Mapping and monitoring of agricultural drought across different land uses and land cover in the North-Eastern KwaZulu Natal

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Abstract

Drought is complex and one of the least understood natural hazards in Southern Africa. Timely information about the extent, the intensity, duration and impacts of the agricultural drought is essential for adaptation and management. In this study, the research aims, are made to monitor and map agricultural drought across different land uses and land cover in north-eastern KwaZulu-Natal as it was declared a disaster area in 2016 (AgriSA, 2016). Droughts occurred throughout South Africa during the summer season of 2014 to 2015 and 2015 to 2016. In this study the adopted methodology was through the use of remote sensing and Geographic Information System (GIS) techniques. Remote sensing and GIS was used to map and monitor the agricultural drought in the study area. To understand the impacts of the drought across different agricultural land use and other land cover types, the land uses and land cover was classified using Landsat earth observation data and maximum likelihood algorithm in the study area, and multi-temporal Normalized Difference Vegetation Index (NDVI) (1997-2017) with a twenty year interval used to map and monitor the agricultural drought and the meteorological (rainfall) in order to validate the NDVIs. Agricultural drought was then determined from investigating changes between 2015 and 2017 which were years that experienced severe conditions. The rainfall data was interpolated using Inverse Distance Weighted (IDW) interpolation to understand the mean rainfall from the weather stations services. Thereafter, Standardized Precipitation Index (SPI) values were determined from the rainfall data in order to understand the severity of the droughts in certain parts of the study area from the weather station data. The meteorological analysis was cross compared with agricultural drought.

The mean NDVI and mean rainfall interpolated shows that their relationship is inversely proportional, because where rainfall is low; NDVI is high for the years 2015 to 2017. The land use and land cover in the study is largely dominated by bush, cultivated cane crop, grassland and plantations. Looking at the overall classification in the year 2015, it is clear that bush land use and land cover was largely dominated in the study area, with other land use and land cover classes which were also part of the year 2015. During the year 2016 the other classes of land use and land cover where also dominating the study area for example grasslands and plantations. In the year 2017 we see cultivated cane crop start to emerge in the study area but land use and land cover is largely dominated by bush land use and land cover. The overall accuracy of the study was 74.2%.

Keywords: Agricultural drought, Land use/land cover, Remote sensing, Landsat 8 OLI/TIRS, Normalized Difference Vegetation Index, Standardized Precipitation Index, Accuracy Assessment.

Preface

The research work described in this dissertation was carried out in the School of Geography, Archaeology and Environmental Studies, University of the Witwatersrand, Johannesburg, from May 2016 to March 2018 under the supervision of Doctor Elhadi Adam (School of Geography, Archaeology and Environmental Studies, University of the Witwatersrand, South Africa).

I would like to declare that the research work reported in this dissertation has never been submitted in any form for any degree or diploma in any tertiary institution. It, therefore, represents my original work. Where use has been made of the work of other authors or organisations it is duly acknowledged within the text or references chapter.

Nondumiso Gwala 1 June 2018

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

Doctor Elhadi Adam Signed: Date:

Declaration 1- Plagiarism

I, Nondumiso Gwala, declare that:

1. The research reported in this dissertation, except where otherwise indicated, and is my original research.
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5. This dissertation does not contain text, graphics, or tables copied and pasted from the internet, unless specifically acknowledged and the source being detailed in the dissertation and the references section.

Dedication

To my beloved father, Charles Mlekeleli Gwala, for your consistent support and raising me up to the woman that I am today. Thank you for spending so much of your time investing in us and making sure we have a decent education background. I thank God for the life he's given you and the chance to share it with you. I will forever and always love you. May your soul rest in peace dad, I miss you.

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CHAPTER 1: INTRODUCTION

1.1 Background

South Africa's economy has remained predominately dependent on agriculture as it is a primary economic driver (AgriSA, 2017). Rain-fed farming systems form an important part of South Africa's agricultural sector. Seasonal rainfall patterns with low and erratic rainfall, variable topography and soil physical characteristics all influence the development of rain-fed farming systems practiced in South Africa (Hardy 2011). Declining farming profitability and water scarcity (drought, declining rainfall or over demand for water) has left South Africa with less than two-thirds of the number of farms it had in the early 1990s (Agricultural Statistics, 2008). In South Africa, rainfall in some provinces has been below normal for the whole of 2014 and 2015 (October 2014-September 2015). The spring season is recorded as the third-driest for South Africa as a whole since the early 1930s, when the country was hit by drought in the midst of the Great Depression (Drought SA, 2017).

Droughts are a major feature of the climate of South Africa (Vuuren, 2015) as it is at the southern tip of Africa between cold and warm sea currents and its unique topography, which creates a variable over space and time (Vuuren, 2015). For such reasons the country is considered to have one of the most variable river flow regimes in the world, and drought is one manifestation of this variability. Drought is one of the major worldwide natural hazards that cause water shortages, which not only increases the vulnerability of the agricultural sector and economic loss but also human life (Department of Agriculture, 2005). Environmental factors such as land or the environment can result in the effect of drought in a different way for example the kind of landscape can affect the way in which drought occurs. As a result when monitoring drought it is important to consider the drought type that has occurred. The use of satellite remote sensing for drought assessment and monitoring can be effective, as satellite covers a large area at high temporal resolutions (e.g. daily) (Park *et al*, 2015).

The results of experiencing an agricultural drought have impacts on land use and land cover in South Africa and also affect crops. The impacts on crop are often on different crop types and agricultural crop, including but are not limited to sugar cane and plantation, respectively. Between different scholars and meteorologists the understanding of drought can be categorized into three types. This research will focus on agricultural drought using meteorological data due to South Africa experiencing a decrease in the agricultural production. For the purposes of this research agricultural drought is defined as a situation when rainfall and soil moisture are inadequate during the crop growing season to support healthy crop growth to maturity, causing crop stress and wilting.

Agricultural drought occurs when the moisture level in soils is insufficient to maintain average crop yields (Disha Experts, 2017). In this research, agricultural drought monitoring through satellite based information will be adopted as a method because of its low cost, synoptic view, repetition of data acquisition and reliability. In addition, remote sensing based indices methods such as Normalized Difference Vegetation Index (NDVI), Standardized Precipitation Index (SPI) and Vegetation Condition Index (VCI) have been accepted globally for identifying agricultural drought in different regions with varying conditions (Nicholson and Farrar, 1994; Kogan, 1995; Seiler *et al*, 2000; Wang *et al*, 2001; Anyamba *et al*, 2001; Ji and Peters, 2003).

The status of crops can be estimated according to the best and worst crop vigour over a particular period in different years that give a more accurate result as compared to NDVI while monitoring drought at a regional scale (Bajgiran *et al*, 2008). Drought stress poses a major threat to trees by possibly causing hydraulic failure. Various remote sensing technologies have been proven useful for mapping health of conifer species such as infrared aerial photography and multispectral satellite imagery. Hyper spectral imagery has an advantage of providing information related to the physiological condition of the vegetation which can be modelled. Even more visual assessment of time series of aerial photographs will record change and dieback in extent of conifer vegetation for select sites.

Field assessment of the crop's condition is usually subjective and prone to observer bias (Boubacar, 2010). This can be emphasized by situations where differences in appearance do not necessarily indicate poor health. There are measures to reduce biasness such as the scale or classification method used. Remote sensed imagery that has cloud cover cannot be used and this poses a major limitation on the study analysis. On the other hand remote sensing can be useful for identifying related stress in drought monitoring.

1.2 Research problem statement

Agricultural drought monitoring has become very important in understanding the land changes within the north-eastern part of KwaZulu-Natal. More than ever researchers (WMO, 1975; Wilhite and Glantz, 1985; White and O'Meagher, 1995; McVicar and Jupp, 1998) have found it difficult to quantify the extent of drought disturbance due to many factors such as the development of the drought; as it is slow and the spread over an area can be undefined as the impact is non-structural; meaning that droughts often do not form part of a given structure.

Furthermore, according to weather reports during the summer of 2015/2016 and 2015/2016, a severe drought affected the Southern African continent (AgriSA, 2016). During this time warm anomalies developed in 2014 in the Pacific Ocean and conditions in austral summer 2014/2015 were nearly El Nino-like and the whole of the strongest El Nino developed in 2015 (AgriSA, 2016). In general, the drought lasted for about two years. Due to crop failure, it has left 2.5 million people in Malawi, Zimbabwe, Mozambique, Madagascar and Lesotho requiring quick humanitarian response while South Africa has a drop of 25% in maize production in the summer of 2014/2015 (AgriSA, 2016).

Agricultural drought monitoring has become very important in understanding the land changes within the north-eastern part of KwaZulu-Natal (KZN). In the study area, the north-eastern part of KZN was affected by a hydrological drought where rivers had dried up, such as the Umfolozi River (AgriSA, 2016). The extent and impact of agricultural drought on farmers and ordinary citizens has had a major effect on their livelihoods.

Biodiversity loss in the world is one of the major drivers towards land cover change. According to Jewitt (2015) using the Intensity Analysis framework for analysis, one of the major drivers and contributors of habitat loss are agriculture, timber plantations, built environments, mines and dams. In KwaZulu-Natal the natural habitat continues to be lost and the associated negative impacts and habitat degradation has been related to land cover threat to the biodiversity. The impact of agricultural drought has been a challenge to natural habitats and degradation of the land causing the drought effect to be difficult to quantify. Land cover maps derived from satellite imagery provide useful tools for monitoring land use and land cover change.

Among the different drought types the agricultural drought is the least quantified, and the most uncertain type (Agricultural Statistics, 2008). This research will monitor and map the drought across different land use/cover in order understand the spatial extent of drought over a specific area. Scientific conclusions about the use of indices can be made to answer whether droughts have had an effect on the land cover/land use in the Northeast KwaZulu-Natal area.

1.3 Objectives of the Study

The aim of this study is to monitor and map agricultural drought across different land uses and land cover in the North-eastern KwaZulu-Natal. Specific objectives of the study area are too:

- Map the land cover and land use using Landsat 8 OLI/TIRS and maximum likelihood algorithm classification.
- To assess agricultural drought conditions across different land use and land cover using Multitemporal Landsat 8 (OLI/TIRS) and different vegetation indices.

1.4 Limitation of the Study

- Satellite data for other years has a lot of cloud cover in the winter months, making it difficult to trace the years before in order to monitor a bigger period for the study.
- North-eastern KwaZulu-Natal weather services stations had data for only a few weather stations and some stations had too much data missing. Data from the four rainfall stations are not enough for proper image interpolation to generate drought severity.

1.5 Outline of the Thesis

This thesis contains five chapters.

- Chapter one outlines the Introduction and highlights the background and objectives of the study.

- Chapter two outlines the Literature Review and covers previous research carried out in the field of drought assessment as well as role of remote sensing and GIS technology in the arena of monitoring of droughts.

- Chapter three outlines the Study area giving a brief overview of the study area and the materials and methods used for the research.

- Chapter four outlines the Results which give a critical observation for agricultural drought indices and their relationships.

- Chapter five outlines the Discussion giving a brief discussion based on the results achieved and the analysis carried out. Recommendations and conclusions are also drawn from this study.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Drought is a term which is difficult to define, according to scholars and researchers (Wilhite *et al*, 1985). Often the term is used to refer to a deficiency in rainfall, soil moisture, vegetation greenness, ecological conditions or socioeconomic conditions; as a result, there are different kinds of droughts that can be referred to (Wilhite *et al*, 1985). In general terms, a drought is essentially a climate phenomenon, a consequence of an abnormal decrease of precipitation (Palmer, 1965). In this study, drought is considered as a period when precipitation is low in regard to long-term average conditions. Even more, a drought is a period of abnormally dry weather, which further results in a change in vegetation cover conditions (Heim, 2002; Tucker and Choudhury, 1987).

The frequency and intensity of drought has increased over the last three decades (Humle and Kelly, 1993; McCarthy *et al.,* 2001), and there has been a trend of drying in many parts of the world which have been suffering from an elevated water crisis (Dai *et al*, 2004; Ghulam *et al*, 2008). According to Bates (2008) the proportion of land surface in extreme drought is projected to increase in the future, particularly in continental interiors during summer months. The results of this trend if it were to continue as projected by climate change scenarios would be catastrophic.

In the present context of climate change and increasing land degradation and desertification (Mabbutt, 1985; Le Houerou, 1996; Geist and Lambin, 2004), say being able to calculate the impact of a drought is crucial in determining the environmental consequences of a hypothetical change in climatic conditions. Due to the interest over the years in climate change, scientists have had interest in detecting drought onsets and ends, assessing its impact on agriculture, the environment and the economy and finding the connection between climate change and spatial-temporal dynamics using satellite-derived information.

The use of remote sensing data presents a number of advantages when determining drought impact on vegetation. Remotely sensed data can cover the whole of a territory and repetition of images can provide multi-temporal measurements (Kogan, 2001). Vegetation indexes gathered from satellite data can also allow areas affected by droughts to be identified, according to researchers, (Kogan 1995 and 1998); (McVicar and Jupp, 1998). Aerial and satellite photographs enable the analysis of an entire landscape and, using multi-temporal sets of photographs, enables processes to be followed over time (Russell *et al*, 2014). In order to monitor the drought assessment through the use of remote sensing effectively products such as Land Surface Temperature (LST), Normalized Difference Vegetation Index (NDVI), and evapotranspiration (ET), are possible to monitor drought using not only in situ measurements at weather stations but also satellite-based drought factors (Anderson *et al*, 2011).

Drawing out a single factor that will fully explain the complexity and diversity of drought is difficult, because drought is caused by a multitude of factors. Blending various indices is thus useful to monitor drought (Hayes *et al*, 2005; Mizzell, 2008; Wardlow *et al*, 2012). This blending approach started in the 1990s (Heim, 2002) and many blended hybrid indices have been developed, for example, some drought indices use not only satellite data, but also climate, biophysical and oceanic data more accurately to monitor drought.

2.2 Drought impacts

The impact of drought can be understood either directly or indirectly, because of its varying impact, for example a loss of yield resulting from drought is a direct or first-order impact of drought. When we have the consequences of the impact (for example, loss of income, farm foreclosures and government relief programmes), then it is considered as secondary or even tertiary.

Inter-annual climate variability over South Africa has been well studied (Preston *et al*, 1988; Preston-Whyte *et al*, 1991; D' Abreton *et al*, 1996), but there is less documentation on climate variability specific to KwaZulu-Natal (Dube *et al*, 2000). In KwaZulu-Natal the period from 1993 to the end of 1995 has exceptionally high positive temperatures relative to the whole period from 1960 to 1995 (Dube *et al*, 2000). Rainfall departures show increasing variability, this shows that the period of 1992 and93 had one of the worst droughts. The impacts of this drought in 1992 and93 shows there is still insufficiency in understanding the characteristic and impact assessment.

In a more recent study for KwaZulu-Natal (Thomas *et al*, 2007) account for the Region 11 in northwest KwaZulu-Natal where recent historical mean rainfall of 800 to 900 millimetres (mm) pa range was recorded. There seems to be an increase in inter-annual variability in the rainfall and higher rainfall in the first half of the growing season (Thomas *et al*, 2007). There is an increase in early seasons of rainy days and a decline in late season (February and March) rains (Thomas *et al*, 2007). Variability in the rain grew in 1990 and 1994, while in 1991 rains commenced in September, but was subsequently limited until January 1992.

The KwaZulu-Natal province faced acute water problems and agricultural loss from the drought in 1992 to93 (Dube, 2002). According to Dube (2002) the complexity of dealing with drought as a threat is compounded by rapid population growth and urbanisation. Furthermore, it is estimated that the normal cycle of droughts will cause water demand in South Africa. In KwaZulu-Natal there is a three to five year cycle and this shows that the frequency and intensity of drought has increased and is intensifying, seen over the last three decades (Dube, 2002).

For the purposes of this research it is important to understand the whole concept of droughts, but it is just as relevant to define both meteorological and agricultural drought in order to assess the impacts of agricultural droughts in the study area. According to Masih *et al*, (2014) meteorological and agricultural droughts remain the main studies. This literature review will then seek to explain both meteorological and agricultural drought as the two are important for the purposes of understanding droughts and the methodology adopted for this research.

2.3 Meteorological drought

According to Wilhite *et al*, (1985) droughts are classified in four distinctive types; meteorological, agricultural, socioeconomic and hydrological. Meteorological drought is stated on the basis of the degree of dryness in comparison to some normal or average amount and the duration of the dry period (NDMC, 2008). This means the main characteristics for a meteorological drought are intensity and duration.

The occurrence of meteorological droughts occurs when the annual precipitation is between 70% and 85% of long-term annual precipitation. At a national level, meteorological drought is said to occur when the annual rainfall is below 75% of the long term mean (Wilhite *et al*, 1985). Long term means a period that exceeds 30 years. A meteorological drought is constituted by a deficit in runoff of rivers, surface reservoirs and ground water (as a result of rainfall).
The occurrence of a meteorological drought can be viewed as the below normal precipitation amount during an extended period of time (months, years, etc.) over a region. The lack of precipitation is the main cause of meteorological drought. The drought is often measures at 3, 6 and 12 months scales (Palmer, 1965). According to researchers, between late 2014 and June 2016, South Africa experienced

the worst meteorological drought in the Southern African region in 35 years (BBC 2015, SAWS 2016a, and WFP 2016) specifically during the period October 2015 to January 2016 (WFP 2016). It also followed the driest season in the last 80 years (Stoddard 2015). In the South African Weather Services meteorological drought is better understood as the basis of the degree in comparison to normal or average amounts of rainfall for a particular area or place and the duration of the dry period (SAWS, 2016b). The recent meteorological droughts in South Africa occurred as a result of the El Niño which caused a lack of rain (BBC, 2015) (Stoddard, 2015), and climate change causing abnormally high temperatures in South Africa (Mojapelo, 2016).

In order to calculate various indexes using meteorological data, the data is used to quantify droughts (Heim, 2002). The commonly used index to determine the drought index calculation is the Standardized Precipitation Index (SPI) because it can be calculated at different time scales, resulting in the ability to understand water deficits of different duration (McKee *et al*., 1993). The SPI is computed by fitting a probability density function to the frequency distribution of precipitation summed over the time scale of interest (Costa, 2011). This index is easier to use than other indexes such as Palmer Drought Severity Index (PDSI; Palmer, 1965), because the SPI requires only precipitation data, whereas the PDSI uses several parameters (Soulé, 1992). Even more the PDSI has some shortcomings in spatial and temporal comparisons (Alley, 1984 & Karl, 1986). The SPI is more preferred as it is comparable in both time and space, and is not affected by geographical or topographical differences (Lana et al, 2001).

Meteorological drought that is prolonged leads to a decrease of soil moisture content that triggers agricultural drought. Meteorological droughts are useful for indicating potential water crisis if the condition is prolonged. Meteorological drought can begin and end immediately. There is no uniform method to characterize drought conditions and there are a variety of drought indices that can be used as tools to monitor meteorological drought (Quiring, 2009).Oftentimes the calculation for input variables for the meteorological drought indices vary depending on the drought index in question, but include precipitation, temperature or available water holding capacity of the soil.

2.4 Agricultural drought

Agricultural drought can be understood through both characteristics of meteorological and hydrological drought that has an impact on agriculture (Wilhite, 2000). This essentially means that the effects of agricultural drought can be understood as the effect of not having enough water available for a particular crop to grow at a particular time. For the purposes of this research, agricultural drought is nothing, but the decline in the productivity of crops due to irregularities in the rainfall as well as a decrease in the soil moisture, which in turn affects the economy of the nation.

As a result of the severe productivity of rain-fed crop and indirect effect on employment as well as per capita income, agricultural drought has become a prime concern worldwide. Agricultural drought is mainly dependent on low rainfall which results in agricultural production (Choudhary *et al*, 2013). Agricultural drought produces a complex web of impacts that span many economic sectors. Agriculture is the primary economic sector affected by agricultural drought. The risks associated with agricultural drought are spatially variable; hence there is an important need to adopt adaption strategies and options for drought monitoring.

The agricultural sector is most affected by the onset of drought as it is highly reliable on the weather, climate, soil, moisture and many more (Sruthi et al, 2015). When crops decline in a certain region and cause irregularities from rainfall patterns, then agriculture monitoring becomes important. The role of remote sensing and GIS in agricultural drought detection, assessment and management is becoming crucial as it provides up to date information in different range of spatial and temporal scales which is time consuming when done by traditional methods such as Field Survey and sampling questionnaires.

Although precipitation deficiencies are important, agricultural drought severity is usually more closely associated with deficiencies in soil moisture. The areas which are affected by drought evolve gradually as the symptoms of moisture stress in plants often develop slowly. Soil moisture condition is an important indicator for evaluating drought reflects recent precipitation and indicated agricultural potential and available water storage (Boken, 2005). Soil moisture conditions are very important in agriculture because they are used directly to assess the irrigation needs for a variety of crops.

Growing crops need continuous supplies of soil water to ensure harvest. Rainfall and irrigation are the main sources of soil water in agricultural fields. When the soil water supply is sufficient for growing crops, evapotranspiration from agricultural fields is high, which leads to the observation of low surface temperature in satellite remote sensing images (Cunha *et al*, 2015). In South Africa, recurring drought conditions have always been an endemic feature of climate, affecting all sectors of society, with agriculture being the first sector to feel the effect as it primarily depends on precipitation for crop growth and production (Vogel *et al*,2000; Wolli, 2010). Although agricultural drought may occur when there is a deficiency in soil, agricultural drought does not only depend on the amount of precipitation received but also the timing and duration of the drought (Fraisse *et al*, 2011).

2.5 Field-based methods for mapping and monitoring drought

The traditional collection of field data currently available is generally difficult to use for predicting regional or global changes, because of the way it is collected at small spatial and temporal scales and vary in their type and reliability. A study by Yongdeng *et al* (2016) conducted a field survey to examine a changing climate and recurrent drought through in-depth interviews from questionnaires. All the input and output data was obtained through field surveys and was mutually compared and verified to avoid individual error.

In a study for drought assessment for agricultural and meteorological analysis using remote sensing and GIS, field work was done before going to field for the study of agricultural drought stress on crop performance (Murad, 2010). During this field collection basic information was collected that was related to the literature, searching for drought stress and its impact on agricultural crops and the advancements in satellite based indices for monitoring drought.

A probabilistic approach to assess agricultural drought risk using field data is time consuming and costly. The traditional field based method of mapping and characterizing drought areas has a number of challenges. In regards to the collection of ground data on agricultural changes in a certain area the task becomes difficult, because of the spatial coverage and the diversity of farming system within its boundaries (Lambin *et al*, 1993). Weather conditions are limiting factors in regards to estimating production because some harvest needs certain conditions in order to grow. The ground data is time-consuming and expensive in its nature because of frequent field trips and airborne surveys (ESRIN, 2004).

2.6 Remote sensing techniques for mapping and monitoring drought

The use of the field based data collection is not the same as satellite sensors as it provides direct spatial information on vegetation stress caused by drought conditions and the information is used to assess the spatial extent of drought situation. Satellite remote sensing technology is widely used for monitoring crops and agricultural drought assessment (Roy et al, 2010). The use of remote sensing in mapping and monitoring agricultural drought can be understood from the context of understanding vegetation abundance and develop information that is related to rainfall in order to assess the drought. In order to understand the capability of agricultural drought conditions using visible, near infrared and microwave, satellite data has been used by researchers with the aim to map and monitor drought activities. Perry and Lautenschlager (1984) provide an extensive review on vegetation indices based on Landsat and NOAA satellite data which includes (but is not limited to) Difference Vegetation Index (DVI), Greenness Vegetation Index (GVI) and Normalized Difference Vegetation Index (NDVI).

The significance of NDVI, according to NRSA, (1991) and Sesha Sai *et al*, (2004), is that in order to avoid problems of non-availability of cloud free optical; data, time composite NDVI over an aggregated period of a fortnight or a month should be generated to cover the entire crop growth to assess agricultural drought. The variations on the progression of NDVI, in terms of the magnitude and rate of progression, in relation to its respective normal NDVI provide information about the prevailing status of vegetation (Roy *et al*, 2010).

Satellite remote techniques are operationally being used to provide intra-seasonal and inter-seasonal information on the spatial distribution of crop distribution at different levels. Analysis of satellite data for crops with the information on other natural resources provides ways for agricultural sustainability, for environmentalists, especially with the use of remote sensing. Unlike point observations of ground data, satellite sensors provide direct spatial information on vegetation stress caused by drought conditions and the information is used to assess the spatial extent of drought situations (Roy *et al*, 2010).

In understanding remote sensing techniques of mapping drought monitoring, remote sensing models and indices have been developed and used in the interpretation of agricultural drought. For example a study was conducted by, (Wu *et al*, 2004) to develop an agricultural drought risk assessment model using multivariate techniques. The model was specific to corn and soybeans where detection was to assess real-time agricultural risk associated with crop yield losses. The results show that the model is suitable in providing information on agricultural drought risks. Vicente- Serrano (2007) evaluated the impact of drought using remote sensing in a Mediterranean semi-arid region. The study determines spatial differences in the effects of drought on the natural vegetation and agricultural crops by means of joint use of vegetation indexes derived from Advanced Very High Resolution Radiometer (AVHRR) images. The results show that the effects of drought on vegetation vary noticeably between areas, a pattern that is determined mainly by the location of land-cover types.

In general, it can be understood as firstly thermal remote sensing methods, secondly microwave remote sensing methods and lastly combined remote sensing methods for agricultural drought monitoring and its applications. It is important to also understand that the remote sensing based methods depend on different factors, including but are not limited to satellite data availability, cost, data quality, pre-processing and post-processing requirements.

2.6.1 Optical remote sensing methods for agricultural applications

A study done by Dalezios *et al*, 2012 on the assessment of remotely sensed drought features in vulnerable agriculture uses optical remote sensing data that are in the range 0.4 and 2.5 μm to add inputs to the agricultural drought indices. In this spectral range, red, near infrared (NIR) and shortwave infrared (SWIR) are the most commonly used bands, due to their obvious response to agricultural drought conditions through vegetation greenness and vegetation wetness conditions. In instances where there is vegetation greenness, healthy vegetation is often greener and tends to absorb most of the incident visible light (e.g. red spectrum) and reflects a significant amount in the NIR spectrum (Dalezios *et al*, 2012).

In understanding optical remote sensing-based agricultural drought indices there are three groups, according to their purposes, which it can be divided into. Group one is the soil drought monitoring indices, group two is the vegetation drought monitoring indices and the third group is the soil and vegetation drought indices (Hazaymeh *et al*, 2016). According to Farooq *et al*, (2009) vegetation could resist drought conditions by utilizing different reactions in their leaves and roots. The cause of this might affect or delay the identification of agricultural drought conditions, especially over more densely vegetated areas and cause uncertainties in the results of the indices. In another study, vegetation indices were found to be more applicable over moderate to densely vegetated areas than sparsely vegetated areas. This was because soil background reflectance might affect the calculations and cause uncertainties in monitoring drought (Ghulam *et al*, 2008).

In general, semi-arid areas are described as sparsely vegetated areas which then mean that neither vegetation drought indices nor soil drought indices can solely provide accurate monitoring of drought in these regions (Hillerislambers *et al*, 2001). Other solutions to this problem could be performing land cover classification and assigning a suitable index for each class or applying different drought indices at different plant growing stages (Wang *et al*, 2010). Scientists and researchers developed solutions to such problems by monitoring agricultural drought for both soil and vegetation at the same time such as, shortwave infrared water stress index (SIWSI), normalized multiband drought index (NMDI) and the visible and short-wave drought index (VSDI) (Fensholt *et al*, 2003; Wang *et al*, 2007 and Zhang *et al*, 2013). These indices do not only provide mapping vegetation and soils on a pixel basis, but they also provide qualitative and quantitative measurements of their conditions (i.e.

greenness and wetness) within a pixel (Hazaymeh *et al*, 2016). Table 1 shows the most commonly used optical remote sensing agricultural drought indices.

Table 1: Commonly used optical remote sensing agricultural drought indices

<table>
<tr><th>Type</th><th>Index</th><th>Expression</th><th>Pros</th><th>Cons</th></tr>
<tr><td>Soil drought index</td><td>Perpendicular Drought Index</td><td>$PDI = 1 + \frac{1}{\sqrt{M^2}} + (p_R + M * p_{NIR})$</td><td>Simple and effective in calculating drought conditions</td><td>Unable to provide high accuracy over variable land cover types especially bare soils and densely vegetated fields.</td></tr>
<tr><td>Vegetation drought index</td><td>Normalized Difference Vegetation Index (NDVI)</td><td>$NDVI = \frac{p_{NIR} - p_x}{p_{NIR} + p_x}$</td><td>Provides a measure of vegetation health or greenness conditions</td><td>Sensitive to darker and wet soil conditions.</td></tr>
<tr><td rowspan="6">Vegetation drought index</td><td>Moisture Stress Index</td><td>$MSI = \frac{p_{SWIR_2}}{p_{NIR}}$</td><td rowspan="2">More sensitive at canopy level rather than leaf level</td><td rowspan="2">Applicable for densely vegetated areas.</td></tr>
<tr><td>Simple Ratio Water Index</td><td>$MSI = \frac{p_{NIR}}{p_{SWIR2}}$</td></tr>
<tr><td>Normalized Difference Water Index ($NDWI_1$)</td><td>$NDWI = \frac{p_{NIR} - p_{SWIR_1}}{p_{NIR} + p_{SWIR}}$</td><td rowspan="3">Effective in monitoring, vegetation water content</td><td rowspan="3">Uncertainties increased considerably in the presence of soil and sparsely vegetated or bare surfaces.</td></tr>
<tr><td>Normalized Difference Infrared Index (NDII)</td><td>$NDDI = \frac{p_{NIR} - p_{SWIR_2}}{p_{NIR} + p_{SWIR}}$</td></tr>
<tr><td>Land Surface Water Index (LSWI)</td><td>$LSWI = \frac{p_{NIR} - p_{SWIR_1}}{p_{NIR} + p_{SWIR}}$</td></tr>
<tr><td>Vegetation Condition Index (VCI)</td><td>$VCI = \frac{NDVIi - NDVImax}{NDVImax - NDVImin}$</td><td>Provides vegetation greenness conditions</td><td>Requires data over a longer time period.</td></tr>
</table>

Soil and vegetation drought index	Modified Perpendicular Drought Index (MPDI)	$MPDI = \frac{1}{1-fx}$ (PDI- fx * PDI_x)	Applicable over variable topography, soil types and ecosystems	Assumption of fixed soil line; however it is highly dependent on the soil type, level of fertilization and soil moisture.

(*Hazaymehet al, 2016)*

A study by Tang *el al*, 2014 on the application of thermal remote sensing in agriculture, drought monitoring and thermal anomaly detection, uses thermal inertia which is a measurement that describes the resistance of the materials (e.g. soil and vegetation) to temperature variations; it depends on the bulk density, thermal conductivity and heat capacity of the materials. It has a proportional relationship with water content levels, therefore if water content decreases, thermal inertia decreases as well. This means it can be used as an indicator of agricultural drought. The study also recognizes that since different materials have different thermal inertia, and bulk density, thermal conductivity, and heat capacity cannot be derived from remote sensing data, mapping thermal inertia was inapplicable through remote sensing (Tang *et al*, 2014).

A different method was suggested where thermal inertia could be derived from remote sensing data by measuring the surface albedo and the diurnal temperature range (Claps *et al*, 2004 and Verstraeten *et al*, 2006). However, the application of this method was found to be restricted to arid regions with bare land or very sparse vegetation areas (Van doninck *et al*, 2011). Even more so, another method known as Ts-based method has employed the surface temperature retrieved from remote sensing systems in measuring agricultural drought over different spatial scales. This Ts-based method was found to be a better indicator over sparse canopies or bare lands than vegetated lands (Hazaymeh *et al*, 2016). With this method, its results show that the accuracy of detecting drought conditions depends on the accuracy of retrieving surface temperature from remote sensing data and the heterogeneity of the earth surfaces which increase the uncertainty of these methods to detect drought (Moran, 2004).

2.6.2 Microwave remote sensing methods for agricultural applications

Microwave remote sensing provides useful information of water content through detecting the change in the dielectric constants between water, soil and vegetation (Wang *et al*, 2009). A study, which mapped daily evapotranspiration at field to continental scales using geostationary, and polar orbiting satellite imagery, shows that passive and active microwave remote sensing based models/indices show satisfactory results for the water content estimation and agricultural drought studies (Moran, 2004 & Anderson *et al*, 2011).

Passive microwave has a solid physical basis for water content retrieval and high temporal resolution, it has different major challenges including spatial resolution (i.e. 10-20kilometres), the available wavelength does not provide adequate water content sensitivity over different levels of vegetation covers, and technical and engineering challenges (Hazaymeh *et al*, 2016). There are various monitoring indices which can be used for microwave remote sensing-based agriculture.

Although, active microwave sensors have the capability to provide higher spatial resolution (i.e. ~tens of metres), they have poor temporal resolution (i.e., ~one month).

2.6.3 Combined remote sensing-based methods for agricultural drought applications

As researchers have investigated and discovered many researches in order to understand agricultural drought, there have been many methods which have been adopted to include different remote sensing indices that have different capabilities for monitoring and detection (Hao, 2013). In the uses of the optical remote sensing domain, indices have been combined into one index since they showed different sensitivity to drought conditions even when applied to the same location. According to Gu *et al*, (2007) the Normalized Difference Drought Index (NDDI) and Normalized Moisture Index (NMI) have been calculated as the same function Normalized Difference Water Index (NDWI) and Normalized Difference Vegetation Index (NDVI).

Combined methods such as thermal and optical remote sensing have been done based on the indices. In a practical example combinations have occurred between Ts and VIs and have been presented as such two approaches (Hazaymeh *et al*, 2016). The first approach is the mathematical approach where Ts and Vis have been incorporated into mathematical operations, such as Vegetation Health Index (VHI) which is a combination of the VCI and TCI to determine overall vegetation health status and to detect drought affected areas in agricultural dominant regions.

The combination of various drought indices from different data sources provides a more comprehensive assessment of drought conditions than the use of one single index (Sun *et al*, 2012). The implementation of combined methods has been challenging due to the lack of systematic methods for combining, implementing and also evaluating this phenomenon. Remote sensed based indices are unable to discriminate vegetation stress caused by sources other than drought (Sun *et al*, 2012). This means the combination of various Indies may offer a better understanding and better monitoring of drought conditions.

3. The use of Landsat data for drought mapping and monitoring

The use of Landsat in understanding drought monitoring offers potential for generating detailed vegetation classification in order to understand the effects of drought in specific classes (for example, moderate, severe and extreme rough classification) even though the dataset offers lower temporal resolutions (Soler *et al,* 2016). There are multiple forms of freely available remotely sensed imagery that is suitable for drought analysis, for example Landsat, MODIS and ASTER imagery, as it provides a wide range of resolutions and spectral channels (Cia *et al*, 2011). Such remote sensed data can be applied to land use assessment or enable the analysis of temperature, through specific indexes (Doi, 2002).

A study conducted by Tran *et al*, (2017) for monitoring drought vulnerability used both MODIS and Landsat data in a relatively small study area. The Landsat data shows many advantages in monitoring drought at the local and national scales compared to MODIS. This is because Landsat showed higher accuracy in the results to a smaller area where the study assessed the performance in characterizing drought severity and monitoring stress on crops. Even more so the Landsat data allowed not only assessment of areas at a severe drought level, but also assessment of drought patterns monitored with identification of specific locations (Tran *et al*, 2017).

Another study assessing drought monitoring using Landsat 8 showed results that Landsat 8OLI and TIRS data performed well in retrieving soil moisture results (Guohua *et al*, 2016).

Nithya *et al*, (2014) used Landsat for early detection of agricultural vulnerability and the study showed the use of this methodology should be adopted for remote sensed based vulnerability assessment studies. Drought mapping in the Central Highland of Vietnam used Landsat imagery generated drought related indices such as NDVI, NDWI to provide an assessment for drought monitoring (Nguyen, 2016). This study presented that Landsat helped to better understand drought in the Central Highland of Vietnam and was extremely useful for detecting drought impacted areas and additional drought causing factors such as local land-use land-cover changes (Nguyen, 2016). The limitation with Landsat is its spatial and temporal resolution is a limitation in certain areas and/or applications. For example, in some areas of West Africa Landsat spatial resolution has been limited in capturing the small agricultural plots. Its temporal resolution, coupled with excessive cloud cover has largely prevented mapping the spatial distribution of different crops in these African environments (Forkuor, 2017). Image fusion approaches can however be used to overcome the spatial and temporal resolution limitations of Landsat.

CHAPTER 3: METHODOLOGY

This chapter presents the study area and the research methodology. The first part briefly describes the study area, by focusing mainly on the location of the study area, the geology, climatic conditions and the fauna and flora. The fauna and flora are presented in limited details, principally due to constraints of using non peer-reviewed documentations. The second part provides detailed descriptions of the methods adopted in the study. In this chapter, the reference data and remotely-sensed data was described first. This will be followed by analysis of data. The chapter concludes with the data analysis performed for the study for satellite imagery.

3.1 Study Area

3.1.1 Location

The study area is conducted in uMkhanyakude District Municipality (DM) between Latitudes (28° 7'34.49"S, 26°51'32.05"S) (31°49'29.84"E, 32°52'48.65"E) (in KwaZulu-Natal (KZN) Province of South Africa (Figure 1). UMkhanyakude DM is a Category C municipality located along the coast in the far north of KZN Province. It shares its borders with Swaziland and Mozambique, as well as with the districts of Zululand and King Cetshwayo. It is the second-largest district in the province. ‘UMkhanyakude’ refers to the Acacia Xanthephloea fever tree and means ‘that shows light from afar’. The name reflects both the uniqueness of its people and their hospitality, as well as the biodiversity and conservation history that the region is proud of (StatsSA, 2011).

The district extends from Mtubatuba (St Lucia) in the South to Kosi Bay in the North, across to the Lubombo Mountains in the west. The district is strategically linked to the provincial markets of KZN and Mpumalanga and to the neighbouring market of Swaziland, via the N2 route. The district is largely rural; Mtubatuba is in the south being the only substantial town. The population is exceptionally young, with 70% being below 18 years of age. The key drivers of the local economy are agriculture, services, tourism and retail.

The proportion of this rural district is under a thicket, grassland and wetland, while the remaining areas are cultivated land settlement. Large areas of land are under communal tenure, located in the traditional authority areas. The remaining areas are under state conservation or private ownership with limited urban area.

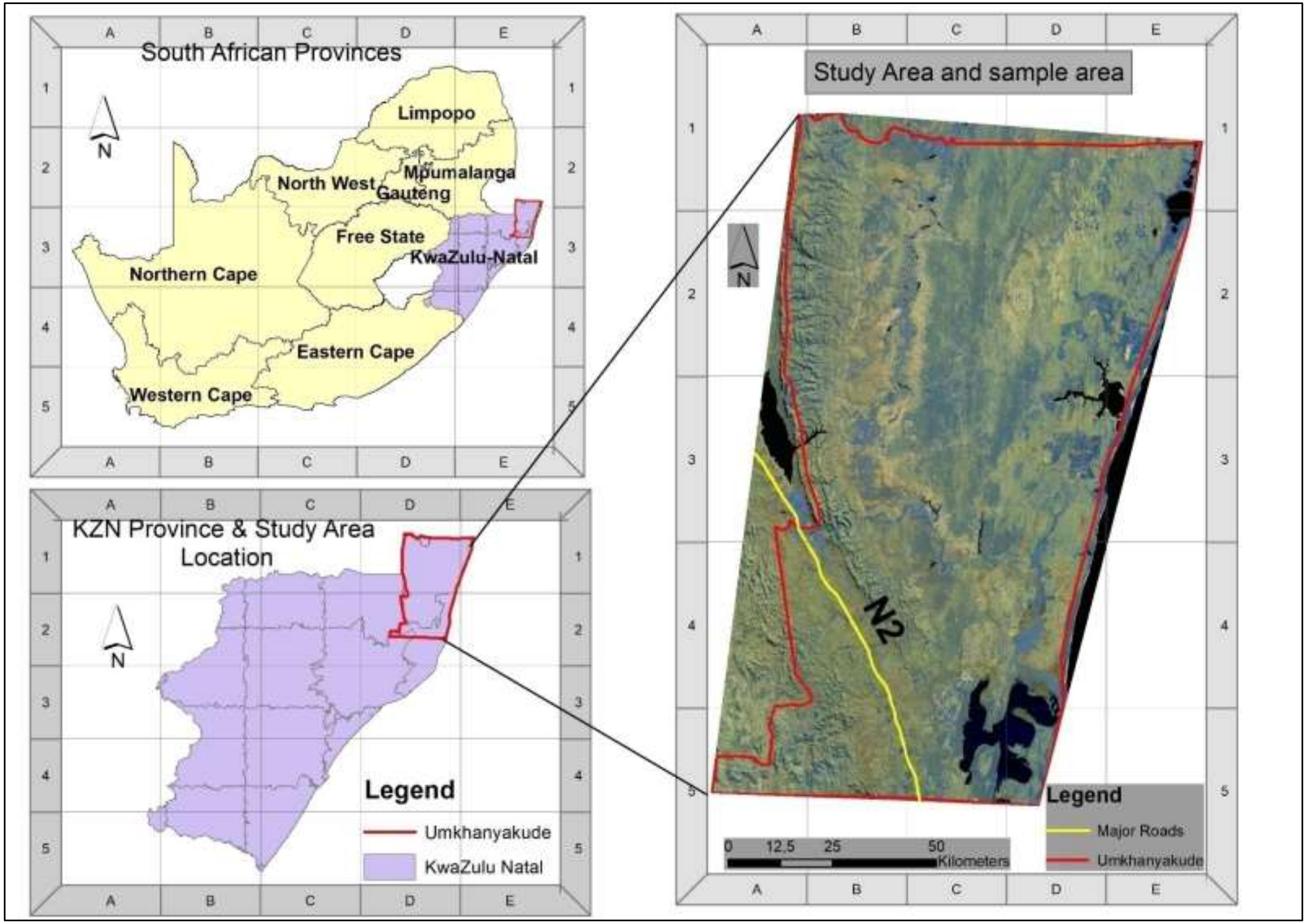


Figure 1: Study area map showing sampled sites

3.1.2 Livelihoods

Agriculture is the principal economic activity in the municipality and the source of livelihood for the majority of households (Municipality, Mtubatuba Local, 2017). The farming in the municipality is largely subsistence farming where the main crops are for large commercial farming. Subsistence agriculture is practiced throughout the region, but is concentrated mostly along the Pongola floodplain and in and around the coastal lake wetland systems.

The Integrated Development Plan (2008/9:37) states that the district has been experiencing severe drought until March 2104. The district contributed R4.9 million to the drought relief programme. According to Integrated Development Plan-UMkhanyakude (2008/9:38) over the last five years drought has become a serious problem such that water resources have dropped drastically. Predictions are the situation will become even worse in the next coming years, probably until at least 2009.

3.1.3 Climate

The area is characterized with coastal areas and the inland areas. Overall climatic conditions are described from inland towards the coast (Nucina *et al*, 2006). The inland areas experience summer rainfall with very little rain in winter. The climate gives natural resources whose comparative advantages are mean annual rainfall decreases from an average of 1200-1400 millimetres along the coastal region with an average of 650 millimeters inland. Similarly, mean annual temperatures decrease varies from 21 degrees Celsius along the coast to 18 degrees Celsius inland (Municipality, uMkhanyakude District Municipality, 2009).

UMkhanyakude has one of the best climatic conditions in KwaZulu-Natal and South Africa. This includes the best sunshine and weather conditions for good agricultural activity. It is one of the few areas that can grow crops all year round (Municipality, uMkhanyakude District Municipality, 2009). The climate observed within the study area, is expected to vary substantially between the coastal areas and the inland areas. Overall climatic conditions are described starting from inland towards the coast (Mucina & Rutherford, 2006). The inland Lebombo Bushveld and Zululand Sourveld areas experience summer rainfall with little rain in winter. The central part of the study area experiences summer rainfall with some rain in winter of approximately 550-800 millimetres.

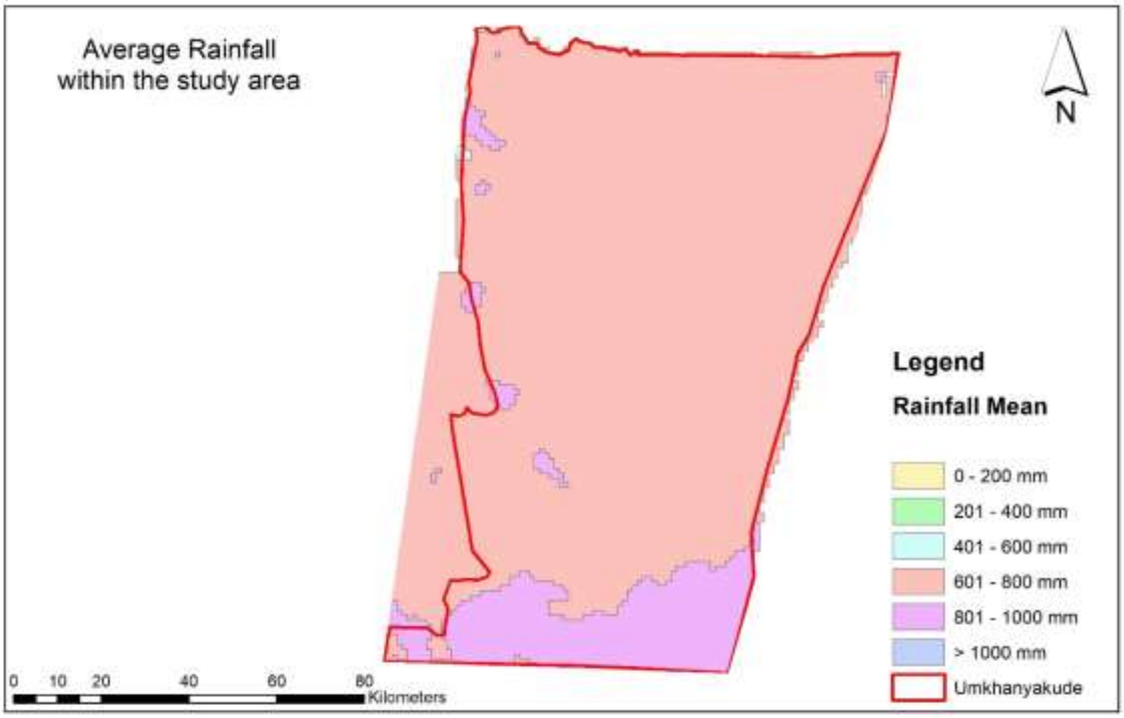


Figure 2: Average rainfall in uMkhanyakude District Municipality

3.1.4 Geology and soil

The North-eastern KwaZulu-Natal geology is underlain by Mesozoic and Cenozoic sediments (Meyer *et al*, 2001). The Cretaceous age deposits of the Zululand Group comprise of the Makhathini, Mzinene and St Lucia Formations from bottom to top, respectively, are the lower most layers underlying the northern KwaZulu-Natal (Meyer *et al*, 2001). The Zululand Group sediments are overlain by the

Maputaland group sediments, these sediments are mostly infertile, windblown distributed sands (Meyer *et al*, 2001). Within the study area the geology comprises of stratigraphic units which comprises of Tertiary and Quaternary periods, and other units consisting of rock from the Cretaceous period, towards the study area. The variation in geology within the study area has a definite effect on the vegetation types found within the study area.

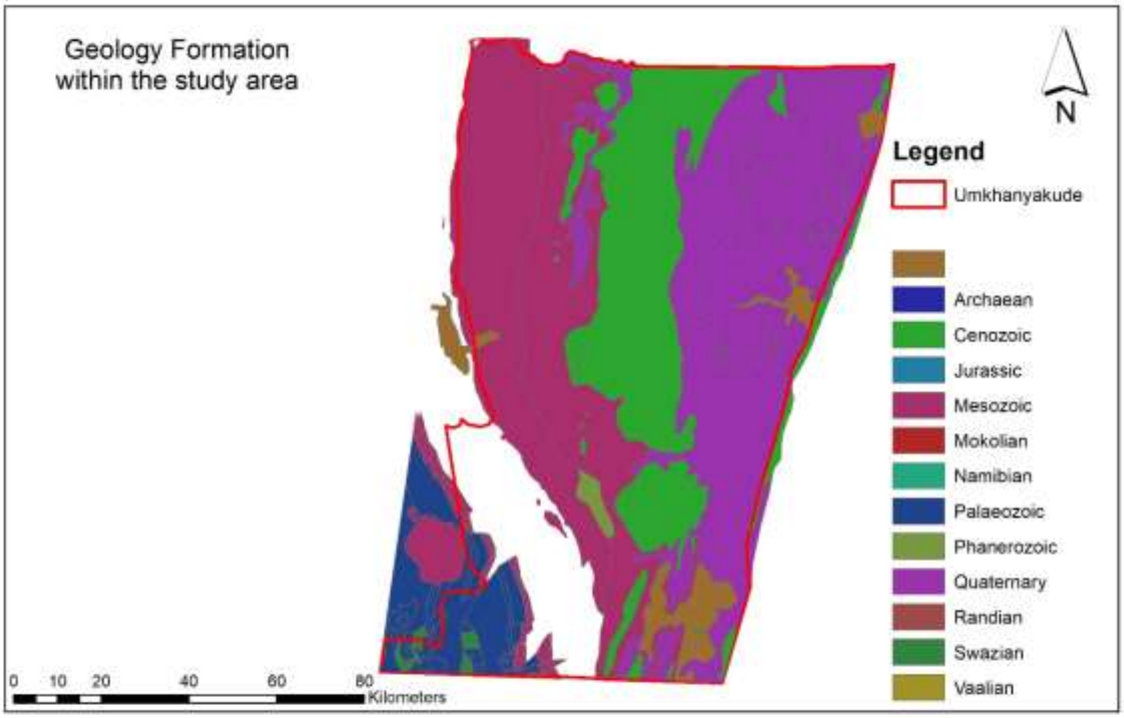


Figure 3: Geology formation within the study area

3.1.5 Fauna and Flora

Maputaland covers a large area, with many different habitats; as a result there is a range of mammal species that inhabit the area. There are a few species that are found in the protected areas of the region, while others are ubiquitous (Rowe, 1992). In addition, there are large mammal fauna within the area where preserved sand and swamp forest, wooded grassland and wetland patches will host higher small mammal, bird and invertebrate diversity (Rowe, 1992).

The Maputaland is recognized for its diverse, complex mosaic of forest types, bushland, thicket, wooded grassland and edaphic grassland (Municipality, uMkhanyakude District Municipality, 2009). There are six biomes in which the area comprises of thus being Azonal Forest, Forest, Indian Ocean Coast Belt, Savanna, Grassland and Wetlands Biomes and contains 15 vegetation types with varying degrees of disturbance and statutory protection (Municipality, uMkhanyakude District Municipality, 2009).

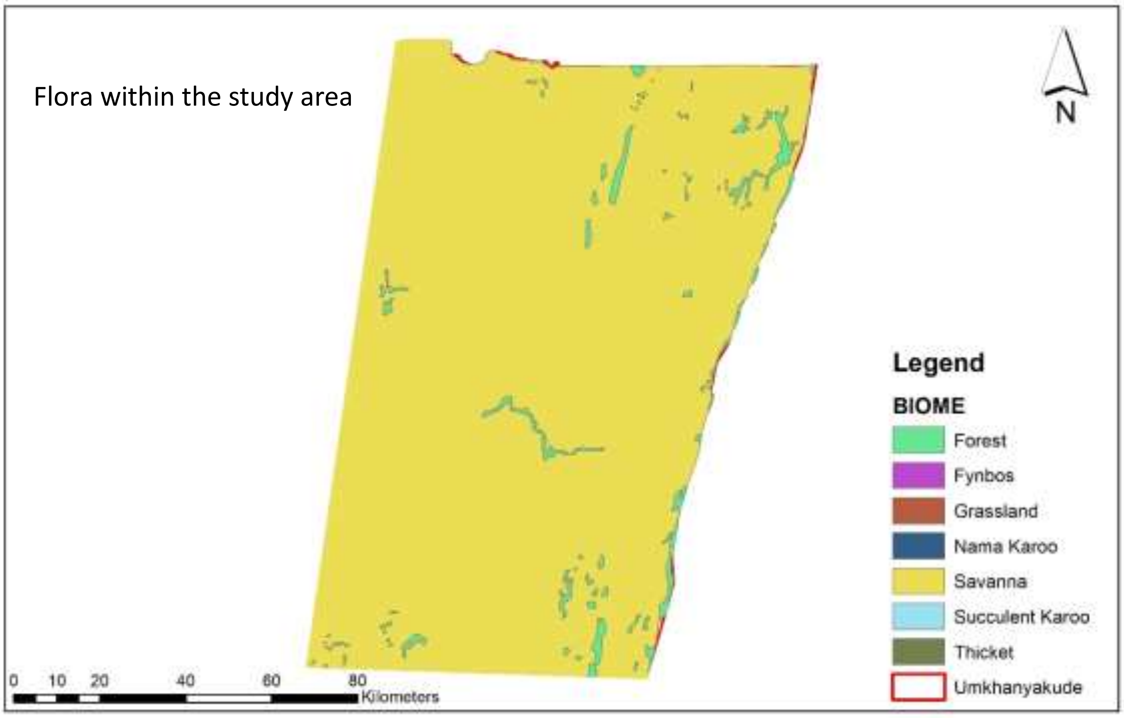


Figure 4: Flora (Biome) within the study area

3.2 Data and Methods

3.2.1 Remotely Sensed Data

3.2.2.1 Landsat 8 data acquisition

For the purposes of this study, Landsat images were used. Landsat 8 OLI/TIRS data were acquired for the purposes of this study. Five separate cloud free Landsat OLI/TIRS both summer (December to February) and winter (June to August) were acquired freely from the United States Geological Survey (USGS) (http://earthexplorer.usgs.gov/). To minimize chances of cloud coverage, cloud-free satellite images were selected. The use of these images is suitable for the calculation of indices. This study used climatic data to correlate the changes from the indices and what rainfall coverage has occurred over the years 2015 to 2017 (three year interval).

Landsat data was used for this study because it is freely available. In addition, Landsat is able to map vegetation because of the highly accurate land cover characteristics that it can discriminate. It has a refined spectral range for certain bands which is critical for improving the vegetation spectral responses across the near-infrared (Pahlevan and Schott, 2013; El-Askary *et al*, 2014). Landsat 8 sensor was launched on the 11th of February 2013 by the National Aeronautics and Space Administration and the United States Geological Survey (NASA–USGS) (NASA, 2015). It carries a two-sensor payload, the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), which are described in detail in Irons *et al*, (2012). It officially began normal operations on the 30th of May 2013; presenting a number of key improvements in design and spectral configuration (Dube and Mutanga, 2015).

Table 2: Spectral and spatial characteristics of Landsat 8 imagery.

Band	**Wavelength (micrometers)**	**Spatial resolution (metres)**
Band 1- Coastal aerosol	0.43 – 0.45	30
Band 2 -Blue	0.45 – 0.51	30
Band 3 -Green	0.53–0.59	30
Band 4 -Red	0.64–0.67	30
Band 5 -Near Infrared (NIR)	0.85–0.88	30
Band 6 -Short-wave infrared (SWIR 1)	1.57–1.65	30
Band 7 -Short-wave infrared (SWIR 2)	2.11–2.29	30
Band 8 -Panchromatic	0.50–0.68	15
Band 9 -Cirrus	1.36–1.38	30
Band 10 -Thermal infrared (TIRS) 1	10.60–11.19	30
Band 11-Thermal infrared (TIRS) 2	11.50–12.51	30

Source: USGS, 2015

Table 3: Characteristics of the satellite imagery used in the study.

Study Area	**WRS-2 path/row**	**Spatial resolution (metres)**	**Bands**	**Sensor**	**Archive**
North-eastern KwaZulu-Natal	167/79	30	2,3,4,5,6,7	L8 OLI/TIRS	USGS

Table 4: Summary of dataset used for the study.

Landsat 8 ID	**Date of Acquisition**
LC08_L1TP_167079_20150623_20170407_01_T1	2015-06-23
LC08_L1TP_167079_20151216_20170331_01_T1	2015-12-16
LC08_L1TP_167079_20160202_20170330_01_T1	2016-02-02
LC08_L1TP_167079_20160625_20170323_01_T1	2016-06-25
LC08_L1TP_167079_20170119_20170311_01_T1	2017-03-11
LC08_L1TP_167079_20170628_20170714_01_T1	2017-06-28

3.2.2.2 Hydro-Meteorological data

Meteorological data pertaining to monthly rainfall has been collected for a period of 20 years ranging from 1996 to2016. Rainfall data was used to analyze and derive Standardized Precipitation Index (SPI). Daily rainfall from four rainfall stations has been used to analyze relations between NDVI and rainfall and also to derive Standardized Precipitation Index (SPI). The data has been collected from South African Weather Service.

3.2.2.3 Rain station distribution

Point map of four rainfall stations in the north-east KwaZulu-Natal region as prepared from the lat/long file has been used to interpolate rainfall and SPI values in the entire region (Figure 5). For monitoring purposes, it is necessary to operationally produce the maps of drought severity and analysis from point measurements to trace drought development in the entire region or country.

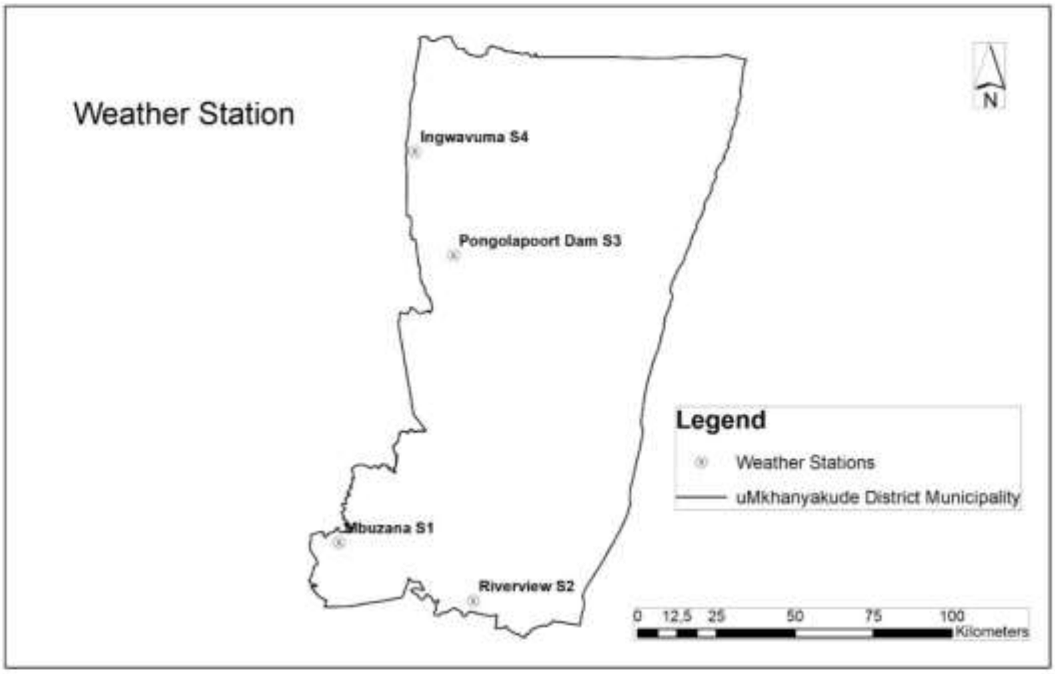


Figure 5: Location of the north-eastern KwaZulu-Natal weather station

The weather station data was collected from the South African Weather Station and a result of the average totals per month from year 2010 to 2015 shows the weather station which received the lowest and the highest rainfall.

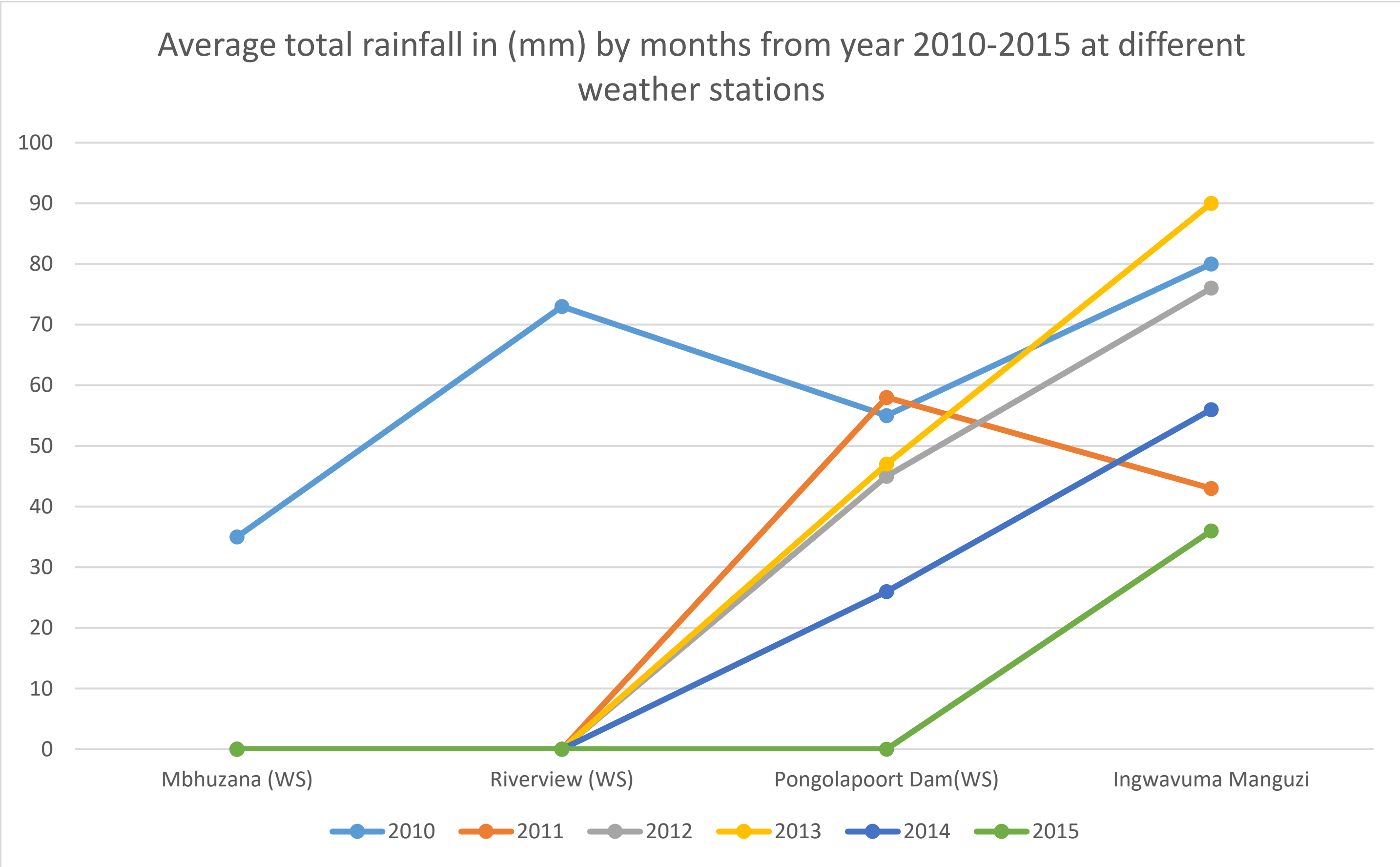


Figure 6: Average monthly rainfall in millimetres (mm) from the four weather stations.

3.3 Data analysis

3.3.1 Landsat 8 data preprocessing

Image preprocessing involved radiometric calibration and atmospheric correction. First, unnecessary bands were removed; that is band 1, 10 and 11. Band 1, which is also called the coastal or aerosol band has two main uses: imaging shallow water and tracking fine particles like dust and smoke (Roy *et al*, 2014; NASA, 2015). This band therefore was deemed unnecessary for drought monitoring in this study. Band 10 and 11 are thermal bands and are sensitive to heat, and thus were excluded too from this study (NASA, 2015).

Atmospheric correction was done with the remaining six bands (blue, green, red, NIR, SWIR1, SWIR2) by subtracting the reflectance of band 9 (cirrus band) from each band to ascertain that even a small amount of clouds is removed from the bands. The band 9 was used due to its ability to detect clouds (NASA, 2015).The cloud free bands were then calibrated to top-of-atmosphere reflectance using the orbital and sensor parameters (USGS, 2015). The conversion was implemented in ArcGIS using Equation 2 provided on the USGS website (http://landsat.usgs.gov).

Conversion to TOA Reflectance

$\boldsymbol{\rho\lambda' = \mathrm{M}\rho\mathrm{Qcal} + \mathrm{A}\rho}$**..................Equation 1**

Where:

$\rho\lambda'$ = Top-of-Atmosphere Planetary Spectral Reflectance, without correction for solar angle. (Unitless)

$M\rho$= Band-specific multiplicative scaling factor available from the metadata

$A\rho$ = Band-specific additive rescaling factor available from the metadata

Q_{cal} = Quantized and calibrated standard product pixel values (DN).

The resultant reflectance was then corrected by factoring in the solar angle using Equation 3 provided on the USGS website.

Correction of reflectance value with sun angle

$$\boldsymbol{\rho\lambda = \frac{\rho\lambda'}{sin(\theta_{SE})}}$$ **………Equation 2**

Where:

$\rho\lambda'$ = TOA planetary reflectance

θ_{SE} = Local sun elevation angle

For the processing of Landsat data 8 image bands were added onto ArcMap 10.13 data management tool called Composite bands. These bands included band 2 (blue), band 3 (green), band 4 (red), band 5 (near-infrared), band 6 (short-wave infrared 1) and band 7 (short-wave infrared 2) to create a multispectral image.

After creating the composites for Landsat, the images were then classified by a Drought Vulnerability Index analysing data in five classes, the least, mild, moderate, severe and critically vulnerable, then the data is entered into Microsoft excel to be represented in graphs, tables and pie charts.

3.3.2 Drought Indices

Drought indices were calculated using Landsat data. This is because satellite-based drought indices such as the Normalised Difference Vegetation Index (NDVI), Standardized Precipitation Index (SPI) and Vegetation Condition Index (VCI) have proven to be useful in detecting drought onset and in measuring intensity, duration, and drought impact in regions around the world (Kogan, 1995; Anyamba *et al*, 2001; Gutman, 1990; Ji *et al 2003*, Nicholson *et al*, 1994; Seiler *et al*, 2000; Unganai *et al*, 1998; Wang *et al*, 2001).

The NDVI was computed using Equation 4 (Rouse *et al*, 1974).

NDVI = (NIR – RED) / (NIR + RED)………… Equation 3

The SPI is based on probability

X - Xm / σ………… Equation 4

Where X = Precipitation for the station

Xm= Mean precipitation

Σ= Standardized deviation

SPI Drought Classes is classified in the table 5 below.

Table 5: Classification of SPI values.

SPI Value	Class	Probability
2.0 and more	Extremely wet	0.977-1.000
1.5 to 1.99	Very wet	0.933-0.977
1.0 to 1.49	Moderately wet	0.841-0.933
-.99 to .99	Near normal	0.159-0.841
-1.0 to -1.49	Moderately dry	0.067-0.159
-1.5 to -1.99	Severely dry	0.023-0.067
-2 and less	Extremely dry	0.000-0.023

(McKee et al., 1993)

Vegetation Condition Index was calculated using ENVI 5.4 software through the following equation

$VCI = 100 * (NDVI – NDVI_{min}) / (NDVI_{max} – NDVI_{min})$ … **(Equation.5)**

Where,

NDVI – Smoothed weekly NDVI value

$NDVI_{min}$ – Multiyear minimum NDVI value

$NDVI_{max}$ – Multiyear maximum NDVI value

NDVI ranges from -1 to 1 and functionally ranges from 0-1. VCI rescales this to 0 to 100

3.3.3 Data analysis

The relationship between climatic data and remotely sensed data can be developed using linear regression models (Rauste *et al*, 1994; Steininger, 2000; Calvao and Palmeirim, 2004; Mutanga and Skidmore, 2004), multiple regression techniques (Hame *et al*, 1997; Foody, Boyd and Cutler, 2003, Hyde *et al*, 2006; Hyde *et al*, 2007) and nonlinear regression methods such as k-nearest neighbour, artificial neural networks and semi empirical models (Castel *et al*, 2002; Santos *et al*, 2002; Wijaya and Gloaguen, 2009; Min, Qu, and Xianjun, 2009).

The purpose of this research was to classify land use and cover in the study area. The methods used were classification of the multispectral image and as a result a maximum likelihood algorithm was used, which does not require prior knowledge about the study area cover. Interpretation of land use/cover through an accurate assessment on the recent Landsat 8 image was done by comparing it with the reference of the same study area from Google Earth. The band combination that was used for interpretation was false colour combination 5, 4, 3 (Near Infrared, Red, and Green) which is used for agricultural analysis.

Accuracy assessment is an assessment done on a classified image to determine the strength of the classification. Classification accuracy assessment for this study used the latest image of 2017 from the digitized polygons and compared with reference data (Google Earth). The sample points were randomly selected across the study area. An error matrix was used to tally the classified and reference data. The reference data was then arranged in columns while the classified data was in rows. Accuracy was then assessed in terms of the overall producer's accuracy and user's accuracy. Overall accuracy is used to assess the accuracy of the entire map while the producer's and the user's accuracies were calculated to get the percentage of the crop cover for each class. The following formulas were used for calculating the overall accuracy, producer's accuracy and user's accuracy.

$$\textit{Overall Accuracy} = \frac{Total\ number\ of\ correctly\ classified\ pixels\ in\ class}{Total\ number\ of\ pixel\ of\ each\ class} \times 100 \ldots$$ **(Equation.6)**

$$\textit{Producer's Accuracy} = \frac{Total\ number\ of\ correctly\ classified\ pixels\ in\ each\ class}{Number\ of\ reference\ pixels\ of\ each\ class} \times 10$$ **(Equation. 7)**

$$\textit{User's Accuracy} = \frac{Number\ of\ correctly\ classified\ in\ each\ class}{total\ number\ of\ pixels\ that\ were\ classified\ in\ that\ class} \times 100 \ldots$$ **(Equation. 8)**

3.4 Summary

The flow chart (Figure 7) summarizes the methodology adopted in this study. Landsat 8 data was pre-processed for atmospheric and radiometric corrections. The computation of NDVI and SPI was processed in order to produce NDVI and SPI averages. Each spectral band value from the preprocessing was then analysed from the data.

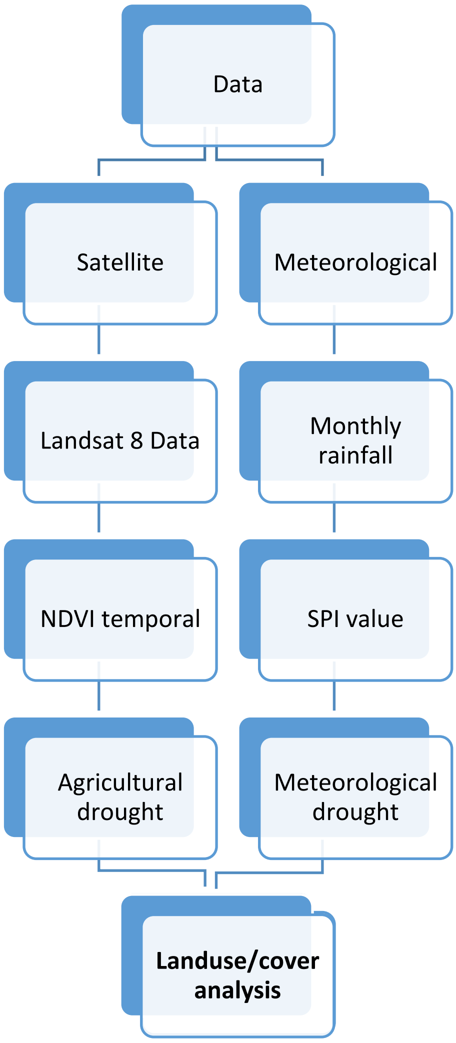


Figure 7 Flowchart of the methodology adopted in this studyd in this study.

CHAPTER 4: RESULTS

The results of the analyses of the data sets using the same method in chapter three (methodology) are presented in this chapter. The results of this chapter are presented in maps and statistically accompanied by detailed descriptions.

4.1 Seasonal Patterns of Rainfall and NDVI

From research investigated and obtained in this study, the mean uMkhanyakude District season rainfall and NDVI patterns for the entire study area for the period 1966 to 2016 can be seen from Figure 8, that their relationship is inversely proportional, because where rainfall is low; NDVI is high for the years 2015 to 2017.

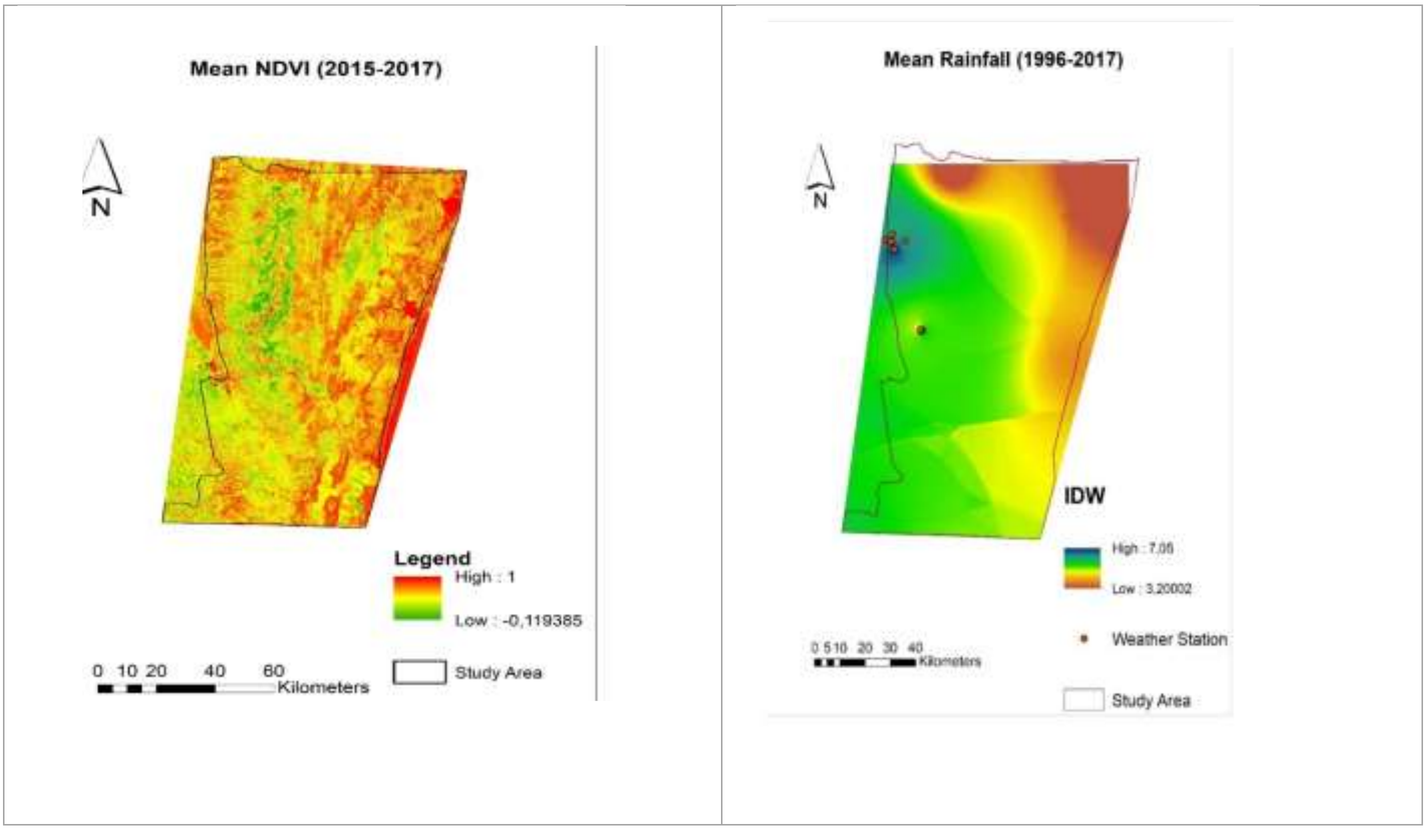


Figure 8 Showing the severity of the droughts using NDVI and IDW at certain years from different weather stations within north-eastern KwaZulu-Natal

4.2 Climatic data

Table 6 presents summary statistics of rainfall data collected at four weather stations. The total sum of rainfall for Mbhuzana, Riverview, Pongolapoort Dam and Ingwavuma Manguzi is 507 millimetres, 687, 8 millimetres, 729, 8 millimetres and 805, 2 millimetres respectively. The average rainfall falls between all four weather stations is 683 millimetres, averaged rainfalls within the north-eastern KwaZulu-Natal. At all weather stations calculations have been made for A, Alpha and Beta which shows parameters which have been used to calculate the SPI. According to McKee *et al*, (1993) the alpha parameter describes the shape of the curve. An extremely low alpha corresponds to a curve that is quite similar to an exponential decay function. Large alphas correspond to near-normal distributions. The beta parameter describes the scale of a curve.

Table 6: Summary statistics of all weather stations showing results of A, Alpha and Beta.

Weather stations	A	Alpha	Beta
Mbhuzana	0,09	5.45	93,04
Riverview	0,09	5,82	118,14
Pongolapoort Dam	0,05	10,86	67,22

Ingwavuma Manguzi	0,15	3,54	227,40

The significance level for the weather stations Mbhuzana, Riverview, Pongolapoort Dam, and Ingwavuma Manguzi was evaluated using the A-statistics at 95% level of confidence (Table 6). Of all the SPI products, the A-statistics has the lowest significance level showing that the model was highly significant.

H0: Model is not significant

HA: The model is significant

<u>For Mbhuzana weather station the A- value is 0, 09</u>

A-value 0.09 > 0.05. The conclusion is that the model is significant because the value is far from zero.

<u>For Riverview weather station the A-value is 0, 09</u>

A-value 0.09 > 0.05. The conclusion is that the model is significant because the value is far from zero.

<u>For Pongolapoort Dam weather station the A-value is 0, 05</u>

A-value 0.05 = 0.05. There is no conclusion because the values are equal.

<u>For Ingwavuma Manguzi weather station the A-value is 0, 15</u>

A-value 0.15 > 0.05. The conclusion is that the model is significant because the value is far from zero.

4.3 Relationship between SPI and Drought frequency

The shape, scale and average values for the precipitation are calculated through the SPI (Figure 10). The SPI results align with the objectives of assessing the agricultural drought conditions across different land use and land cover using Multitemporal Landsat 8 (OLI/TIRS) and different vegetation indices. From the four weather stations that are within the study area, it can be seen that SPI values decreased from 2014 which means classification of moderate to severe drought conditions were starting to be transparent in the area. The years 2015 and 2016 are the most drought stricken years from all the weather stations where drought has been from severe drought to very severe drought.

Figure 9 shows the average rainfall of certain years from different weather stations used for this analysis. The unit of measurement for the SPI is millimetre. The Mbhuzana weather station shows the highest rainfall experienced was in the year 1996 with (1mm) the lowest year was 2015 with (-2.5mm). At the Riverview weather station the highest year was 2000 with (2mm), the lowest was in the year 2016 with (-3mm). At the Pongolapoort Dam weather station the highest year was in 2000 with (2.00mm), the lowest was in the year 2003 with (1.5mm). The Ingwavuma Manguzi_weather station had the highest value in the year 2000 with (1.5mm) and the lowest year was 2016 with (-4.00mm).

SPI drought categories from McKee *et al*, (1993) indicates that 0 to -0.99 of the drought category is mild drought; -1.00 to -1.49 is moderate drought;-1.5 to -1.99 is severe drought and -2.00 or less is extreme drought. From figure 9 below the extreme drought years are 2015 and 2016 taken from Mbhuzana and Ingwavuma Manguzi respectively.

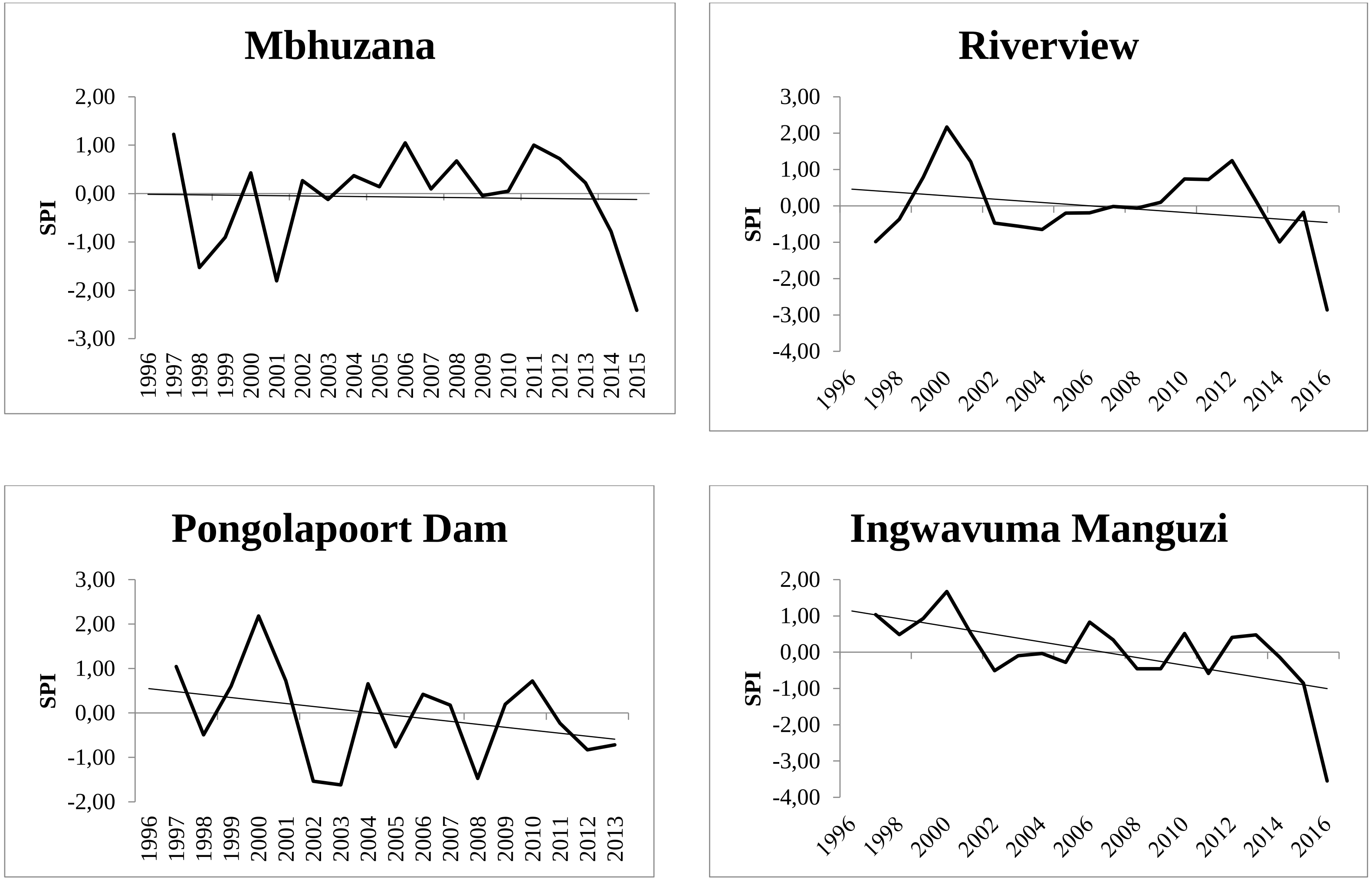


Figure 9 Showing the severity of the 3-months drought using SPI at certain years from different weather stations within north-eastern KwaZulu -Natal.

4.4 Reference data

Google Earth was used in this study to create reference data that could be used to assess the performance of the satellite products. A total of 100 samples were classified into five classes, those being bush, plantations, grasslands, cultivated cane and wetlands. Researchers (Foody, 2002, Olofsson *et* al, 2014) who have used various sampling techniques have suggested an approach of how many samples are needed to be collected, and it is concluded that a size allocation of 50 to 100 is suitable for the number of samples adopted. This allows a reasonable indecision in the size needed to achieve certain standard errors (Olofsson *et al*, 2014).

The classification results were confirmed using reference data set obtained through visual interpretation of Google Earth, which has a fine spatial resolution and good geometric precision. This study focussed more on the extraction of the agricultural spatial distribution. Random sampling separated the distribution of the land use and land cover classes. A total of one hundred samples were used in comparison with Landsat derived classification and reference data.

Bush land use and land cover and plantations were recognisable on Google Earth by their brown and green colour which stood out from grasslands that they intermixed with. Grassland was distinctly visible on Google Earth; it was recognised by its green colour which stood out from plantations. Cultivated cane crops were recognisable by their low light green colour.

4.5 Land use map

After the interpolation of SPI, selected satellite in digital format with path 167 and row 97 were obtained from the years 2015 to 2017 of summer (December to February) and winter (June to August). Composites from Landsat imagery were created to identify the land class within the study area. Classification was achieved using unsupervised classification and the land use maps were created by employing digitized polygons for different land use classes to provide ground data for training sites. Signatures were developed and used for classifying the satellite imagery into the land use maps. Purification of signatures was carried out by deleting and / or adding new signatures, with the refined signatures producing a better land use map which was used in GIS for further analysis (Muthumanickam *et al*, 2011).

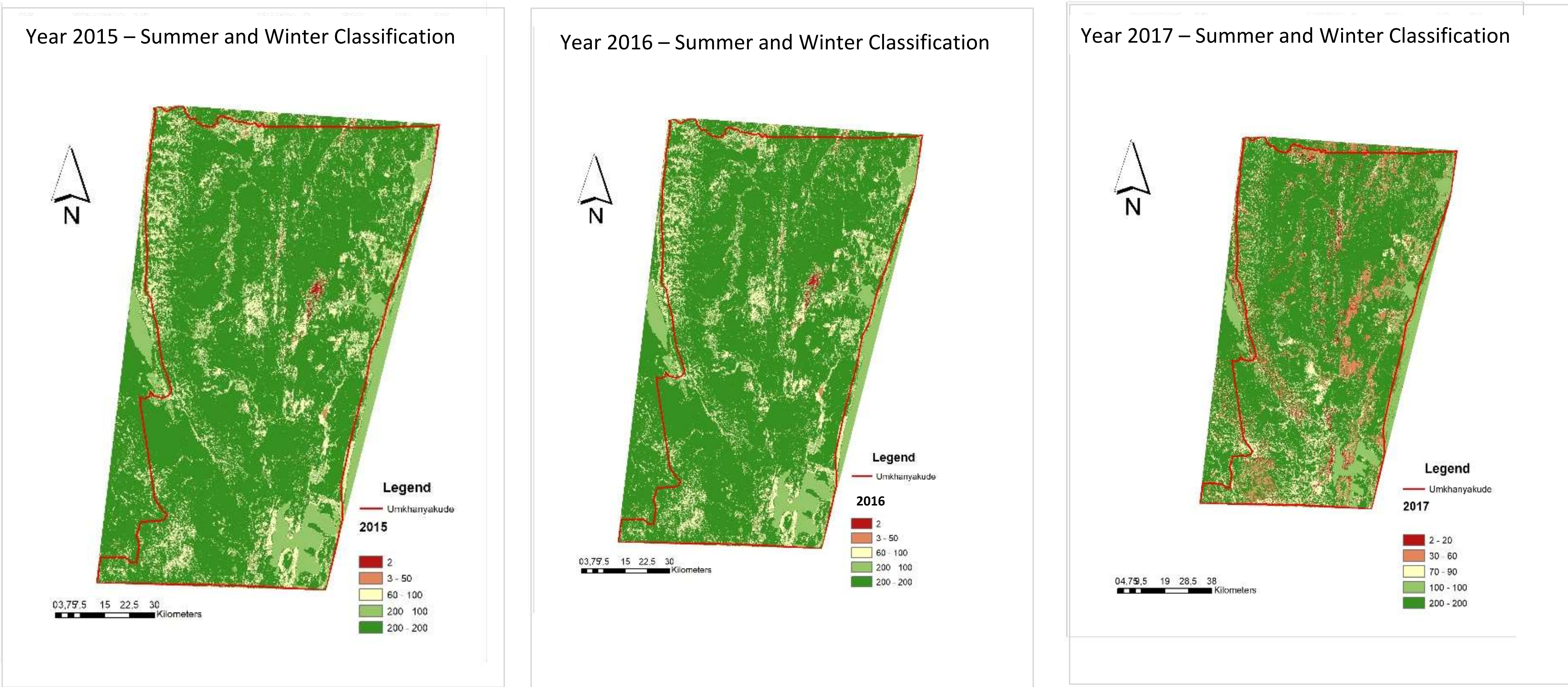


Figure 10 Classification results for land cover and land use 2015-2107

4.6 Classification of land use classes and NDVI comparison

The classification for the purposes of this research is for identifying the land use from the year 2015-2017 that has experienced drought conditions. This is through the use of a raster calculator where winter and summer imagery were added together to get a resultant raster image that was classified into five classifications.

4.7 Results of the VCI in comparison to the NDVI

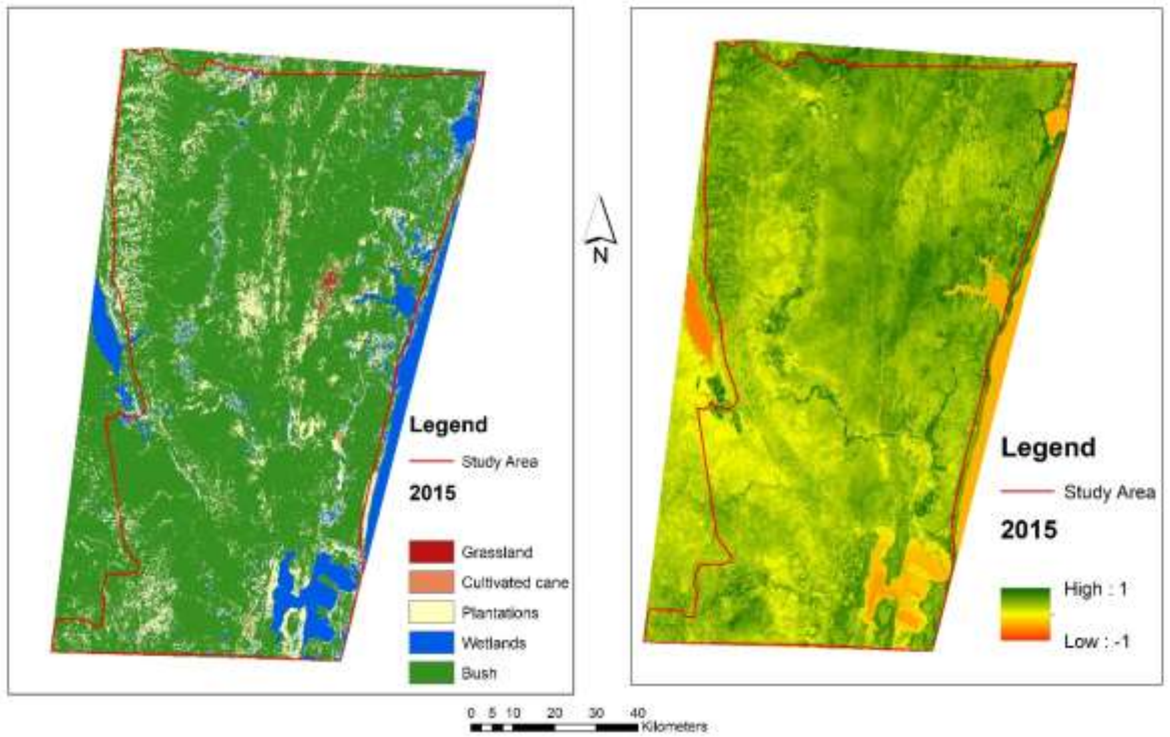
Through the classification from the Landsat imagery it is important to compare the results from the NDVI and the VCI in order to understand which land use and land cover experienced drought in the study years (2015-2017). The classification scheme to indicate different stages of drought hazard severity using VCI is shown in the table 7 below.

Table 7 Vegetation Condition Index (VCI) values for drought classification

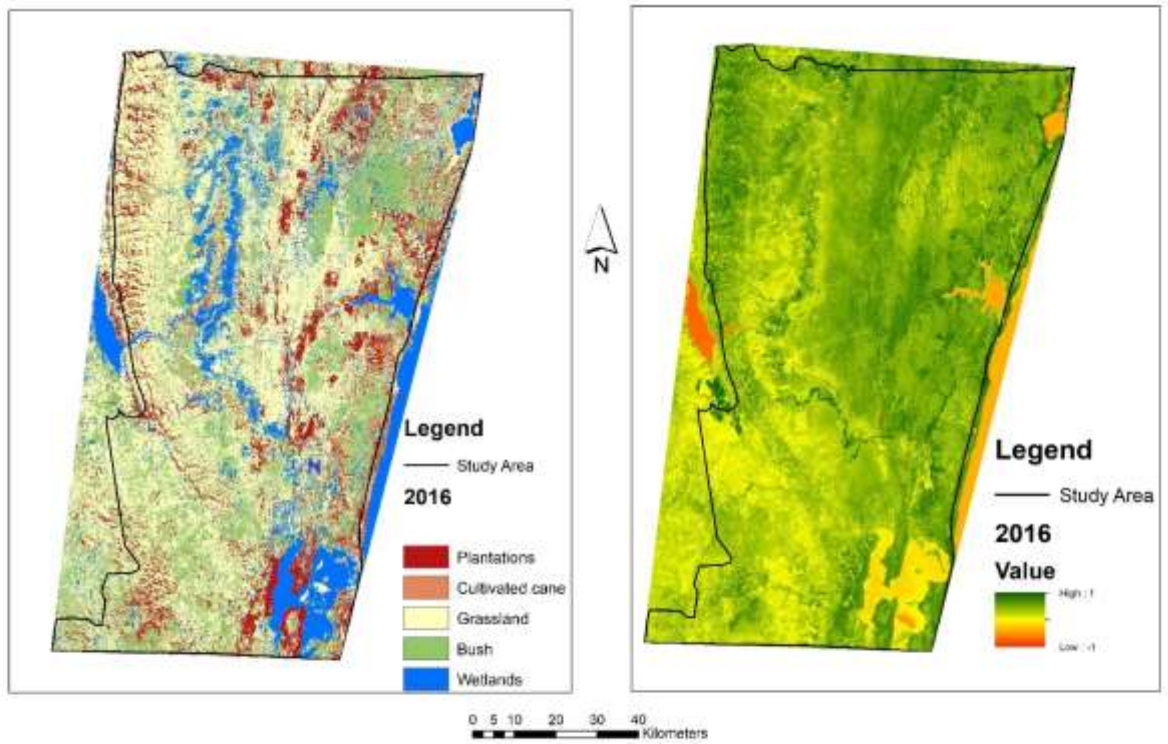
Drought Hazard Severity Classes	VCI Values
No Drought	>40
Mild Drought	30-40

Moderate Drought	20-30
Severe Drought	10-20
Extreme Drought	<10

Landsat imagery and NDVI for winter 2015



Landsat imagery and NDVI for winter 2016



Landsat imagery and NDVI for winter 2017

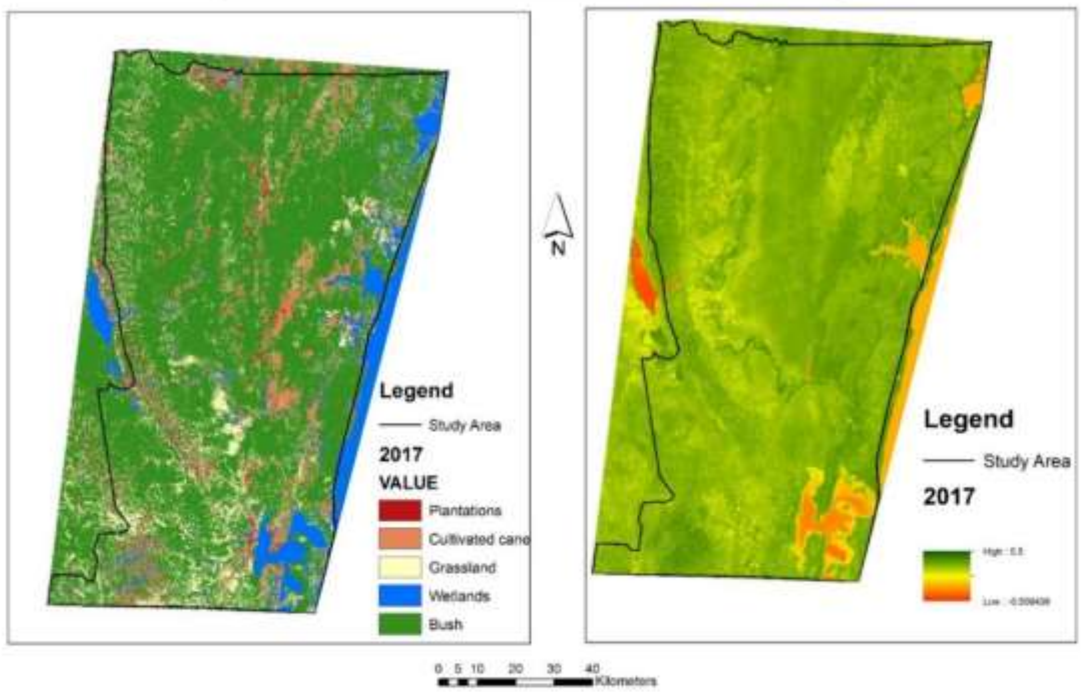


Figure 11 : Classification for and NDVI winter land use land cover 2015-2017

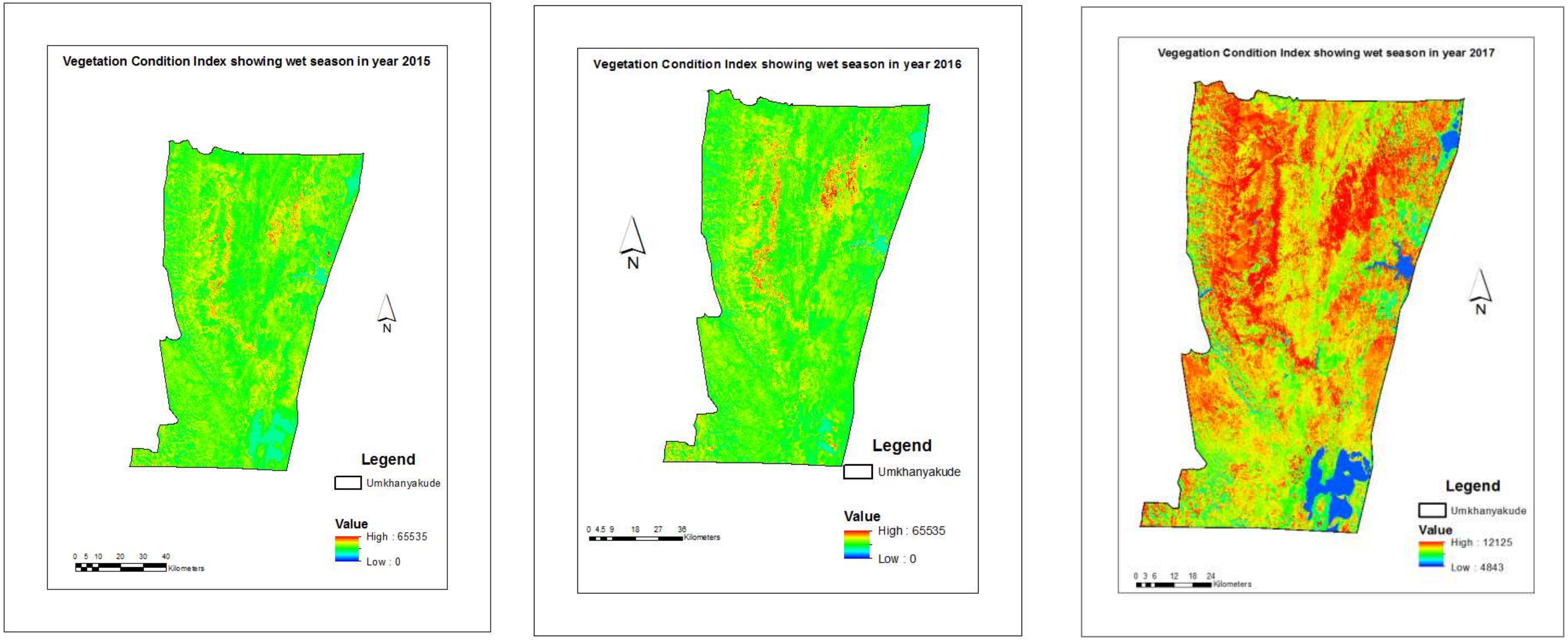


Figure 12 VCI of wet season land cover in years 2015, 2016 and 2017 respectively

Figure 12 shows that the results show that in 2015 the area is covered mostly with bush land use and land cover and the NDVI shows the highest reflectance at 1 showing vegetation in the area is healthy. From the NDVI in areas where red is shown it is mostly wetland which is accurate in reflection as wetlands have a low reflectance in the green band and reflectance.

In 2016 distribution is more varied where bush is not dominating in the study area, but also grasslands land use and land cover is more visible. In the NDVI results it shows high reflectance where vegetation is healthy and areas where there is grassland the NDVI value is slightly away from the highest value of 1. In 2017 the areas of bush are more dominating in the study area whilst cultivated cane is emerging and rather visible as compared to the year 2015 and 2016. The NDVI shows bush to be closer to 1 where reflectance shown is healthy for land use and land cover. When looking at specifically cultivated cane, land use in the years 2015 and 2016 the Landsat imagery shows very small patches of land use for both the years, however in the year 2017 the cultivated cane is strongly distinct in the classified imagery. This means that certain land use and land cover experienced strain from drought occurrences in the area.

In figure 8 the results show that the VCI in the year 2015 shows that bush land cover as per the classification from Figure 12 is between the values of high and low. The green shade in 2015 shows a medium reflectance on land cover and land use indicating low agricultural output. Through this analysis drought conditions in the study area can be true for the year 2015. In the year 2016 areas where land cover is mostly bush is seen to be represented as medium which is similar to that of the year 2015 indicating drought occurrence during the wet season. In the year 2017 land cover and land use shows drought conditions on certain land cover and land use. This can be seen in red which indicates bush land cover (refer to figure 12) as the most stressed land cover experiencing drought conditions in the wet season. The VCI analysis was conducted based on all images available over the growing seasons within the observation period 2015 to 2017 to detect possible drought hazard severity during the observation period.

4.8 Land use map analysis

In the year 2015 classification shows the land cover is dominantly bush and the least land cover and land use is plantations. In comparison to the year 2015 classification shows that the land is mostly dominated by both bush and small patches of plantations. In the year 2016 classification shows the land cover and land use is dominated by mostly both a distribution of all classes being plantations, cultivated cane, bush and wetlands.

In the year 2017 the land use and land cover is largely dominated by wetland and cultivated cane crop and in the winter of 2017 the land use and land cover is largely dominated by bush and cultivated cane wetlands and cultivated cane crop. In the year 2015 the classification for the highest range is between 200-200 displayed as green in the classification which is largely cultivated cane crop land use and land cover. The second range is 200-100 which is wetland cover. In the year 2016 the highest range is 130-150 which constitutes the wetland classification and then the second range is 95-120 which constitutes cane crop classification.

In the year 2017 the highest range is 200-200 which constitutes the cultivated cane crop and second highest range is 100-100 which constitutes wetland classification. Overall the dominant land use and land cover studying from the post classification results is for both the land cover, land use of cultivated cane and bush.

4.9 Accuracy Assessment

The assessment of the classification results is critical in satellite image classification. Reference data (Google Earth) and error matrix was used for the recent 2017 classified image.

Table 8 Error matrix for classified multispectral of 2017 (all values are in percentage).

		REFERENCE DATA FROM GOOGLE EARTH						
		Plantations	**Bush**	**Wetlands**	**Cultivated cane**	**Grassland**	**Total**	**USER'S ACCURACY**
CLASSIFIED DATA FROM THE MAP	**Plantations**	**9**	4	0	0	0	13	69.2%
	Bush	8	**24**	0	2	0	34	71%
	Wetlands	0	1	**14**	1	3	19	74%
	Cultivated cane	0	0	4	**8**	2	14	57.1%
	Grasslands	0	0	0	0	**17**	17	100%
	Total	17	29	18	11	22	**97**	
	PRODUCER'S ACCURACY	53%	83%	78%	73%	77.3%		**OVERALL ACCURACY = 74.2%**

A total of 100 samples were collected for ground truth all over the study area. Each sample was used to identify different land use and land cover classes that were used to create ground truth maps for assessing supervised classification performed by remote sensing techniques. Considering that imagery needed to be corrected atmospherically, this at times affects the accuracy of the imagery when classifying.

4.10 Summary

The results of the study were reported in this chapter. For the rainfall data the SPI was used in order to determine and monitor droughts. The use of this index allows an analyst to determine the rarity of a drought at a given time scale of interest for any rainfall station with historic data. For the satellite imagery classification of land use and land cover was adopted through maximum likelihood in order to determine both winter and summer occurrence in the classification. Classification was in the form of five classes which are bush, plantations, grassland, cultivated cane and wetland. The year 2015 appears to have most areas as bush with small patches of grassland. Wetlands land use and land cover in this winter imagery are distinctly clear and small patches of grasslands appear.

It appears that plantations are strongly defined in the year 2016 and wetlands appear in those areas. Another land use and land cover that appears in the year 2016 is grassland. In 2017 the area is covered mostly by bush and plantations. Areas that appear to have bush have been classified most accurately.

CHAPTER 5: DISCUSSION

5.1 Introduction

The purpose of this study was to identify drought by remote sensing and GIS techniques application over a three year period (2015-2017). This identification occurred through mapping both summer and winter land uses and land cover using Landsat data and SPI.

From the results in figure 9 (showing the severity of the droughts in certain years from different weather stations within north-eastern KwaZulu-Natal), it shows that in Mbhuzana in the year 1998 (-1.5) it was severely dry in that year. In the year 2001 (-2.00) and 2015 (-2.50), it was extremely dry. At the weather station Riverview in the year 1997 and 2014 (-1.00) experienced moderately dry conditions. In the year 2016 (-3.00) the conditions were extremely dry. At the weather station Pongolapoort dam, we see in the year 1998 and 2005 it experienced near normal conditions (-0.50). In the years 2002, 2003 and 2008 the conditions were extremely dry (-2.50). In the year 2012 conditions experienced were moderately dry (-1.00). At the river station Ingwavuma Manguzi drastic changes in conditions are in the year 2015 and 2016. In 2015 conditions experienced were moderately dry (-1.00) and in 2016 the conditions dropped to being extremely dry (-3.00).

SPI is advantageous as it is simple because it requires only rainfall data. SPI can be used for variable time scale that being meteorological, agricultural and hydrological drought. SPI is standardized where the frequency of extreme drought events at any location and time scale is consistent. The disadvantage however is that extreme droughts (over a longer period) occur with the same frequency in all locations meaning that SPI cannot identify drought prone regions. Areas with small seasonal precipitation can mislead large positive or negative SPI values which could result.

5.2 Climate data

From figure 9 the four weather stations show that conditions for the years 1997 and 1998 experienced moderate to severe droughts. Making reference to the 3 months drought analysis on figure 9 the year 2000 has the average rainfall experienced from the four weather station, however in year 2002 the results show extreme drought conditions. In the year 2015 conditions of moderate to extreme drought was experienced from the four weather stations. Table 6 shows the summary statistics of all weather stations as a result of A, Alpha and Beta. Beta parameter describes the scale of a curve. This coefficient describes the values associated with the distribution (McKee *et al*, 1993). The alpha parameter describes the shape of the curve. The lowest alpha in table 6 is from the weather station Ingwavuma Manguzi (3.54) this means the curve of the shape is quite similar to an exponential decay function. The largest alpha from the table is from the Pongolapoort Dam, which is said to correspond to near-normal distribution.

5.3 Landsat 8 image-based land use and land cover assessment

5.3.1 Relationship of mean rainfall and mean NDVI

The use of four weather stations has shown fairly short interpolation results for the mean rainfall of the years 1996 to 2017 (Figure 4.1). The use of inversely distance weighed interpolation was used for the rainfall data to understand the assumption that things that are close to one another are more alike than those that are further apart. In stations where the highest distribution is around 6.41 – 7.05 there are more weather results that are distributed and in comparison with the mean NDVI it is where the highest distribution of healthy vegetation is found. The NDVI values were averaged over time to establish 'normal' growing conditions in a region for a given time.

5.3.2 Relationship between summer and winter land use and land cover

In the year 2015 the classification that is shown is mostly cultivated cane crop with small patches of grassland. In 2016 there is a varied distribution of bush, plantations, cultivated cane crop, grassland and wetlands. In2017 there are areas where wetlands are shown as land covers and land uses which are classified as something different in 2016 winter. The dominant land use in 2017 is cultivated cane crop although some areas where there were plantations are seen to be covered by cultivating cane crop.

5.3.3 SPI and land use and land cover classification

To quantify the impact of drought on certain land use and land cover correlation between certain years results are shown from figure 10 In the year 2016 conditions were extremely dry (-. 3.00) from the Riverview weather station, which can be interpreted as times where there was exceptional drought. Looking at figure 10 from the year 2016 winter, it is clear that some areas were extremely dry as plantations classification is barely visible in the classification and the cultivated subsistence.

From the Ingwavuma Manguzi weather station conditions for 2015 were also moderately dry (-1.00) and for the purposes of understanding the drought experienced it was more moderate drought over that year and this is seen in the land use and land cover changes in summer and winter of 2015. In summer, classification is mostly of the cultivated cane crop and small areas of grassland, but in winter this changes and a wider land use and land cover is seen in the year 2015 in winter.

From the results from classification for comparing year 2015 to 2017 there were categories of lowest to highest values for a certain land cover and land use (Figure 12) and results show that over this three year period that looking at wetlands and cultivated cane crop there has been a decrease in wetlands since 2015-2017 (200-100, 130-150 and 100-100 respectively). In terms of cultivated cane crop in 2015- 2017 it is 200-200, 62-94 and 200-200 respectively. This has shown that in the year 2016 cultivated crop production decreased due to drought conditions experienced.

The classification of grasslands (shown in green) (figure 4.1) from the NDVI (2015-2017) shows values are that are away from 1 which indicated that crop and agricultural distribution in the area is not healthy and changes have been experienced from 2015-2017.

5.4 Conclusion

This research monitored and mapped agricultural drought across different land uses and land cover in the north-eastern KwaZulu-Natal area. The findings of this work demonstrated that:

1. Satellite derived index of drought has been shown by using meteorological derived index Standardized Precipitation Index.
2. It is found that temporal variations of NDVI are closely linked with SPI and there is a strong linear relationship between mean NDVI and mean rainfall. Areas where the interpolation is high is where there is more weather rainfall recorded

at the weather station showing that the closer things are to each other the more alike they are.

3. The pattern of rainfall and NDVI obtained between 1977 and 2017 data shows that where SPI value is low the corresponding NDVI values are also low. Conclusion such as the NDVI and SPI share a strong correlation where water is a major limiting factor for plant growth. This spatial distribution oppositely confirmed that vegetation grew better accordingly with a continuous increase of rainfall in rainless areas. As a result of consistent declines in winter, this is why NDVI and rainfall showed detectable negative relationships.

Overall, this study has identified agricultural drought by using remote sensing and GIS techniques over a three year period (2015-2017). The results have been through the use of SPI and mean NDVI through ArcGIS tools. It is shown that SPI has accounted for significant relation with NDVI and rainfall, which suggests that SPI can be used as an indicator of vegetation status. This study also assessed drought conditions across different land using temporal images from Landsat 8TM.

5.5 Recommendations

Though the present work deals with satellite and meteorological parameters to arrive to the understanding of drought conditions across different land use and land cover.

- For better results NDVI and SPI values should be more than 30 years.
- SPI values in the fourth rainfall station is not appropriate to be the representation of the area around it, thus it is recommended to use maximum number of rainfall stations to identify meteorological drought.

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