The application of remote sensing in drought monitoring: A case study of KwaZulu-Natal, South Africa

By

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“We never know the worth of water till the well is dry”

(Thomas Fuller)

Abstract

Drought is a severe natural disaster which occurs across wide spatial boundaries and inconsistent temporal patterns. The slow onset and gradual formation of drought highlights the importance of early detection, allowing for appropriate time in implementing relief and mitigation procedures. The vague extensiveness of drought raises concern on the ability for site specific ground based weather stations to assess the full extent of a drought occurrence. This problem is further compounded in developing nations, such as South Africa, where weather stations suffer from missing historical records and are poorly distributed across harsh inaccessible rural areas. Remote sensing seeks to resolve this problem through the high resolution, near real-time and multitemporal spatial coverage it possesses.

Based on that premise, this study sought to evaluate the evolution of remote sensing on drought monitoring and subsequently conduct a remote sensing drought assessment, to determine the accuracy and potential for future drought occurrences.

The scope of this study was to *firstly* to evaluate the evolution and progress of remoting sensing approaches in drought monitoring, which was completed as a systematic literature review. *Secondly,* a drought assessment was conducted in KwaZulu-Natal, South Africa. Focusing on the ability of the Normalized Difference Vegetation Index (NDVI) to observe any trends of vegetation drought over the past 16 years, confirmed through rainfall data.

Findings from this study concluded the following. *Firstly,* there has been substantial growth in research papers pertaining to remote sensing on drought; particularly over the past decade. *Secondly,* developing nations have limited resources available and should consider the advantages possessed by remote sensing. *Thirdly,* remote sensing results complimented climate conditions recorded over the past 16 years. *Fourthly,* future studies should look to include additional indices to strengthen the broadband NDVI, which was affected by the saturation of vegetation biomass.

Preface

The research work described in this thesis was carried out in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from February 2016 to November 2017, under the supervision of Professor Onisimo Mutanga to fulfil the requirements of Master of Science.

I declare that the work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgements have been made.

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Plagiarism declaration

I Simon Duncan Lang, declare that,

1. The research presented in this thesis, except where otherwise indicated is my original research.
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Table of contents

List of Figures

List of Acronyms

AVHRR: Advanced Very High-Resolution Radiometer

BMDI: Bhalme Mooley Drought Index

DFI: Drought Frequency Index

DSI: Drought Severity Index

DTx: Agricultural Drought Index

ENSO: El Nino Southern Oscillation

ETM+: Enhanced Thematic Mapper Plus

GIS: Geographic Information System

GPCP: Global Precipitation Climatology Project

GRI: Groundwater Resource Index

IR: Infrared

LST: Land Surface Temperature

MODIS: Moderate-resolution Imaging Spectroradiometer

MW: Microwave

NDIIb6: Normalized Difference Infrared Index-band Six

NDMC: National Drought Mitigation Centre

NDVI: Normalized Difference Vegetation Index

NDWI: Normalized Difference Water Index

NIR: Near Infrared Wavelength

NPOESS: National Polar-Orbiting Operational Environmental Satellite System

NPP: NPOESS Preparatory Project

NRI: National Rainfall Index

PDSI: Palmer Drought Severity Index

PERSIANN: Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks

PVI: Perpendicular Drought Index

R: Red Wavelength

RAI: Rainfall Anomaly Index

RDI: Reclamation Drought Index/ Reconnaissance Drought Index/ Regional Streamflow Deficiency Index

RS: Remote Sensing

RSM: Relative Soil Moisture

SAVI: Soil Adjusted Vegetation Index

SPI: Standardized Precipitation Index

SWSI: Surface Water Supply Index

TCI: Temperature Condition Index

TIR: Thermal Infrared

TIRS: Thermal Infrared Sensor

TM: Thematic Mapper

TRMM: Tropical Rainfall Measuring Mission

TVI: Transferred Vegetation Index

USGS EROS: United States Geological Survey Earth Resource Observation and Science

VCI: Vegetation Condition Index

VegDRI: Vegetation Drought Response Index

VHI: Vegetation Health Index

VIS: Visible

CHAPTER 1

General Introduction

Drought affects more people than any other natural disaster and yet is one of the least understood natural disasters. Quantifying drought is problematic as it occurs across erratic spatial boundaries and inconsistent temporal patterns. Furthermore, there is no universal definition of drought. Predicting drought is the reason for drought monitoring. Prediction enables real time analysis and evaluation of current conditions, assisting timely solutions and relief programmes in affected areas, as well as providing a deeper understanding of drought occurrence and patterns of potential future incidence. Drought prediction is derived from anomalies in temperature and precipitation, which, as historical archives indicate, can be extremely variable (Vicente-Serrano et al., 2012). Furthermore, ground based weather stations are sparsely and unevenly distributed, site specific and are unable to represent the true nature of events across broader expanses. There is roughly one weather station per 5000km^2 of land surface (Aghakoucak et al., 2015). Yuan et al., (2016) and Vicente-Serrano et al., (2011) criticised the accuracy and discrepancies of meteorological indices across different seasons and areas across the globe.

As technology continues to evolve, so do the techniques used in drought monitoring, thus providing a limitless future of possibilities (Zargar, 2011). The innovation of remote sensing boasts a significant advantage over traditional approaches. High resolution and multi-temporal spatial coverage remote sensing has bridged the gap that traditional methods have lacked. This allows for real time analysis and evaluation of current conditions, assisting timely solutions and relief programmes in affected areas, as well as providing a deeper understanding of drought occurrence and patterns of potential future incidence. However, discrepancies are found in the quality of resolution, revisit times, sensor malfunctions and the limited historical archives.

1.1 Defining Drought

Drought is considered as one of the most complex, yet least understood, natural disaster that affects more people than all others (Carrão et al., 2016; Hao et al., 2014; Hagman et al., 1984; Wilhite, 2000). It has a slow onset that establishes itself and builds over time (which can be a considerable period), whilst maintaining a low visual impact. Its devastation is wide-spread and can last for a substantial period (Prathumchai et al., 2001; Waldrow et al., 2012). Redmond (2002) described drought as the inability of water to meet needs. The World Meteorological

Organization defines drought as “a sustained, extended deficiency in precipitation” (WMO, 1986). Palmer, (1965) describes drought as “a significant deviation from the normal hydrological conditions of an area”. Mckee, (1963 p. 17), described drought as “a condition of insufficient moisture caused by a deficit in precipitation over some period of time”. Tucker and Chaudhury (1987) defined drought as a period of declined plant vigour, relative to the historical average caused by reduced precipitation.

Although there is no shortage in definitions of this phenomenon, one common feature across all definitions is that drought originates through the lack of precipitation over a relatively short interval, which results in a shortage of water resources (Willhite and Glantz, 1985; Panu & Sharma, 2003; Fadhil, 2011; Heim, 2002; Keyantash, 2002; Redmond, 2002).

Drought can be categorised into four distinct categories (Wilhite & Glantz, 1985)

- **Meteorological drought**: Is the lack in precipitation over a time period due to the seasonal precipitation falling below the long-term mean (Heim, 2002; Keyantash & Dracup, 2002; Waldrow et al., 2012).
- **Hydrological drought:** Is the lack in water supplies within water bodies such as streams and ground flow. It therefore represents the long-term effect of meteorological drought (Muirhamieed, 2013).
- **Agricultural drought:** occurs when there is insufficient moisture in the soil that directly results in insufficient growth support for crops (Waldrow et al., 2012; Belal et al., 2014; Carrão et al., 2015; Willhite, 1985).
- **Socio economic drought:** is the inability of water resources to meet the demands of providing economic utility (Belal et al., 2014).

The past few decades have seen a surge in drought occurrences (Kogan & Guo, 2016), whilst future predictions conclude that an increase in these events is anticipated. Solh and Van Ginkel (2014) surmised that all predictions on climate change show that our planet will become drier and hotter. Rising global temperatures will affect the hydrological cycle, leading to a decline in precipitation and an increase in evaporation, further compounding the occurrences of extreme events, specifically drought (Sheffield & Wood, 2007; Sheffield et al., 2012). Trenbath (2014) concluded that global warming may not be responsible for causing future droughts, however, it is expected that once a drought occurs, then onset will be quicker and intensity amplified.

1.2. Drought monitoring methods

The mitigation of the effects of drought through prediction and monitoring strategies is perilous (Wilhite et al., 2000). The complexity of monitoring natural disasters such as drought arises as a result of the wide spatial boundaries the drought inhabits, its untimely manner of onset and departure and its severity.

1.2.1 Traditional Approaches

Meteorological or traditional monitoring methods make use of ground based weather data, measuring the difference of precipitation anomalies compared to historical norms (Belal, 2014; Wilhite & Glantz, 1985). Early drought studies date as far back as Munger (1916) who created a drought index by measuring the number of consecutive days where precipitation values deviated from 1.27mm (Heim, 2002). The main advantage of a weather station is that it is an accurate representation of conditions pertaining to that specific point/area. However, weather stations in turn have a major disadvantage. These include point location representations rather than larger areas, as well as the sparse spatial distribution of these stations (Kogan & Gue, 2011). Wilhite et al., (2000) indicated that an important component in planning for drought is the availability of reliable and timely climatic information. Many weather stations suffer from missing historical data records, thus the interpolation of data points is affected.

1.2.2 Remote Sensing

"Early drought detection is fundamental to proactive decision making and disaster preparedness" (Aghakouchak et al., 2015 pg. 466). The past few decades have seen an explosion in remote sensing; offering a vast array of tools and effective opportunities in collecting and manipulating data in a timely cost-effective manner (Aghakouchak et al, 2015; Chopra, 2006; Kogan, 1997). The multi-temporal and high resolution spatial coverage of remote sensing allows for continuous monitoring of a drought occurrence, whilst using significantly few instruments (Unganai & Kogan, 1998; Wang, 2014; Wang et al., 2001). Remote sensing boasts a few advantages over meteorological methods in drought monitoring. These include, the improved spatial-temporal acquisition of near real-time data compared to the sparse spatially bound positions of weather stations (Chopra, 2006). The main advantage in satellite technologies is that satellite sensors and algorithms are continually evolving and have enabled improvements in remote sensing on the characterisation of drought (Zargar, 2011). The assumption in developing technologies regarding remote sensing is that developing indices will produce greater accuracy in combining spectral bands. This will subsequently produce vital information on ground based conditions, vegetation structure, water content, photosynthetic capacity, and mineral deficiencies (Dutta, 2016).

The growing volume of remote sensing observations and data products has provided opportunities to develop innovative drought monitoring techniques using multiple data sources (Aghakouchak et al., 2015). However, these opportunities are not without challenges. A constant challenge within this field of science includes uncertainty assessments, working with large data sets, incorporating multiple data sources, and ensuring accuracy as well as consistency between data sets and observations. Furthermore, historical data dates as far back as the inception of remote sensing (1980's), which is a relatively short period when compared to the meteorological data captured by weather stations.

Remote sensing can assist drought monitoring in rural areas and developing nations such as South Africa, through timely analysis of wide spatial and inconsistent temporal patterns of drought incidences. Traditional methods are further worsened in these areas due to poorly distributed weather stations, accompanied by missing data in the historical archives, making it difficult to conduct comprehensive site-specific studies. Kogan and Gue (2016) pointed out that within Africa, the total count of satellite 4km^2 observation pixels are 1800 times larger than the total weather stations, thus remote sensing has effectively filled the gaps between weather stations (Kogan & Guo, 2016). The validity of remote sensing against *in situ* data in drought monitoring has been established across various countries, thus confirming its validity and accuracy in drought monitoring (Kogan et al., 2012). Developing nations are often extremely susceptible to the effects of drought due to the lack of comprehensive drought relief programmes. As noted by de Ville de Goyet et al. (2006) roughly 90 percent of natural disaster related deaths take place in developing nations. Borrowed money is often spent fruitlessly, rather than being used for effective and constructive measures to end drought devastation. Implementing an appropriate infrastructure to aid in drought prediction, including monitoring and severity analysis, can notably improve the response to a drought episode before it becomes a crisis.

1.3 Research Questions

1. Is remote sensing growing as an approach to drought monitoring assessments?
2. Can remote sensing be used effectively to identify trends in drought events?

1.4 Objectives

1. Provide a systematic literature review on the evolution of drought monitoring approaches.
2. Identify Normalized Difference Vegetation Index (NDVI) and rainfall trends within KwaZulu-Natal and evaluate the effectiveness of NDVI to identify dry and wet spells over the past 16 years.

1.5 Summary of chapters

This thesis is composed into 4 chapters.

1. The first chapter provides an introduction of the study, defines drought and drought monitoring methods and presents the research questions and objectives.
2. Chapter 2 investigates the progress in remote sensing of drought, through a systematic literature review.
3. Chapter 3 focuses on the application of remote sensing towards drought monitoring.
4. Chapter 4 comprises of the synthesis, exploring the important findings in connection to the objectives of the study. Limitations and recommendations for future research are presented.

CHAPTER 2

Progress in the remote sensing of drought: *A systematic literature review*

Abstract

Early detection of drought is imperative to assist in appropriate decision making, disaster monitoring and mitigation procedures. The evolution of monitoring techniques and inception of remote sensing technologies provides a new approach to drought monitoring. It supplies a unique toolset for the timely monitoring and assessment of the various impacts of drought episodes. This systematic literature review aims to identify, categorise, and synthesise the results obtained from academic and other publications focusing explicitly on the remote sensing of drought. The literature studied consists of 1204 scientific papers published from 1955 to 2015, categorised into the various indices. Results showed an increase in scientific papers; with a notable surge in the past ten years. There has also been a notable rise in the combination of traditional and remote sensing approaches. Remote sensing continues to evolve, with technological improvements leading to enhanced resolutions and advanced indices, particularly in developed nations. Linking remote sensing archived data such as AVHRR-MODIS-NPP-NPOESS will create the largest data source of global spatial data. The implementation of a comprehensive index such as Vegetation Drought Response Index (VegDRI) in African countries may be pivotal in improving near real-time monitoring and drought predictions.

Key words: Drought; Systematic literature review; Traditional approaches; Remote sensing

2.1 Introduction

The increasing presence and severity of drought occurrences accompanied by pressing concerns about climate change has led to a greater desire to understand the drought phenomenon, as it continues to wreak havoc across human, environmental and economic facets of life (McCarthy et al., 2001).

Of the plethora of research papers pertaining to drought, the majority focus on monitoring and assessing a specific drought event (Prathumchai, 2001; Jeong et al., 2014). The area of interest for this thesis is those few research papers that review and compare the effectiveness of the diversified indices used in longitudinal drought monitoring (Mishra, 2010; Zargar, 2011) and those that have monitored the evolution of indices. Understanding the developmental phases of remote sensing and its progress as a tool to monitor droughts can provide an improved understanding of the analysis and monitoring of natural hazards. This review aims to explore the evolution of remote sensing as a tool for drought monitoring, and develops an understanding of what strategies to utilise in future drought monitoring.

Consequently, the research paper aims to provide a systematic review of scientific literature covering the evolution of remote sensing as a tool for drought monitoring. It objectively compared meteorological and remote sensing techniques as well as reviewing integrated approaches. This was done by ascertaining the various indices and methods used in research papers relating to drought; subsequently providing a methodical chronological review of the evolution and progress in drought monitoring techniques, highlighting implications for future work.

2.2. Methodology

2.2.1 Search and Selection

The methodology adapted for this systematic literature review made use of research papers extracted from various scientific libraries and search engines such as Scopus, Ebscohost and Google scholar. Key words used in the query were adapted to avoid unnecessary and irrelevant results, namely “drought monitoring indices”, “meteorological drought indices” and “remote sensing drought indices”. The input of these phrases into the various libraries produced a vast array of journals and research papers, some of which did not pertain explicitly to drought, but may have mentioned it. In cases where the paper mentions “drought” or “indices” but did not make its fundamental focus on the occurrence of drought, it was excluded from further analysis.

Therefore, a set of criteria was established when selecting papers. *Firstly,* the results were required to be from a published scientific paper; pertaining to a specific drought event or mentioning indices used in examples of drought occurrences. *Secondly* the paper must have been English or translated into English. *Thirdly,* the defined key words must exist in the title, abstract or key words. In cases where the abstract mentioned “remotely sensed indices” but did not define the specific “indices” used, the journal was briefly reviewed to find which index was being used and recorded. Furthermore; in the case where the drought specific paper was not accessible but mentioned of “remotely sensed indices” or “meteorological indices “in the title or abstract, the paper was categorised as such.

The scientific libraries and journal sources were limited to; Scopus, Google Scholar, Science Direct, Wiley, Taylor and Francis and Springer. Grey literature was obtained through a paper by Zargar (2011) which mentions various journal sources and their respective remotely sensed indices.

Upon accepting a scientific paper for inclusion, the results of that paper were entered into a table categorising the method used e.g. traditional, remote sensing or both, (journals categorised as “both” would not be accounted for in meteorological and remote sensing categories). Furthermore, the indices were tallied based on regularity. Indices of higher popularity such as the Palmer Drought Severity Index (PDSI), Standardized Precipitation Index (SPI) or NDVI were given their own column, whilst scarcely used indices were categorised into "meteorological" or "remote sensing" indices, respectively. The date of the respective papers was recorded to create a schematic timeline displaying the various approaches adopted for drought monitoring over the years. The author and source (e.g. Scopus, Taylor and Francis) and where necessary the definition of index, were also recorded so as to avoid repetition

2.3 Drought monitoring indices

This section reviews the meteorological, remotely sensed, and combined indices used in research papers collected from various scientific libraries. The literature studied consists of 1204 scientific papers published from 1955 to 2015, categorised into the various indices.

Drought monitoring methods vary across different hemispheres, countries, regions, and climates. Some indices are capable of being used across a variety of climates whilst others have been adapted to only suit a certain climatic region (Heim, 2002). The results captured in this research ranged from 1955 to 2015. Over this period, there was consistency in research papers up until the early 2000's. Post this period, there is a notable expansion in research papers as seen in ***figure 2.1***.

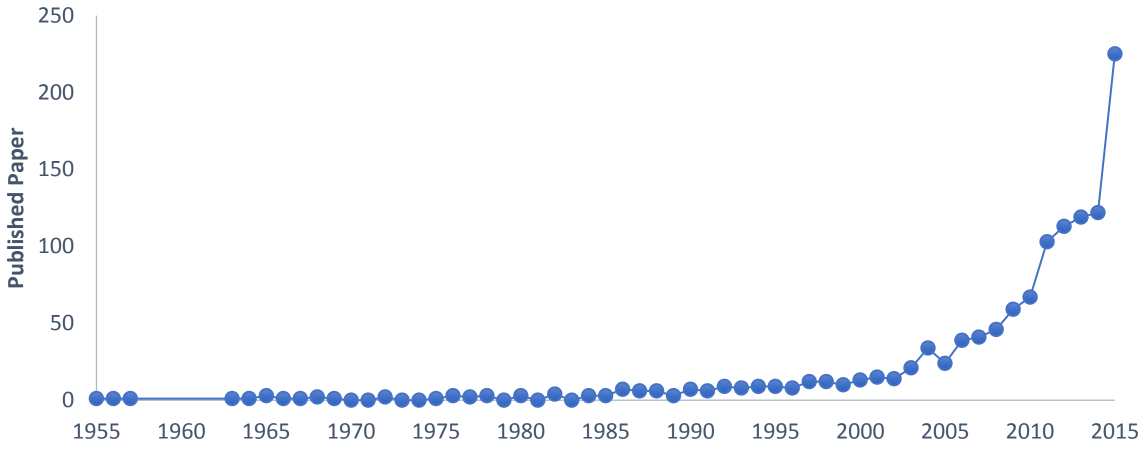

Figure 2.1. *Total number of published papers on drought monitoring (1204) between years 1955 and 2015.*

This result indicates the growth in development of the research into drought monitoring. Other reasons pertaining to this expansion may be due to the advancement made in technology, notably the internet, which has allowed for research papers to be easily obtained, reviewed and published. Another probable contributing factor is the growing presence of drought worldwide and the increasing threat it poses to the economic, environmental and societal wellbeing of human life. Increasing population growth and industrial development leads to an increased demand for natural resources (in this case water), prompting research gaps in how to better manage the increasing demand for vulnerable water resources (Chopra, 2006; Woodhouse, 2009). Further compounding effects can be seen from a global warming perspective, where increasing surface temperatures, unstable weather systems and rising sea levels are all contributing in different ways towards the increase in droughts and their severity. This has prompted an increase in scientific research, bridging the gap to understanding one of the most complex yet least understood natural disasters (drought) (Carrão et al., 2016).

2.3.2 Meteorological Indices

Over the decades, many indices have been developed and used including RSM (Thornthwaite and Mather, 1955), RAI (Van Rooy, 1965), PDSI (Palmer, 1965), Deciles (Gibbs and Maher, 1967), BMDI (Bhalme and Mooley, 1980), SWSI (Shafer and Dezman, 1982), DSI (Bryant et al., 1992), SPI (Mckee, 1993), NRI (Gommes and Petrassi, 1994), DFI (Gonzalez and Valdes, 2006), RDI (Tsakiris and Vangelis, 2005), GRI (Mendicino et al., 2008) and DTx (Matera et al., 2007). The most common indices were that of the PDSI and the SPI which continues to make regular occurrences in the contribution to meteorological indices in drought monitoring studies today and contributed significantly to the rise in research papers over the past few years as seen in ***figure 2.2.***

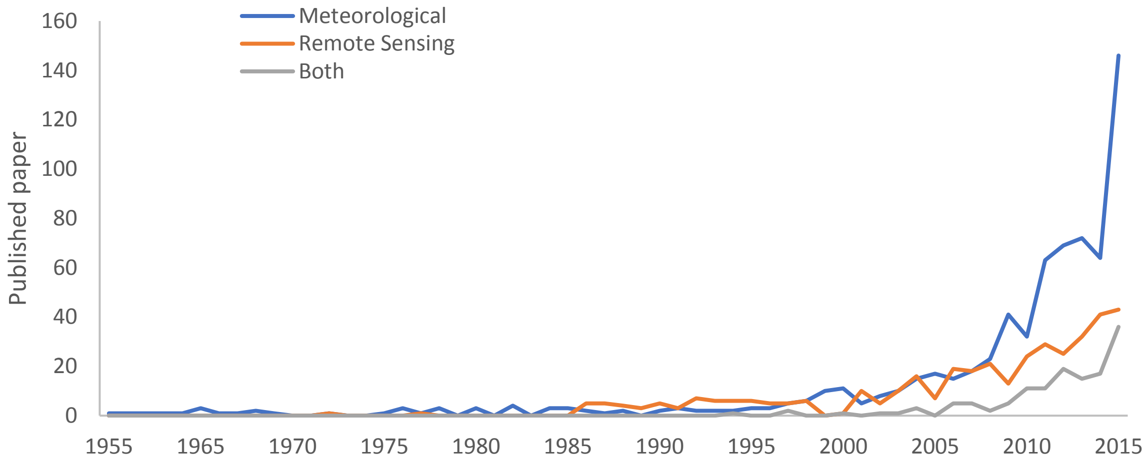

Figure 2.2. *Number of publications that used, meteorological, remotely sensed and both approaches for drought monitoring*

2.3.3 Remotely Sensed Indices

Monitoring drought using remotely sensed indices is a relatively new method compared to the extensive presence of meteorological indices. Initial satellites launched in the 1980's were designed to aid in weather forecasts, however, they were soon found to be useful in monitoring vegetation (Kogan, 2000). In 1979 the Advanced Very High-Resolution Radiometer (AVHRR) was launched, providing impressive temporal resolution data for monitoring vegetation conditions (Aghakouchak et al., 2015). The contribution of remote sensing to assess drought impacts is through an assessment of the photosynthetic value of plants (Aghakouchak et al., 2015; Tucker and Choudhury, 1987). The respective decline in vegetative health is related to the deficits of precipitation being experienced. Combinations of various wavelengths, namely the visible red (R) and near-infrared (NIR) regions are used extensively to monitor changes in plant and water stress (Waldrow et al., 2012; Aghakouchak et al., 2015; Tucker and Choudhury, 1987). Introduced by Tucker (1979), the Normalized Difference Vegetation Index (NDVI) was the first remote sensing based index used to monitor agricultural drought and has since become the most popular remotely sensed drought index (Dutta, 2016; Thenkabali, 2004; Tucker, 1979). Other indices include the Perpendicular Vegetation Index (PVI) (Wiegand et al., 1991), Vegetation Condition Index (VCI) (Kogan, 1997); Normalized Difference Water Index (NDWI) (Gao, 1996), Transformed Vegetation Index (TVI) (Tucker, 1979), and the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988) to name a few.

Remote sensing of drought is not limited to one variable such as monitoring vegetation vigour. As technologies and sensors developed on satellites, the ability to routinely capture rainfall data through multiple wavebands became available (Aghakouchak et al., 2015). This can be achieved by converting the temperatures of cloud tops, through the visible (VIS) and IR images, using an empirical statistical relationship to determine the precipitation rate (Turk et al., 1999; Joyce et al., 1997). A more physical approach to capturing precipitation can be achieved through passive microwave (MW) sensors (Aghakouchak et al., 2015). However, the more accurate precipitation values gained through MW are limited to less overpass (roughly two observations per day). Joyce et al. (2004) suggest combining the strengths of IR and MW data sets to allow for an increased accuracy on precipitation patterns. Examples of such satellites are the Tropical Rainfall Measuring Mission (TRMM) (Sahoo et al., 2004); Global Precipitation Climatology Project (GPCP) (Adler et al., 2003) and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN) (Hsu et al., 1997). Although remote sensing of precipitation data sets has been used in drought monitoring, the main limitation of these products is the lack of historical records (i.e. limited to 16 years) (Aghakouchak et al., 2015). ***Figure 2.3***, indicates the growing presence of remote sensing for drought monitoring. The data, post the millennium, display an increase in the number of remote sensing on drought papers being conducted. This correlates with the increase in the amount of remote sensing observations and satellite sensors being launched during this period, whilst many more are in developmental phases (Aghakouchak et al., 2015).

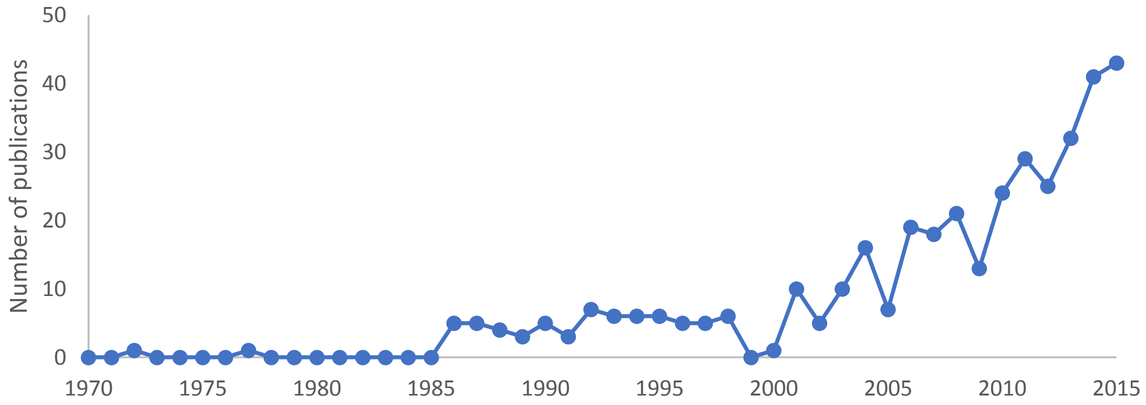

Figure 2.3. *Yearly scientific papers making use of remote sensing approach for drought monitoring.*

Further quantification of drought stress can be achieved using remote sensing that measure surface temperature or brightness, based on the thermal bands aboard multiple satellite sensors such as AVHRR, MODIS, Landsat 5 TM and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Thermal Infrared Sensor (TIRS) (Aghakouchak et al., 2015). Gutman (1990) explained that valuable surface moisture conditions can be provided through the Land Surface Temperature (LST) which is computed through the Thermal Infrared (TIR) band. The Temperature Condition Index (TCI) is a commonly used index in explaining the temperature related stress in drought analysis (Kogan, 1997). It uses the Brightness Temperature (BT) which represents the difference from the current month's temperature to that of maximum recorded for that specific area (Belal et al., 2014). Kogan (1997) combined the VCI and the TCI as an index (VCI-TCI) to determine the vegetation stress, and subsequently drought, as the major cause. The results showed that it performed admirably and was extremely useful in real-time diagnosis and assessment of the weather impact on vegetation condition.

2.3.4 Combination of Meteorological and Remotely Sensed indices

As mentioned, both meteorological and remotely sensed indices have respective advantages and disadvantages over one another. Whilst the NDVI has been proved to provide valuable information on vegetation vigour, in some cases it may be difficult to identify the main reason for vegetation stress solely from the NDVI (Aghakouchak et al., 2015; Heim, 2002). This deviation may be due to fire, plant infestation, land cover change or flooding which can subsequently lead to NDVI anomalies indicating similar data to that of drought. In order to overcome this, many studies incorporate both meteorological and remotely sensed indices for drought prediction.

Results in the combination of meteorological and remotely sensed indices favoured the use of the NDVI with the SPI as a comprehensive approach to drought monitoring. As seen in ***Figure 2.4***, combined SPI and NDVI studies account for 53% (71/135*100) of the 146 total combined research papers. Furthermore 40% (54/135*100) accounts for either the SPI or the NDVI as the respective index being combined with a separate traditional or remote sensing index. Lastly, a mere 7% (10/135*100) makes use of indices excluding the SPI or the NDVI in the study. This result firstly reiterates the popularity of the SPI as a meteorological index and the widely used NDVI as a remote sensing index and secondly the effectiveness of combining the two indices.

The increase in percentage of combining meteorological and remotely sensed indices can be seen in ***Figure 2.5***; this result was obtained by dividing the amount of papers categorized as "both" by the amount of papers retrieved for that specific year. The year 2015 recorded the highest increase with above 25% of scientific papers utilising both approaches towards drought monitoring. Success in combining meteorological and remote sensing approaches towards drought monitoring can be seen in the following examples. Ji and Peters (2003) found that a 3-Month SPI had the highest correlation to the NDVI due to the lag time associated with vegetation response to precipitation. Jain et al. (2010) concluded that the NDVI correlated accordingly with a 1-month, 3-month and 9-month SPI at three different sites receiving higher, normal and poor rainfall respectively. Wang et al. (2014) found that the VHI and the SPI shared valiant consistency during the drought period. Caccamo (2011) determined that the Normalized Difference Infrared Index-band six (NDIIb6) shared similarities with the 3 and 6-month SPI distribution during a drought. Anwar et al. (2013) showed that the NDVI and PDSI were consistent during changes in precipitation intensity over a 10-year period. Mu et al. (2012) found the drought severity index (DSI), which makes use of satellite based Evapotranspiration and NDVI products, to correspond well with the PDSI, both capturing similar wetting and drying patterns.

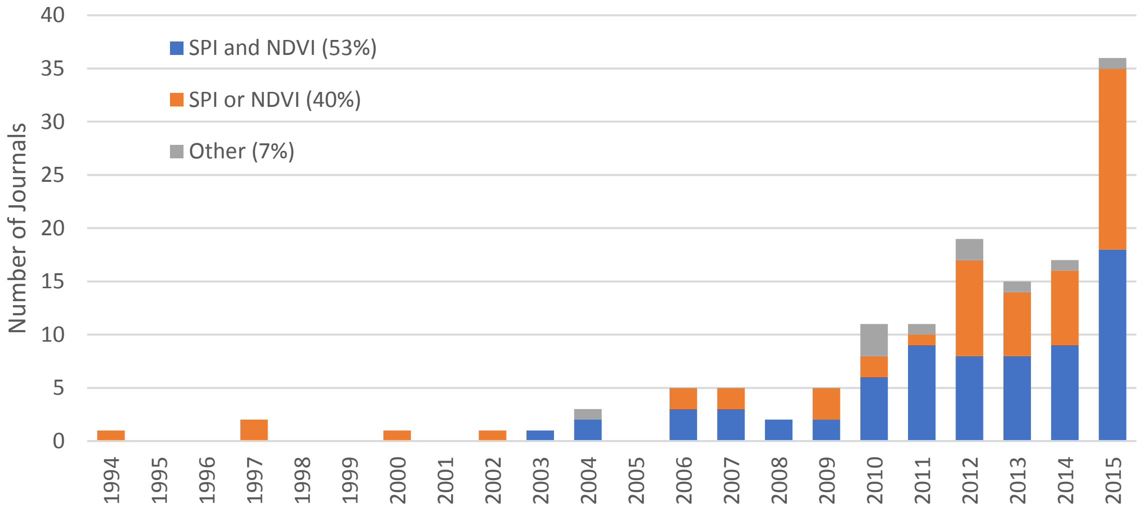

Figure 2.4. *Progress of combined SPI and NDVI indices in research papers for drought monitoring.*

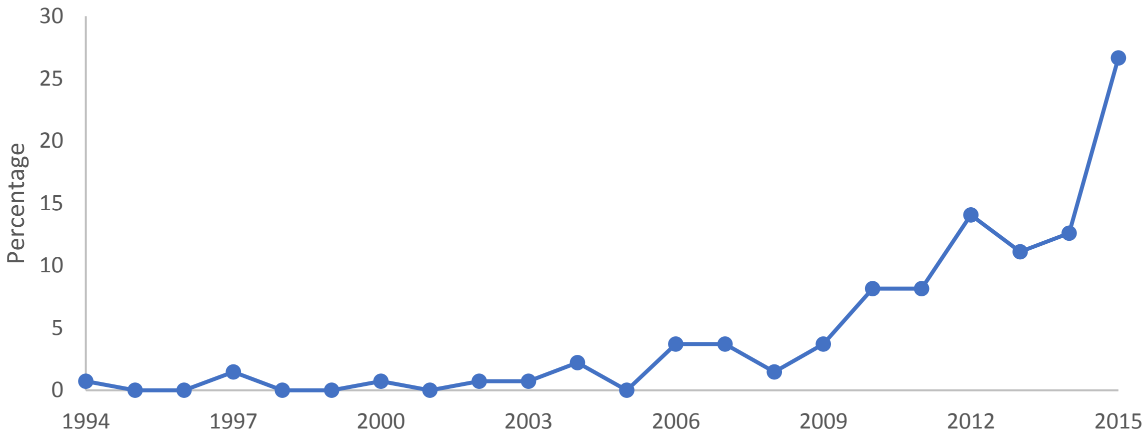

Figure 2.5. *Yearly percentage growth in combining meteorological and remotely sensed indices in research papers for drought monitoring*

2.4 Limitations of using RS and opportunities for improvements

The use of remote sensing within drought monitoring research is still relatively new, and until the mid-2000's had limited progress. As seen in ***figure 2.2*** the general trend is an increasing number of research papers integrating remote sensing in drought research. This is possibly as a result of continuous improvements in remote sensing technology. Further findings in this study include the dominance of the NDVI which continues to be an integral component in drought monitoring since its inception in 1979. Whilst NDVI is an important index, the incorporation of other indices such as the LST, TCI, SAVI, VHI etc. have assisted in improving the accuracy of remote sensing of drought. Furthermore, the combination of both traditional and remotely sensed indices has seen a rise in recent years. Combining remote sensing variables with ground based data increases the data from multiple different data sources for an assessment. ***Figure 2.5*** illustrates the increase in combining these two approaches over recent years.

One major limitation of remote sensing is that the high resolution and near real time data sets have a relative short history of data (10-14 years) (Aghakouchak & Nakhjiri, 2012). Thenkabail et al. (2004) looked to combine the historical archives of AVHRR sensor data, which spans from 1982-1999, to that of the more established MODIS sensor, 2000-Present. This was not without challenges as the two sensors use different resolutions (10km AVHRR and 0.5km for MODIS) as well as different pre-processing methods. It was concluded that linking these two data sets as an AVHRR-MODIS land cover archive will be vital for future monitoring of drought as MODIS data is only guaranteed until 2018. MODIS's successors, the National Polar-orbiting operational Environmental Satellite System (NPOESS) and NPOESS

Preparatory Project (NPP), are planned to take over. This will establish data sets from the AVHRR-MODIS-NPP-NPOESS which will provide the largest data source of global spatial data, greatly improving the historical archive for future drought monitoring studies (Hayzaymeh & Hassan, 2016; Thenkabail et al., 2004).

2.5 Potential for future research

Niemeyer, (2006) suggested that instead of developing new singular drought indices, it would be better to combine more comprehensive drought detection and monitoring tools, as this could lead to improved detection and monitoring. Suggestions for future drought studies include the use of microwave-based monitoring, offering a unique niche in monitoring drought impacts on vegetative presence, vigour and density. Combining optical and microwave monitoring methods can lead to a better understanding of the response of an ecosystem to climatic variability (Aghakouchak et al., 2015). This avenue of research can potentially lead to a greater understanding of the changes in ecosystems (phenology, carbon cycling and biomass) during the presence of a drought.

The Vegetation Drought Response Index (VegDRI) is one of the most comprehensive drought indices currently in use (Niemeyer, 2008; Tadesse et al., 2015). Introduced by Brown et al., (2008) it makes use of climate data (e.g. SPI and PDSI anomalies), satellite observations (e.g. NDVI) as well as various biophysical data (e.g. elevation, soil type and land cover). As mentioned, the NDVI as a sole indicator of drought can be subjective as plant infestation or fire can falsely depict drought conditions. By combining climate-based data as well as satellite observations, the VegDRI seeks to overcome this limitation. The VegDRI data sets are easily accessible through the National Drought Mitigation Centre (NDMC) http://vegdri.unl.edu/. However, a disadvantage of the VegDRI includes the fact that it is not widely used outside of the United State of America. Although it has a 1km resolution; there can be limited precision over areas that contain sparse weather station distribution, due to the reliance on interpolated anomalies (Tadesse et al., 2015).

2.6 Concluding remarks

The following conclusions can be drawn from this study

1. There has been a significant growth in remote sensing as an approach to drought monitoring, as well as the combination of meteorological and remotely sensed indices in drought monitoring.
2. A significant increase in research pertaining to drought monitoring was noted in the early 2000's, prompting a raised concern on the phenomena as a natural hazard.
3. Linking AVHRR-MODIS-NPP-NPOESS will in turn create the largest data source of global spatial data; this will prove pivotal with the NDVI clearly dominating as the prime index in remote sensing on drought.
4. Given the growth in drought monitoring indices and in remote sensing; a focussed study of this information will explore the usability and validity of these measures in a rural area in a developing country.

CHAPTER 3

Drought assessment and monitoring in KwaZulu-Natal, South Africa using Remote Sensing and Geographic Information Systems.

Abstract

In recent decades KwaZulu-Natal and greater parts of southern Africa have, been experiencing very severe episodes of drought. The side effects have affected almost all facets of human life, especially agricultural practice, which is very prevalent in KwaZulu-Natal. By analysing the past 16 years’ worth of NDVI and provincial mean rainfall, this study has successfully identified fluctuations of inter-annual climatic variations. The NDVI can identify drought patterns as well as severity, indicating 2015 to be the worst year across the study period. Further results included the strong relationship between NDVI and rainfall, especially during dry years as compared to the wet years. Possible solutions to the NDVI saturation level included the use of adjusted wavelengths in the red-edge band as well as the MNDVI and updated satellite platforms. Increased rainfall in 2016 did little to reprieve drought conditions as Albert falls dam was unable to fully recover prior to the dry season. The study is critical to understanding trends in southern African droughts within a spatially explicit context, setting the basis for future predictions and early warning.

Key words: Drought; KwaZulu-Natal; Remote sensing; NDVI

3.1 Introduction

Southern Africa is currently experiencing one of the worst droughts it has seen in recent decades (Carnie, 2016). Although records show drought occurrences dating back to 1910, there has recently been an increase in the frequency and intensity of drought episodes highlighted on a two-year scale since the 1970's (Dube & Jury, 2000; Roualt & Richard, 2005). Within southern Africa most countries rely on agriculture, from small subsistence farms to advanced commercial farming, for food production. All are extremely susceptible to the inter-annual and intra-seasonal rainfall (Dube & Jury, 2000).

Most of the droughts in southern Africa coincide with the El Nino Southern Oscillation (ENSO); the event has a large influence on the rainfall variability in southern Africa. Prolonged periods of below average rainfall greatly exacerbate the effect of current or growing drought episodes (Lindesay, 1988; Richard & Poccard, 1998; Mishra, 2003; Ujenza, 2014). Dube and Jury (2002) noted that the 1992/3 ENSO phase had no significant influence on the rainfall over southern Africa; however, in a study by Roualt and Richard (2005), most of the severe droughts occurring in southern Africa from 1901-2004 were ENSO related. Furthermore, over the course of the twelve recorded dry years in southern Africa, eight have been ENSO years (Roualt & Richard, 2005). Other causes of climate variability in this region can be related to the contribution of the Aghulus current along the south-eastern portion of southern Africa (Jury, 2015). Adedoyin, (1997) stated that man-made climate change as well as poor agricultural practices such as overgrazing has renewed concerns on drought within Africa.

The average temperature in the subtropics has risen exponentially over the past five years, with a further 3^{o}C to 5^{o}C increase expected over the tropics by the end of the century. Further warming in the tropics will lead to the southern and northern latitudes to becoming drier. As a result, southern Africa will become significantly warmer and subsequently experience more extreme weather conditions in the form of floods and droughts (Nhemachena & Hassan, 2007). Dube and Jury, (2000, p. 51) stated that "the cycle of droughts will cause water demand in South Africa to exceed total available supply around the year 2020".

During 2014/2015, another ENSO process has taken place affecting southern Africa, significantly exacerbating the weather conditions, and subsequently leading to one of the worst droughts in recent history.

The inception of remote sensing as a tool for drought monitoring in the mid 1980's has offered a new technique in providing near real time, accurate, multi-temporal and high resolution spatial coverage of ground based conditions (Wang, 2014; Wan, 2004; Kogan, 1995; Wang et al., 2001). This tool set is ideal for global drought watch, and is a key approach for developing nations which possess lightly populated weather stations and many remote and hard to access areas (Wan et al., 2004).

This study's objectives were firstly to identify NDVI and rainfall trends within KwaZulu-Natal over the past 16 years and secondly, to determine the effectiveness of NDVI in identifying and assessing drought in KwaZulu-Natal, specifically the recent drought episode. Lastly, confirmation of the recent drought is shown with the surface area changes of the largest water body in KwaZulu-Natal.

3.2 Study Site

KwaZulu-Natal is located within the south-eastern portion of South Africa, positioned between 27^0 and 31^0 south and 29^0 and 31^0 east. The area encompasses 94,000 km^2, and contributes 7% of the area of South Africa (Camp, 1999). Across South Africa, KwaZulu-Natal receives above average annual rainfall, with precipitation ranging from 500 mm up to 2000 mm. The region receives most of its rainfall during the summer months; between October and March. Temperatures can range from a high mean of 32^0C in summer to a low mean of 0^0C in winter.

There is a substantial change in elevation across KwaZulu-Natal, ranging from the coastal plains across Maputaland, to the deep incised valleys and broken terrain in the high altitudes of the Drakensberg (uKhahlamba) region located 3000m above sea level (Dube, 2003). The area offers a plethora of diversity in natural resources. However, increased agriculture processes in the south east accompanied by expanding urban and industrial centres have placed an increased demand for water resources (Dube, 2003).

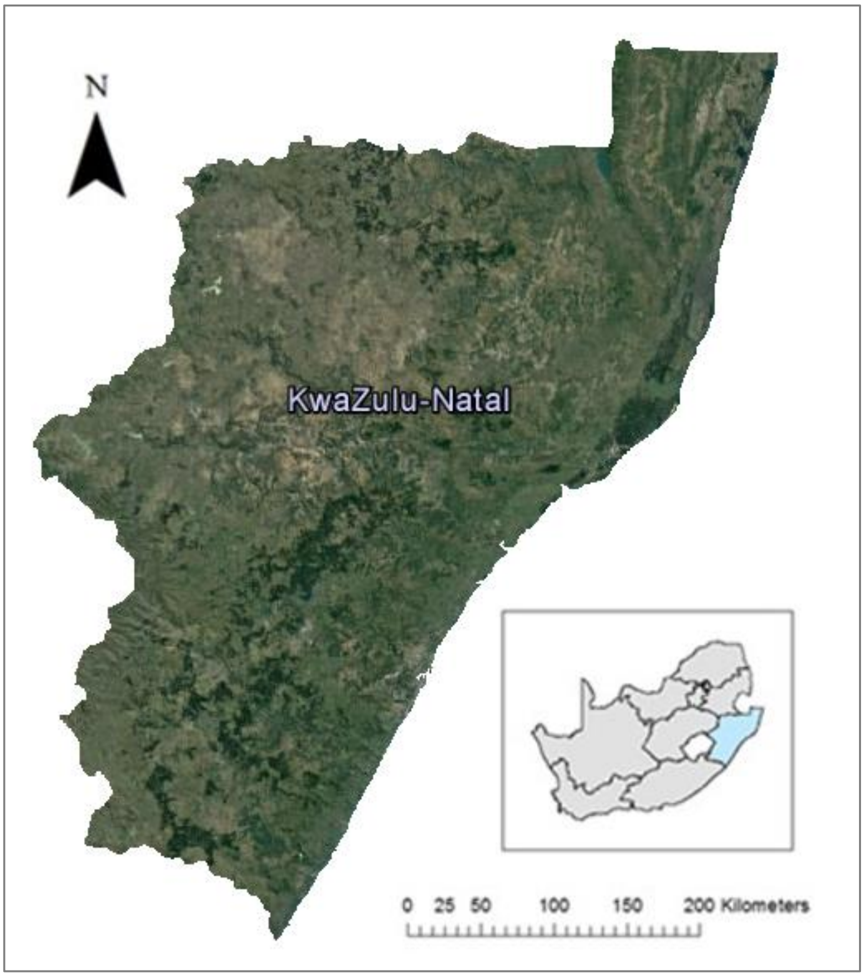

Figure 3.1. *Study Area, KwaZulu-Natal, South Africa, Overlain on Google Earth image*

3.3 Methodology

3.3.1 Data

Meteorological data for this study consisted of rainfall data obtained from the South African Weather Service. The data consisted of monthly averages for KwaZulu-Natal, ranging from 2001-2016.

The satellite data was retrieved from the Moderate-resolution Imaging Spectroradiometer (MODIS) sensor, which has noticeable improvements over its successor, the Advanced Very High-Resolution Radiometer (AVHRR), and is widely used in agricultural and drought monitoring applications (Gu et al., 2008; Huete, 2002; Pittman, 2010). The sensor offers an increased 36 spectral bands as well as narrow spectral bandwidths on the red band (R) (0.62-0.67µm) and the NIR band (0.84-0.87 µm) offering increased sensitivity to chlorophyll as well as being less influenced by water vapour absorption (Waldrow et al., 2012). The sensor used in this study is the MOD13A1 V6, incorporating 500m pixel resolution as well as a 16 day revisit time. It makes use of the gridded level 3 product in the Sinusoidal projection which is tiled 10 by 10 degrees from the equator (Persendt, 2009; Solano et al., 2010). Due to the spatial extent of the study site, two tiles were required (h20v11, h21v11). The imagery is readily available from the USGS EROS website (http://earthexplorer.usgs.gov). MODIS data sets undergo frequent pre-processing, calibration and normalisations allowing for the data to be available as processed products, as opposed to raw digital numbers (Thenkabali, 2004). The study made use of 368 satellite images extracted from January 2001 to December 2016, the images were calculated as monthly means according to the respective date of capture.

The site boundary layer was obtained through the University of KwaZulu-Natal Cartography Department. The satellite images were analysed and manipulated using ArcMap 10.3. Microsoft Excel was used for statistical analysis as well as presenting the results. Digitizing of the Google Earth product allowed for the boundary of the Albert Falls dam on the selected two dates for comparison. The dam levels for the selected dates was obtained through Umgeni Water in Pietermaritzburg.

3.3.2. Pre-processing

The satellite images were processed, mosaiced and rescaled before being analysed in ArcMap. The images were geometrically corrected to the WGS84 datum.

3.3.3. NDVI

The NDVI is one of the most widely used indices to date. It is an effective index in measuring vegetation presence including its density and health. It has a desirable scale of -1 (indicating non-vegetative surface) to 1 (indicating dense vegetation) whilst 0 depicts an approximation of no vegetation. Making use of the R (0.62-0.67µm) and NIR (0.84-0.87 µm) bands, the NDVI can reduce undesirable effects from sun angles, topographic and external noise (Fadhil, 2011).

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

The NDVI is calculated by the above algorithm. Where NIR equals the near infrared reflected by vegetation, R is the red band absorbed by the chlorophyll found in vegetation (Belal et al., 2014; Thenkabail et al., 2004). Vegetation will only depict signs of water stress after the level of available soil water has decreased to the level that is less than the loss through evapotranspiration (Liu, 2001). Subsequently, an increase in temperature of the vegetation under stress leads to closure of the leaf stomata, reducing further moisture loss through evapotranspiration (Nichol & Abbas, 2014).

The NDVI is an effective indicator of vegetation vigour. However, a reduction in rainfall can only be detected after the vegetation shows a decrease in vigour (Persendt, 2009). Therefore, the NDVI correlates well with rainfall requirements for good vegetation health after a certain lag period, roughly 3 months depending on the area and climate. Thus, near real-time analysis of drought can be an issue, as it can take up to 3 months for observed rainfall to be reflected through the NDVI (Liu & Juarez, 2001).

3.4 Results

3.4.1. Relationship between NDVI and rainfall

The relationship between rainfall and NDVI can be analysed in a variety of different ways. Here we compared the mean monthly NDVI and rainfall for the province over a 16 year period. As seen in ***figure 3.2***, there is a positive correlation between the mean seasonal NDVI and rainfall, (R^2=0.44).

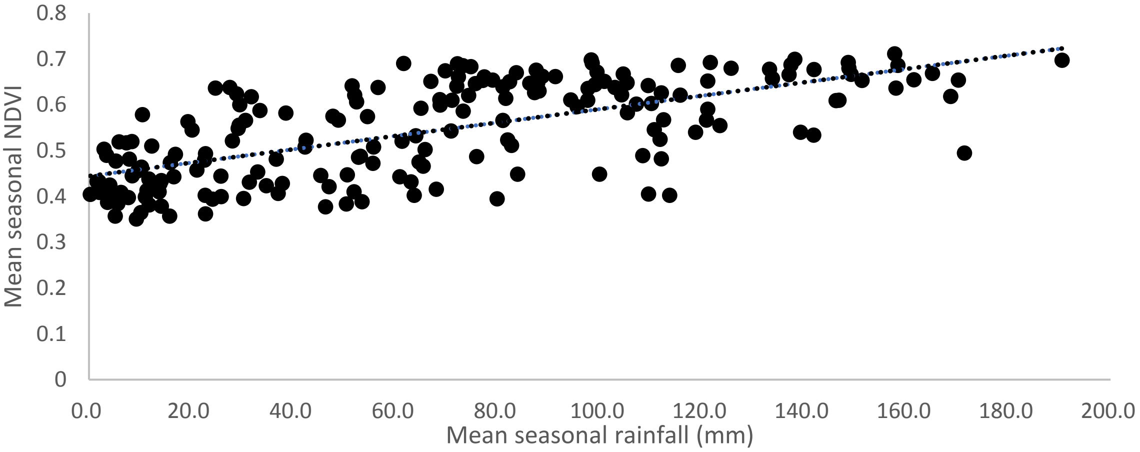

Figure 3.2. *Mean seasonal NDVI/Rainfall correlation 2001-2016*

Seasonal patterns of rainfall and NDVI can be noted in ***figure 3.3*** which displays the below average rainfall that the Northern interior of KwaZulu-Natal receives, which corresponds with the lower NDVI values associated in the area. The south eastern-coastal patterns are consistent with higher rainfall and NDVI values.

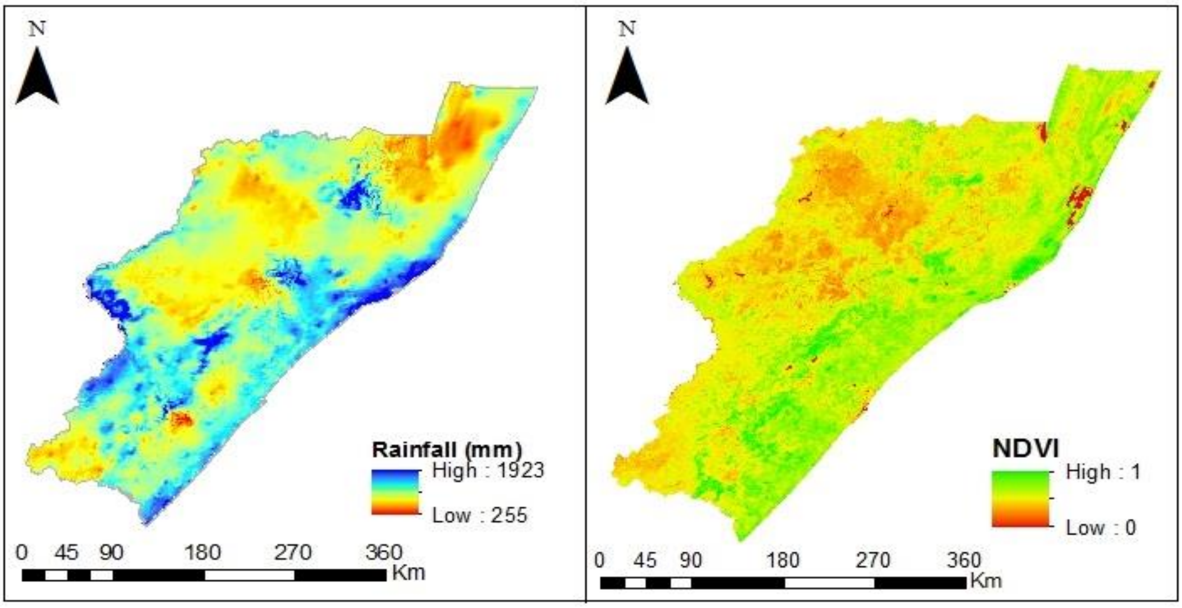

Figure 3.3. *KwaZulu-Natal Average rainfall and NDVI (2001-2016)*

Figure 3.4 combines the mean NDVI and rainfall patterns spanning the 16 year period. Both variables correspond with an observed decrease in 2003 and 2015, whilst the year 2006 displays above average in both NDVI and rainfall. A slight discrepancy is noted in 2009 indicating that the increase in NDVI is greater than rainfall whilst 2012 indicates the reverse. Furthermore, ***figure 3.4*** demonstrates a noticeable lag of a couple of months between the rainfall and NDVI from 2013 through to 2016.

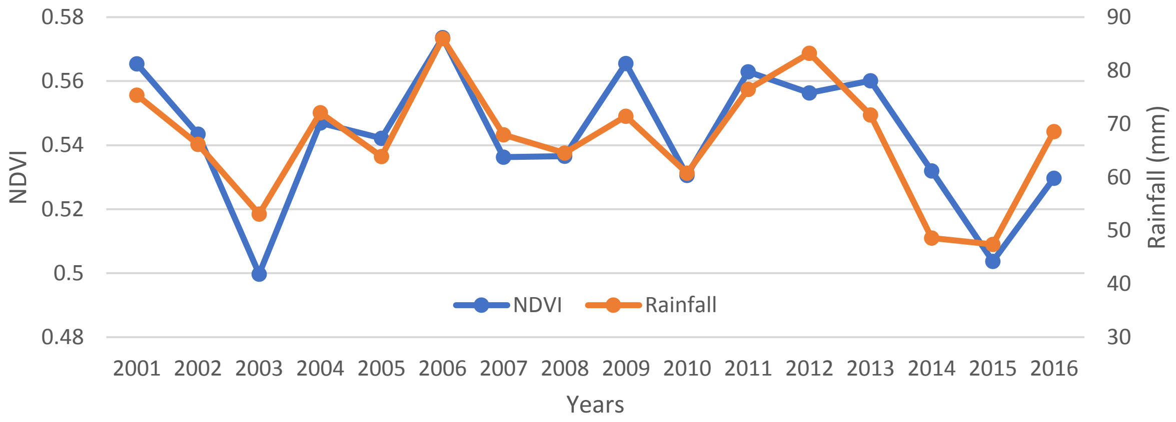

Figure 3.4. *Temporal trends of NDVI and Rainfall (2001-2016).*

To explore the correlation of NVDI and rainfall further, the mean NDVI for the two years of above average greenness (2001;2006) is compared with the periods of significant decline in greenness (2003; 2015) ***(figure 3.5)***. The difference between the non-drought and drought years are clearly illustrated providing further validity to the correlation of variables. The interior of

KwaZulu-Natal is characterised by arid and dry conditions, which are extremely exacerbated during periods of limited rainfall as this directly affects the vegetation found in this area. Similarities in high NDVI patches across all four NDVI years can be noted from central to the south east of the province. This is a result of the agricultural practice of consistent irrigation.

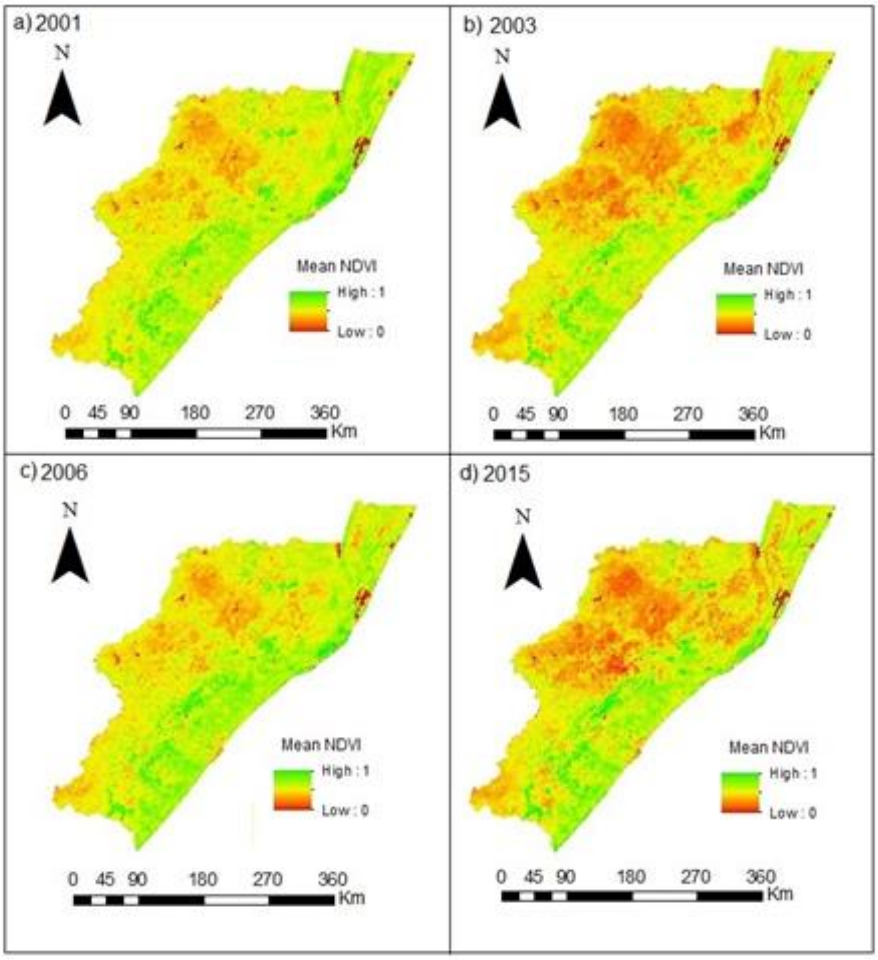

Figure 3.5. *Mean NDVI of non-drought years shown in (a) 2001 (b) 2003; Mean NDVI of Drought years shown in (c) 2006 (d) 2015.*

A further comparison between measured rainfall and the NDVI score over the past 16 years is illustrated in ***figure 3.6***. The years 2015 and 2003 show the lowest NDVI and rainfall across the observed period, whilst 2006 shows the highest amounts across the 16 year period. Noticeable features include 2014 being very low; indicating possible drought in 2015. The two back to back years of lower scores are indicative of a period of prolonged dryness and drought. Year 2016 improved considerably, however it is still below average in NDVI, as the vegetation cover continues to recover.

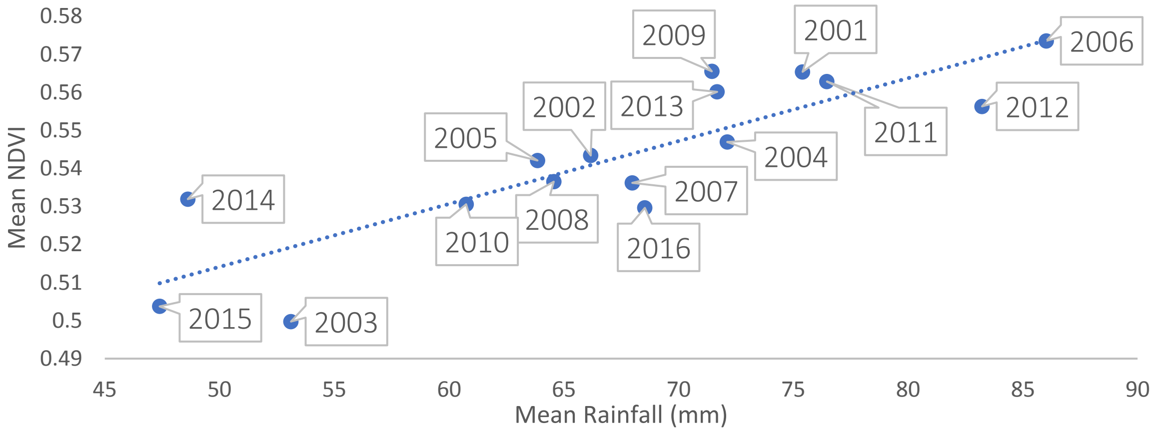

Figure 3.6. *Correlation of yearly mean NDVI and rainfall over the past 16 years.*

Figure 3.7 shows the correlation between NDVI and rainfall during the driest years (2003; 2014; 2015) and the wettest years (2006; 2011; 2012). The higher rainfall received during the wet years does not necessarily equate to significantly higher NDVI values (R^2=0.41). However, there is an improved relationship between rainfall and NDVI during drier years (R^2=0.43).

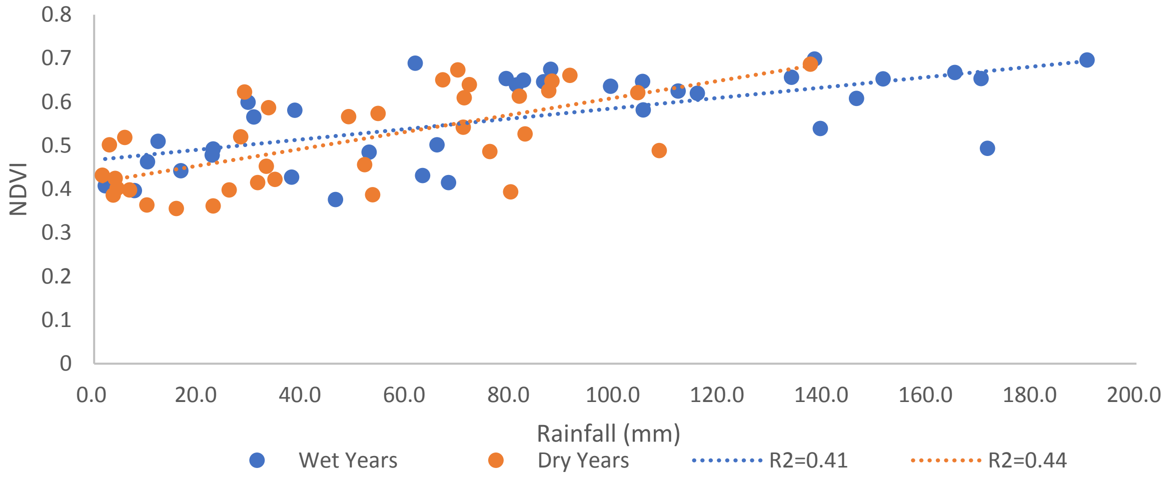

Figure 3.7. *Correlation of NDVI and Rainfall for Wet years (2006; 2011; 2012) and dry years (2003; 2014; 2015).*

3.4.2. Driest December in 16 years

December 2015 was the driest recorded month during the past 16 years. ***Figure 3.8*** shows the NDVI for December years of 2014, 2015 and 2016. Clearly the year 2015 and parts of 2016 show significantly lower NDVI scores in comparison to December 2014 (indicating significant dryness). A specific area surrounding the coordinates *29^{O}33'10.5"S 30^{O}07'43.5"E* show the variations in NDVI values across the three years illustrated in the graph on the side of the figure. The notable decline in rainfall since 2013 is evident in ***figure 3.8***, however, signs of improvement are noted in 2016. These NDVI observations of drought are confirmed by the decline in water levels in the Albert Falls dam ***(figure 3.9)***. The Dam experienced significant dryness from 2014 to 2016. In August 2014, the dam was 83.71% full and its surface area was 20.98km^2. In October 2016, the level had dropped to 47.50% as well as the surface area encompassing only 12.47km^2. The surface area had decreased by 40.5% and the water level had seen a 43.25% decrease. Furthermore, in 2014 the dam was 83.71% full, whilst in 2016 the level dropped to 47.5%. As of June 2017, the water level was only 34.29% full (Umgeni Water, 2017), suggesting current conditions still reflect a severe drought.

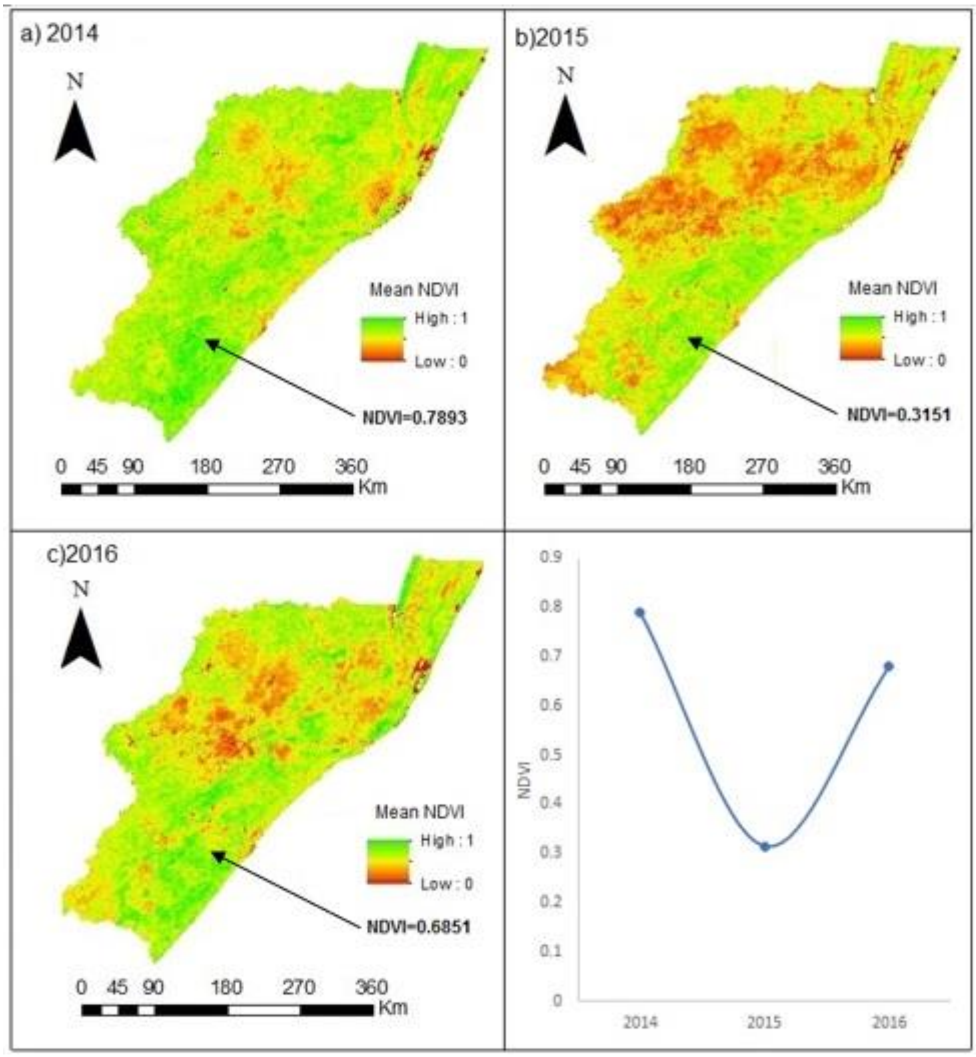

Figure 3.8. *Mean NDVI for the month of December for years 2014, 2015 and 2016, changes in NDVI of specific location across the three years.*

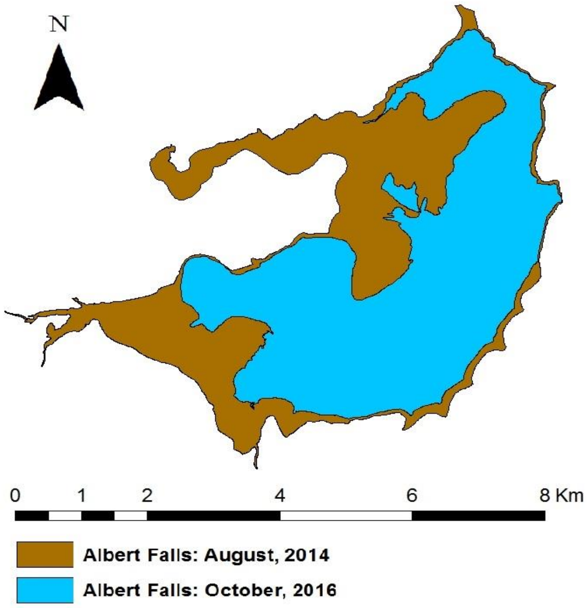

Figure 3.9. *The shrinkage in surface area of the Albert Falls Dam in just over two years.*

3.5 Discussion

It is evident that across the past 16 years there has been a strong relationship between rainfall and NDVI. During periods of decreased rainfall, there is a notable weakening in NDVI whilst during years of above average rainfall, the NDVI showed an increase. The NDVI is capable of indicating past periods of drought as well as displaying the severity of the drought in 2015-2016. This was noted through the prolonged period of below average rainfall and NDVI in comparison to the past mean across the 16 year period of data.

The significant decrease of rainfall and NDVI in 2003 is confirmed through Rouault and Richard (2005) who noted that 2002 was dryer than usual during the main rainy season across southern Africa. Subsequently, 2003 was a significantly dry year recording the lowest NDVI values across the study period. The cause was found to be the ENSO event associated with that period. This study found similarity in results for the 2014/2015 period, which also experienced an ENSO event (FEWS, 2015). However, the recent prolonged period of below average rainfall has significantly affected the NDVI and thus the current period of drought.

Furthermore, December 2015 was recorded as the driest December in 16 years (Mitchley, 2016). Traditionally KwaZulu-Natal receives over 150mm of rainfall during December months; however, nearly half of that was received in 2015. Noticeably the effect of lack of rainfall during 2014 was only observed in 2015, once all ground water supplies had been exhausted and vegetation cover had begun to decline as it reacted to water loss through evapotranspiration, evident in the NDVI. July to December 2016 saw higher rainfall means, prompting a slight recovery for December 2016.

Increased rainfall in 2016 indicates a possible recovery; however, the availability of water resources remains a problem as demonstrated by the lack of recovery of the Albert Falls Dam. As reported, the dam has experienced a significant decline in area (up to 43%) between 2014 and 2016. The Albert Falls dam is the main source of water to Durban and the surrounding areas which require upwards of 400 million litres of water a day, and is therefore releasing more water than it is receiving (DWAF- *Albert Falls Resource Unit*). Indicating the dam has had insufficient time to recover due to the constant and increased demand for water during winter months in KwaZulu-Natal.

3.5.1 Effectiveness of NDVI to analyse drought

An interesting finding was the relationship between NDVI and rainfall during dry and wet years. During a dry year, the level of precipitation decreases, as does the vegetation cover, and if reflected by a decline in NDVI. During periods of prolonged dryness, the vegetation begins to wilt and decrease in size until rainfall is received. Thus, consistently low rainfall anomalies lead to lower NDVI scores. During wet years, the presence of precipitation prompts the growth in vegetation. However, once the vegetation has fully saturated it reaches a threshold. The use of NDVI in these areas of 100% vegetation cover offers poor estimates and is not an accurate index during peak seasons (Nicholson et al., 1990; Thenkabail et al., 2000). Mutanga and Skidmore (2004) concluded that biomass saturation estimations can be overcome by using narrow band vegetation indices, more specifically the shorter (700-750nm) and longer (750-800nm) wavelengths of the Red portion of the electromagnetic spectrum. During a drought, the NDVI is not saturated in terms of vegetation cover and biomass; therefore, it is able to give a better indication of the dryness. Bearing in mind that there is a lagged response time of vegetation relative to that of the received rainfall (depending on region), which is normally three months (Thenkabail et al., 2004). Therefore, the NDVI is a better indicator of drier conditions as opposed to wet ones (Nicholson et al, 1990), thus suggesting the use of a Modified Normalized Vegetation Index (MNDVI) as well as further indices during wet years. The MNDVI’s makes use of a slightly adjusted spectrum which broadens the accessible vegetation, allowing for the selection of specific areas of interest (Skianis et al., 2009). Mutanga and Skidmore (2004) concluded that MNDVI calculated from shorter and longer wave lengths in the red edge band, leads to a greater correlation coefficient with biomass compared to the average NDVI. Furthermore, recent developments in satellite systems namely WorldView-2 and Sentinal-2 offer a reprieve in biomass estimation as the enhanced near-infrared and red-edge bands, greatly improved the prediction accuracy when compared to the traditional NDVI (Dotzler et al., 2015; Mutanga et al., 2012).

3.5.2 Limitations and improvements for future work

Limitations found in this study include the relatively short timeline of MODIS NDVI data; 16 years is very short. Accurate NDVI results from previous drought episodes in KwaZulu-Natal, 1992/93 and 1980's would have offered an interesting comparison to the current drought. Furthermore, poorly distributed weather stations, coupled with incomplete data hinder research opportunities in developing nations such as South Africa.

3.6 Concluding Remarks

In conclusion,

1. Trends of dryness and wetness were identified over the past 16 years. Correlation analysis showed a close relationship between rainfall and NDVI during dry and wet years.
2. The NDVI is an effective index to use in analysing the effect of extended dryness and drought. Implementing additional indices will further reinforce the NDVI, which is affected by the saturation of vegetation (as highlighted).
3. The current drought is the most severe within the study period, although rainfall and NDVI anomalies indicate a slight recovery, water resources are still under immense pressure as highlighted by the levels of the Albert Falls Dam.

KwaZulu-Natal has experienced one of the most severe droughts in recent decades. This study identifies trends across the observed period, highlighting the presence of the current drought episode in 2015. Future research should seek to include further appropriate indices to improve the remote sensing accuracy and hopefully aid in drought prediction.

CHAPTER 4:

Synthesis

4.1 Review objectives and conclusions

Drought has proven to be a complex phenomenon to understand and study. Although general definitions agree that drought is caused by a deficit in water resources, it is often the extent and severity of a particular episode which is over looked. It is believed that extensive research and appropriate planning using current near real time data can greatly lessen the devastating affects (Persendt, 2009). The use of traditional methods, in developing nations, has various limitations. These regions require accurate up to date data analysis, allowing for an effective response time to alleviate drought side effects. Furthermore, prediction and monitoring strategies are vital in reducing the effects of draught (Wilhite et al., 2000). Remote sensing allows for high resolution analysis of rural locations incorporating a timely analysis of large data sets enabling prediction to assist timely solutions and relief programmes, as well as providing understating of drought patterns. It is therefore imperative to expand on the application of remote sensing which as a science is constantly evolving and improving.

4.1.1 Research Question: Is remote sensing growing as an approach to drought monitoring assessments?

Objective: Provide a systematic literature review on the evolution of drought monitoring approaches, highlighting remote sensing as an application to drought monitoring, as well as strategies towards future drought monitoring.

Scientific reports provide little data on systematic drought monitoring. Consequently, prior understanding of the advancements made in remote sensing as a drought-monitoring toolset is fundamental to conducting any assessment in a specific area. The literature review showed significant growth in scientific papers pertaining to drought over the past decade. Although meteorological approaches still dominate the field of drought assessments, significant growth in remote sensing on drought monitoring was observed. Specifically noted was the NDVI and derivatives of this algorithm. There has been notable success in combining meteorological and remotely sensed indices, specifically the SPI and NDVI (Caccamo, 2011; Jain et al, 2010; Ji and Peters, 2003; Wang et al, 2014). Strategies toward future drought monitoring should look to incorporate microwave sensors as a unique niche in vegetation monitoring. The combination of microwave and optical sensors allows for extensive understanding on the fluctuations in an ecosystem during a drought episode (Aghakouchak et al, 2015).

4.1.2 Research Question: Can remote sensing be used effectively to identify trends in drought events?

Objective: Identify NDVI and rainfall trends within KwaZulu-Natal, focusing on the effectiveness of NDVI to identify dry and wet spells over the past 16 years; making note of the recent drought episode

The study area is located in South Africa, and is characterised by limited ground based observations as reported by Unganai and Kogan (1988) thus, the decision to investigate remote drought sensing, focusing on NDVI data. Findings across the 16 year analysis indicated years of above average wetness and, more importantly, years of prolonged dryness. Slight discrepancies were found in years where rainfall and the NDVI differed slightly, however, results confirmed the current drought being experienced. Furthermore, the decline in water levels of a major dam in KwaZulu-Natal were confirmed. December 2015 was also confirmed as the driest December recorded in the past 16 years. NDVI and rainfall results from this chapter indicate the effects of the drought episode to be improving. However, the availability of water remains a problem as the area progresses into winter. Although the NDVI was effective in analysing periods of wet and dry spells over the 16 year period, future drought episodes should make use of integrated approach. The implementation of a comprehensive drought tool applicable to conditions in southern Africa will significantly aid in drought monitoring and resource allocation. Combining our knowledge of climate, biosphere, oceanic and atmospheric precursors can better aid in drought monitoring and prediction.

In conclusion, the literature review indicated the growing concern about droughts supported by the significant increase in scientific papers as well as an increase in remote sensing and combined techniques that are potentially more appropriate in developing areas. A detailed study suggested NDVI as the favoured remote sensing tool for analysis of the pre-determined study site. The second chapter included results which compared rainfall records for climate conditions during the recent drought, indicating potential for its use in future studies. Saturation levels proved to be a slight problem which can be overcome through incorporation of further indices, specifically narrowband vegetation indices.

4.2 Recommendations

- Future drought monitoring in KwaZulu-Natal should seek to implement, multi-sensor derived spectral vegetation indices. The NDVI as a sole index is criticised, thus further indices (narrow band) will strengthen the accuracies of remote sensing.
- Explore possibilities of a South African comprehensive drought index such as VegDRI, incorporating real-time meteorological and satellite data.
- Explore in more detail the ability of various indices and updated satellite platforms (Sentinal-2 and WorldView-2) to predict and monitor drought occurrences.
- Identify drought relief programmes/initiatives utilised in this region and assess whether future drought prediction could have informed the deployment of these resources.
- Analyse the effectiveness of local approaches used to respond to drought (financial and other) compared to other nations.

Drought is an extreme climatic condition which will continue to exist and inevitably worsen as the demand for water resources increases accompanied by concerns on climate change. It is evident that more effort needs to be made to implement effective relief procedures in drought prone areas. Importance should be allocated to prediction and resource management since it is significantly easier to manage a risk rather than a crisis.

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