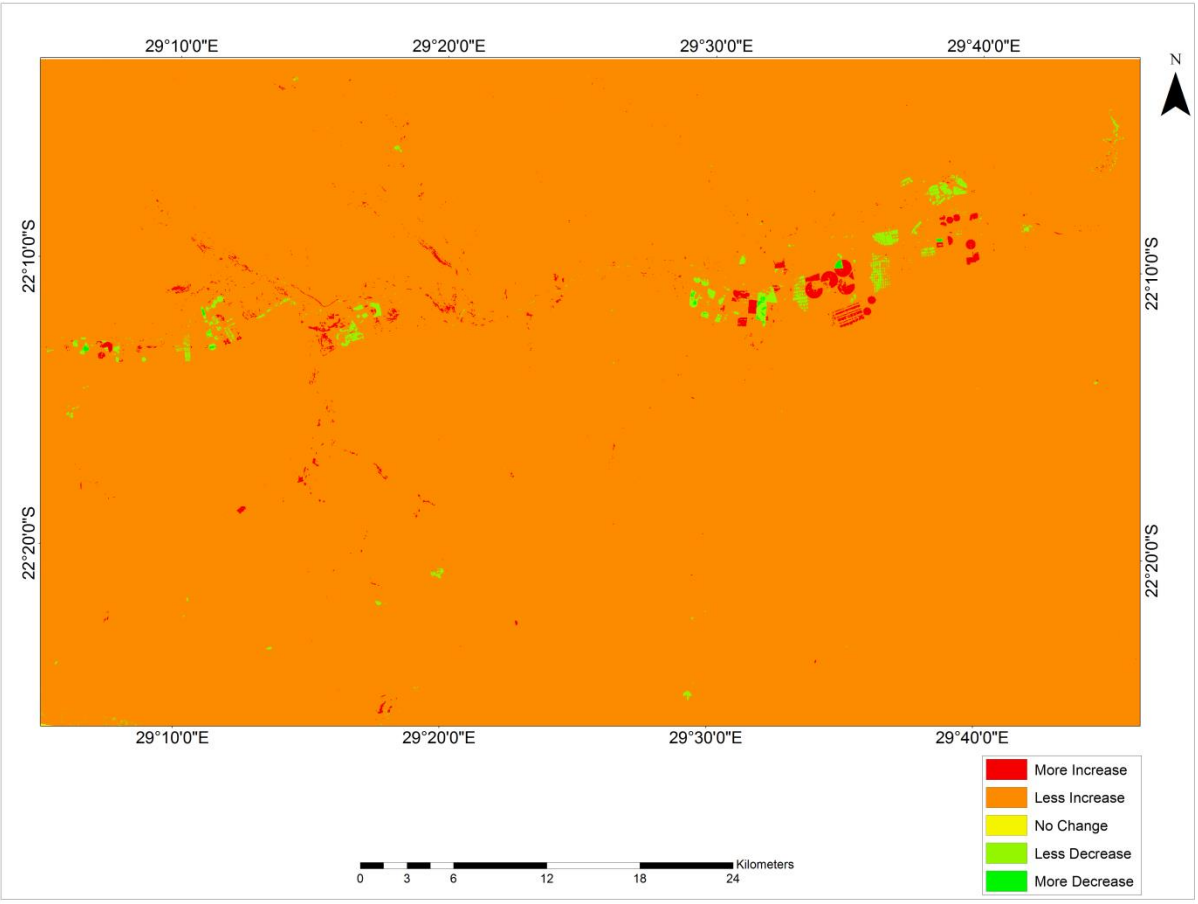


Figure 12: Change Detection for the 2013 flood event

The image above represented by figure 12 shows the NDVI Differencing results for the before as well as the after the 2013 flood images. From the results shown above, it is clear that between the initial state of capture and the final state of capture there has been more of the 'Less increase' than any other class. These results are showing that there is a less positive change in vegetation as compared to the NDVI Difference map for the 2000 floods. The vegetation that has increased more has been shown as that which was classified as 'Light vegetation'. The results are simply showing that there are more areas that have developed vegetation that did not have any vegetation seen in the initial state of capture. The results also show that other areas where there was more vegetation there is much lighter vegetation or no vegetation at all in the image of the final capture.

4.3.Change detection using Classification

To support the NDVI results, change detection for supervised classification images was done using change detection statistics. The maps below show a representation of the classification results for before and after the floods of both the 2000 as well as the 2013 events.

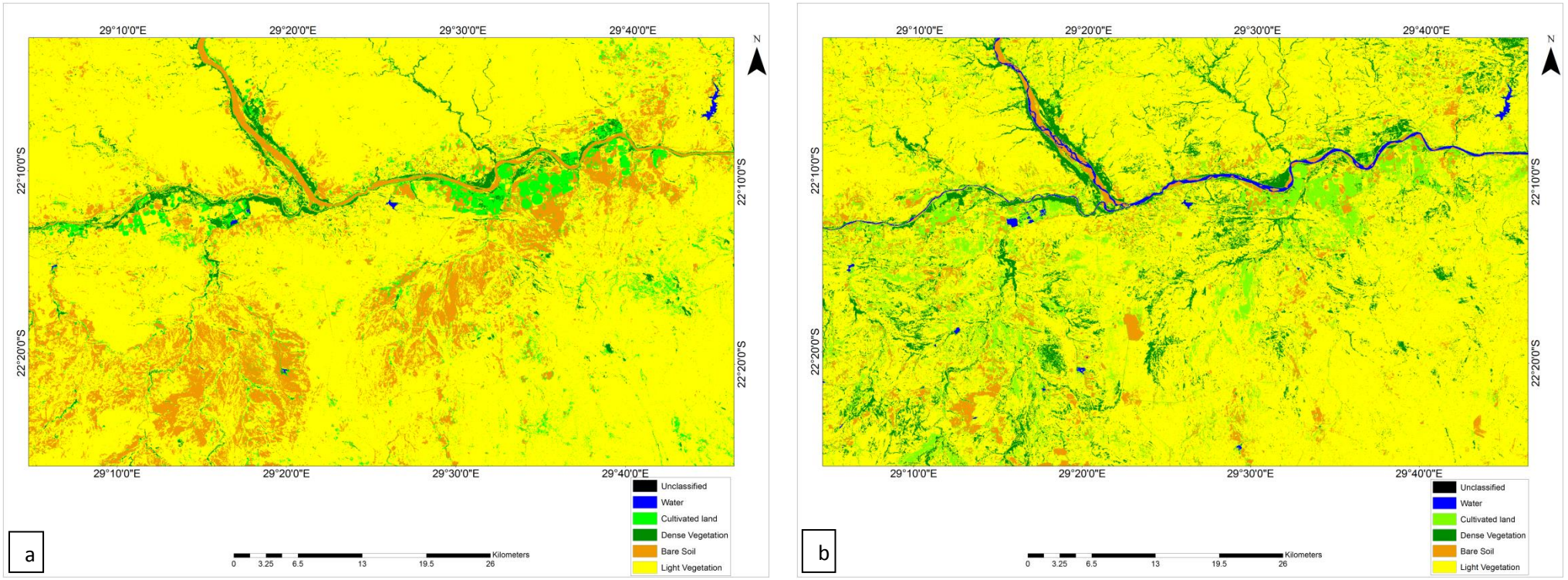


Figure 13: MLC results for the image after the 2000 floods. a) Image before floods, b) Image after floods.

The results shown above are the representation of the classification using the images before and after floods. The images are classified using 5 different classes which are Water, Cultivated land, dense vegetation, Light vegetation as well as bare soil. The study puts more interest on the vegetation which in this case is represented using the two classes which are dense and light vegetation. The reason for this is that, using Landsat Imagery it is complex to determine the type of vegetation that covers the area. Dry vegetation, burnt vegetation as well as any sparse vegetation is represented using the class Light vegetation whereas much healthier as well as the much more assembled vegetation is represented using the class Dense Vegetation.

The above classified images shows somewhat changes as compared to the before image. It is clear that there is more increase in vegetation than decrease in vegetation. The changes between two images are also visible looking at the table presented for statistical change detection (Table 9).

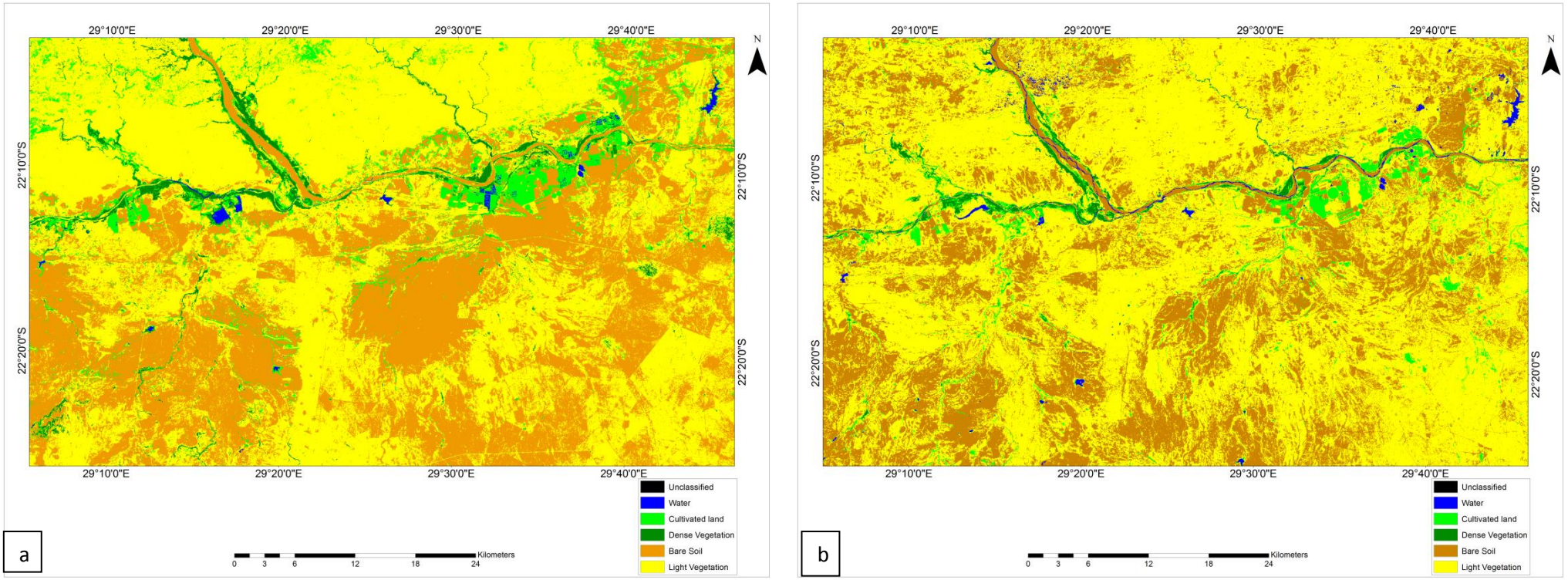


Figure 14: MLC results for the image after the 2013 floods. a) Image before floods, b) Image after floods.

From the results above it is evident that vegetation tends to be denser along the river side and as the area extends outwards the vegetation becomes more scattered and may be reference to as light vegetation. It is also evident from the maps presented above with regards to the 2000 flood event that the changes from the before and the after image has changed in a positive way or most of the vegetation has increased from the initial state of capture. The 2013 floods had somewhat changes. However the changes during the 2013 flood event were not as excessive as those from the initial flood event which is the 2000 event.

4.3.1. Change Detection Statistics

Using change detection statistics on ENVI, the following tables below were derived in percentages with reference to changes that have occurred during the initial state of capture and the final state of capture for both the flood events. The change detection statistics show the image difference of all 5 classes used for the classification as shown in the maps above (figure 13 and 14).

Table 8: Change detection statistics results in percentages for the 2000 floods

Year	Initial State (12 September 1999)					
Final State (23 April 2000)	Percentages					
	Class	Water	Cultivated land	Dense Vegetation	Bare Soil	Light Vegetation
	Water	82.31	0.94	1.379	3.88	0.089
	Cultivated land	3.23	28.85	12.745	24.33	6.311
	Dense Vegetation	0.19	15.64	70.536	1.66	6.72
	Bare Soil	0.48	7.14	0.714	22.97	2.779
	Light Vegetation	13.78	47.43	14.626	47.17	84.1
	Class Total	100	100	100	100	100
	Class Changes	17.69	71.15	29.464	77.03	15.9
	Image Difference	350.90	138.07	207.974	-58.03	-5.062

As presented in table 8 cultivated land which represents the vegetation in farmlands has had a 71.15% change before and after the floods. The change detection results is showing that from the initial state of capture to the final state of capture, the cultivated land class has changed greatly to the class light vegetation (by 47.43%) and has also changed to dense vegetation by

15.64%. The cultivated land class has also changed to other classes such as bare land and water by a small fraction (7.14%; 0.94% respectively)

One class that is also of great interest is presented as dense vegetation. According to table 8 which is a representation of change detection percentages for the 2000 flood event, the class dense vegetation has had a class change of 29.464%. More change on the Dense vegetation has been to Light vegetation which is by 14.626% as well as cultivated land with a percentage of 12.745%

The other class which is of great interest is classified as light vegetation. This type of vegetation for our study includes dry vegetation, burnt vegetation as well as any sparse vegetation. Light vegetation in table 8 is shown as having a class change of 15.9% which compared to the other vegetation types is the lowest change. Part of the change is shown in the mentioned table as cultivated land as well as dense vegetation (6.311%; 6.72% respectively).

Table 9: Change detection statistics results in percentages for the 2013 floods.

Year	Initial State (04 December 2012)					
FINAL State (27 April 2013)	Percentages					
		Water	Cultivated land	Dense Vegetation	Bare Soil	Light Vegetation
	Unclassified	0	0	0	0	0
	Water	38.792	1.272	1.074	0.406	0.605
	Cultivated land	26.939	17.693	28.111	0.915	1.705
	Dense Vegetation	2.895	2.481	34.163	0.027	0.13
	Bare Soil	10.198	24.691	2.42	52.063	19.337
	Light Vegetation	21.176	53.863	34.232	46.589	78.223
	Class Total	100	100	100	100	100
	Class Changes	61.208	82.307	65.837	47.937	21.777
	Image Difference	120.388	-46.536	-56.319	-15.384	17.11

The results which are represented by table 9 are showing change detection statistics in percentages for the 2013 flood event. As presented in the table cultivated land is showing an 82.308% of class change. More than 10% change as compare to the cultivated land for the 2000 flood event. The cultivated land for the year 2013 is showing to have changed more to

Light Vegetation by a percentage of 53.863%. More of the cultivated land has changed mostly to Bare Soil by 24.691% with dense vegetation only covering the cultivated land change of 2.481%.

The dense vegetation class has also changed greatly as compared to the 2000 flood event. The class change is shown as 65.837% double the change of the 2000 flood event. This type of vegetation has shown change to light vegetation (by 34.232%) as well as Cultivated land by the percentage of 28.111%. Water as well as bare soil classes covers the rest of the class change which is 1.074% and 2.42% respectively.

Light vegetation class has also shown some changes as shown in the table 9. The class change is shown in percentage as 21.777%. This class is also showing more change as compare to the 2000 flood event. The class is shown to have change greatly to bare soil with a percentage of 19.337%. Another change is shown of 1.705% to cultivated land. Water as well as dense vegetation is not showing much change as it is showing coverage of only 0.605% and 0.13% respectively.

Table 10: Change Detection Statistics results in Percentages between the two images captured before the two flood events.

Year	Initial State (12 September 1999)					
Final State (04 December 2012)	Percentages					
		Water	Cultivated land	Dense Vegetation	Bare Soil	Light Vegetation
	Unclassified	0	0	0	0	0
	Water	40.773	2.139	2.451	0.145	0.084
	Cultivated land	1.156	29.645	15.719	3.43	4.481
	Dense Vegetation	0.974	6.663	50.114	0.165	0.992
	Bare Soil	56.184	39.052	1.77	81.354	30.26
	Light Vegetation	0.913	22.503	29.945	14.906	64.183
	Class Total	100	100	100	100	100
	Class Changes	59.227	70.355	49.886	18.646	35.817
	Image Difference	71.855	34.143	-9.169	166.833	-30.973

The table above is showing the change detection statistics for the images that were captured before both the events understudy. The results for the change detection analysis are showing

that in terms of vegetation, 29.9% of vegetation that is classified as dense vegetation has been changed to light vegetation from 2000 to 2013. 30% of what is classified as Light vegetation has also changed to bare soil as indicated on Table 10. Where it was shown to have dense vegetation on the initial state which is in 2000, it is shown in 2013 to be having a class change to cultivated land. This is shown to be a real change on the image; however some of these changes could be as a result of misclassification. Other classes such as water have also changed greatly to bare soil class.

Table 11: Change Detection Statistics results in Percentages between the two images captured after the two flood events.

Year	Initial State (23 April 2000)					
		Water	Cultivated land	Dense Vegetation	Bare Soil	Light Vegetation
Final State (27 April 2013)	Unclassified	0	0	0	0	0
	Water	31.287	1.411	0.529	0.717	0.305
	Cultivated land	1.473	7.119	15.751	2.397	1.217
	Dense Vegetation	0.089	1.147	9.421	0.186	0.184
	Bare Soil	59.828	44.952	3.661	77.678	27.963
	Light Vegetation	7.323	45.37	70.638	19.022	70.331
	Class Total	100	100	100	100	100
	Class Changes	68.713	92.881	90.579	22.322	29.669
	Image Difference	-12.956	-69.013	-87.32	449.222	-14.781

The above table is showing change detection statistics for the images that were captured after the floods for both the events. Changes in vegetation that are much visible in terms of the classes are those of the class dense vegetation into light vegetation. The results are showing that from the year 2000 to the year 2013 after the floods 70.6% of dense vegetation has changed to light vegetation. Also, some of the light vegetation has changed to bare soil by 27.9%. The results also show that slight change of the light vegetation has occurred since 2000.

The change detection results that are presented for both before the event images as well as the after the floods images are showing that there was more change in vegetation with the 2000

floods as compared to the 2013 flood event. These changes are shown more on the dense vegetation changing to light vegetation as well as change to bare soil or built up areas.

Chapter 5

Discussion

5. Introduction

Impacts of floods on vegetation have been studied intensively throughout the world over the past years (Basak, 2015; Banach, 2009; Yanosky, 1982). The results have been shown to be different depending on the area of study. In this study, the results of these floods impacts are shown. The aim of this study was to determine the impacts of floods on vegetation species within the Shashe-Limpopo confluence Area. Using remote sensing as well as field data, the results were presented in the previous chapter. The objectives of this study, as well as the final outcomes of each objective, are discussed in this chapter.

5.1.Mapping vegetation species

The first objective of this study was to map the common vegetation species in the area using remotely sensed data. This objective was fulfilled using the Maximum Likelihood classification on the World View-2 image. Using WV-2 has provided detailed classification of the tree species as this imagery has an improved spatial resolution.

According to the results that were shown on the map in chapter four, the vegetation species types that were recognized are Different types of acacia tree, *Colophospermum Mopane, Stuhlmanni Terminalia*, as well as the *Ficus* trees and the *Croton Megalobotrys* along the river/confluence edges. These vegetation types are the ones that are more common in this area of many other vegetation species. These results are aligned with the findings by Gotze *et al* (2008) who noted the different types of vegetation in the Mapungubwe landscape. From Gotze *et al* (2008) findings vegetation in this area can be classified into more classes than the classes that were presented in the results section. This shows that more attention is needed on the vegetation species classification of this area. According to SANParks, acacia tree species within this area are about 24. This study only identified three types of acacia that were mostly recognised in the field.

The study shows that WorldView-2 satellite data is highly suitable to classify the presented tree species. However, it was difficult to classify these tree species on the image because some of these tree species have similar spectral signatures. Therefore, some of the errors presented by the confusion matrix may be due to this reason (Immitzer, 2012). Li *et al*.

(2014) used the same imagery to classify urban tree species but obtained a much higher accuracy than the current study. The authors' noted that the high accuracy may be due to the fact that the trees that were used are more spectrally separable than those in the current study. Mapping tree species using Maximum Likelihood classification on WV-2 has proven to work successfully. However, the errors of misclassification remain. Using WV-2 as well as the MLC algorithm, all types of vegetation species were classified and the distribution of these tree species was noted regardless of the errors.

This objective was presented in order for the study to be able to understand and identify what types of vegetation species around the study area thrive or are damaged when the area is affected by floods. The results from this section shed light on the behaviour of the common vegetation within the flooded environment.

5.2.Flood extent Mapping

One of the objectives of this study was to map the two different flood events using remotely sensed data (Landsat Imagery). This objective was done using a comparison of two different water indices (MNDWI and NDWI).

The two water indices were compared to determine which one of the two presented better results when it comes to water features identification. After comparing the two indices the results showed that the Modified Normalized Difference Water Index (MNDWI) shows much-improved results than the Normalized Difference Water Index. These results are supported by a number of authors (Xu, 20006; Mcfeeters, 1996) who have shown the effectiveness of the MNDWI as well as the NDWI. Studies show that water information using the NDWI is often mixed with built-up land noise thus overestimating or underestimating the area of the resulting extracted water. The MNDWI shows to be more suitable than the NDWI for the reason that it is implemented in a way that it reduces and removes the built-up land noise (Xu, 2006).

The results for mapping the flood extents where then presented using the outcomes that were acquired from the MNDWI. The results show accurately open water features however, this was not what the objective required. The objective was to map the flood extents for both the flood events. This index only showed open water features for both the flood events. The objective was also to see if the water indices are useful in mapping the flood extent. The result shows the ineffectiveness of the water index in showing the extent of the floods. The water indices are mostly implemented to map open water features (Mcfeeters, 1996) hence

the failed attempt to achieve the objective. The results show similarities with other studies that used MNDWI to map water features. This water index does not show water according to moisture contents on a feature instead it detects visible water features. This is one of the limitations of using water indices; it only detects open water features.

5.3. Climate data

The differences between the two floods under study were shown using river discharge data from the two rainfall station by the Limpopo River. The discharge data shows clearly which months in each flood year understudy had high volume of water discharge. From the presented graphs (Figures 2 and 3) more discharge volume is shown on the 2013 year instead of 2000. However (Maposa, 2016; Spaliviero *et al*. 2014) noted that the 2000 flood event was the most intense as compared to the 2013 floods. This problem in the station data could be because the data is from different stations hence the inaccurate presentation. This was one of the limitations of this study. Data for both flood events could not be found in one station.

5.4.Vegetation cover change due to flood events

One of the objectives of this study was to quantify the vegetation changes caused by floods events. To achieve this objective two methods were used: the Normalized Difference Vegetation Index (NDVI) as well as the supervised land cover classification. NDVI Differencing was used to acquire the change detection results for the NDVI resulting images. The Statistical change detection method was used for the classified images.

5.4.1. NDVI Vegetation change analysis using NDVI

The NDVI results as well as the NDVI Differencing results are showing that vegetation has increased greatly looking at the before and after the floods images. The results also show some negative impacts where the area had vegetation before the floods and no vegetation after the floods. The NDVI change maps are showing more slightly vegetated areas.

The areas that are shown by the NVDI to have decreased in vegetation are those areas that are considered to be the agricultural areas according to the vegetation classification on the results section. This is aligned with a number of studies that include a study by Banerjee (2010) who noted the disturbances of flood events on agricultural crops. The author noted that although floods have negative impacts on the crops it can also be beneficial on the long run if the flood is not too severe. The benefits include that of soil richness which is beneficial for the agriculture. Also the areas that are characterized by the acacia species as well as a small percentage of the mopane trees are shown to have decreased after each flood event. Negative

changes of the acacia species are aligned with the findings by Basak *et al* (2015) who noted that out of all the tree species that could be affected by floods the most affected species in most areas include the acacia tree species. The changes with these tree species may depend on their adaptation.

These results are showing that floods do have an impact on vegetation. These impacts can be negative or positive. However negative impacts that include total wipe out of vegetation is highly unlikely within the area of study. The most vegetated areas that can be more affected negatively by the floods are the agricultural areas which are the areas that are showing more vulnerability than the others. The vulnerability of agricultural areas to floods has been noted by a number of authors including Armah (2010) who noted that the agriculture remains one of the most vulnerable sectors mostly in Africa when there is flood hazard, this lead to a scare in food security as well as the economy. The mortality of other vegetation species can also be determined by these flood events depending on their intensity and their frequency (O'Connor, 2010).

5.4.2. Vegetation dynamic using change detection techniques

Landsat images were classified to determine the changes in vegetation cover using change detection method.

In both the flood events, the results have clearly indicated that change on vegetation extent and density due to flood events. These results is supported by Banach *et al* (2009) who noted that vegetation development after the floods is mainly determined by the soil quality which in most cases has shown a great decline in the vegetation species. The class classified as light vegetation also show changes to the bare soil class. What the results mean is that, some percentage of what was classified as light vegetation has now changed to bare soil. This means that vegetation in those certain areas has been uprooted, wiped out, or has become dry. Many authors support this theory with their findings. However; these changes in these types of vegetation maybe due to a number of factors including drought as this area can be very dry, as well as the animals more especially the Elephants. O'Connor (2010) noted that the tree species in the Mapungubwe area is being reduced yearly because of the factors such as drought, animals as well as floods. Evidently there is somewhat reduction in tree species density; however flood events are not the only contributing factors in the mortality of the tree species.

This study shows some minor changes in vegetation after floods. However, most of the vegetation in this area has shown a positive change according to the results obtained. An increase in most of the vegetation after floods shows a great deal of species adaptation after these events.

5.5.Vegetation species adaptation to floods

The study classified different types of vegetation species that are common within the Shashe-Limpopo Confluence Area. The study shows us the results on what tree species change after the floods looking at the tree species classification as well as the change detection results from the NDVI as well as the supervised classification.

According to Parolin & Wittmann (2010) the acacia as well as the mopane trees species are said to be less tolerant to flood hazards. However, according to the results obtained from this study acacia trees are shown to be thriving under such hazards. These trees species do show some minor changes but the changes shown by these species are not as great as those explained by the above mention authors. Both the mopane and the acacia appear to be thriving under these flood conditions from the results presented in this study.

The area understudy is subjected to flooding almost every year. The need for these tree species to survive these frequent floods has given rise to a large variety of adaptation within most tree species. Hence the minor changes within the vegetation in this area. The tree species in this area have adapted to the frequent flood events. The agricultural land however, is said to be always vulnerable to these flood events.

Chapter 6

6. Conclusions

The study was conducted in the Shashe-Limpopo Confluence Area in the Mapungubwe area in Limpopo Province. The aim of this study was to determine the impacts of flood events on vegetation distribution. The main questions of the study were to find out if quantifying the extent of the flood was possible as well as to find out if there are any changes within the study area after it has been affected by the flood events. This chapter consists of the conclusions as well as the recommendation for this study. The recommendations are made based on the findings from the results. From the results obtained in this study the following conclusions are drawn:

1. The study demonstrated the usefulness of the water index for mapping the extent of the floods. The main findings with regards to this objective were shown using the before as well as the after floods Landsat satellite imagery. From the results obtained it is concluded that the water index that was used as an attempt to map flood extent had not achieved the objective. The index is only able to detect the open water features.
2. Vegetation plays a vital role in the ecosystem in shaping the landscapes as well as the whole surroundings. Floods as a result of heavy rainfall are bound to have an impact on the vegetation. From the conducted study, it is concluded with evidence from the results that flood events do have an impact on vegetation cover and distribution. It is concluded that although vegetation is not wiped out, there are somewhat negative changes in the vegetation within the study area. Not only are the changes negative but there is also some positive change. Positive change meaning that there is more increase in the vegetation than a decrease. So the study agrees that within the study area, flood events have an impact on vegetation cover. Some vegetation species tend to adapt to the frequent flood events, hence the slight negative changes shown within the vegetation results and more increase. The study also shows a strong relationship between the intensity of the flood events and changes in vegetation cover. This simply means that the stronger the flood event is the more severe the impacts are on the vegetation. The study also emphasises the impacts of vegetation on agricultural crops. The crops are more affected by floods than most other vegetation cover types within

the study area. For each studied flood event, the agricultural crops are shown to be the most affected.

6.1. Recommendation

With regards to the findings, the study recommends the following:

- The study quantified the changes in vegetation with reference to flood events that occurred within the years 2000 as well as 2013. The study shows changes in vegetation looking at one factor which is flood. The study area has animals; it is also prone to drought as it tends to be dry. These are some of the factors that can be considered as contribution to the vegetation changes in this area. Therefore it is recommended that all factors be considered in assessing vegetation cover change within this area. This is to avoid biased results.
- The study showed a few challenges in using the water index where, the results were showing much higher reflectance of non-water features. The techniques that are used to resolve this problem are not detailed in most studies. It is then recommended that the MNDWI pixel mix-up resolving technique be studied in detail to understand how the mix-up comes about and how it can be resolved.

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