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Department of Applied GIS and Remote Sensing
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<u>Title:</u>

Assessing the vulnerability of resource-poor households to disasters associated with climate variability using remote sensing and GIS techniques in the Nkonkobe Local Municipality, Eastern Cape Province, South Africa.

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Clearance by Supervisor

I certify that the content of this dissertation was done by the undersigned student and has not been formerly submitted to any other university for an award of a qualification either in part or in its entirety.

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Signature Date

Abstract

The main objective of the study was to assess the extent to which resource-poor households in selected villages of Nkonkobe Local Municipality in the Eastern Cape Province of South Africa are vulnerable to drought by using an improvised remote sensing and Geographic Information System (GIS)-based mapping approach. The research methodology was comprised of 1) assessment of vulnerability levels and 2) the calculation of established drought assessment indices comprising the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) from wet-season Landsat images covering a period of 29 years from 1985 to 2014 in order to objectively determine the temporal recurrence of drought in Nkonkobe Local Municipality. Vulnerability of households to drought was determined by using a multi-step GIS-based mapping approach in which 3 components comprising exposure, sensitivity and adaptive capacity were simultaneously analysed and averaged to determine the magnitude of vulnerability. Thereafter, the Analytical Hierarchy Process (AHP) was used to establish weighted contributions of these components to vulnerability. The weights applied to the AHP were obtained from the 2012 - 2017 Nkonkobe Integrated Development Plan (IDP) and perceptions that were solicited from key informants who were judged to be knowledgeable about the subject. A Kruskal-Wallis *H* test on demographic data for water access revealed that the demographic results are independent of choice of data acquired from different data providers ($\chi^2(2) = 1.26$, $p = 0.533$, with a mean ranked population scores of 7.4 for ECSECC, 6.8 for Quantec and 9.8 for StatsSA). Simple linear regression analysis revealed strong positive correlations between NDWI and NDVI (($r = 0.99609375$, $R^2 = 1$, for 1985), 1995 ($r = 0.99609375$, $R^2 = 1$ for 1995), ($r = 0.99609375$, $R^2 = 1$ for 2005) and ($r = 0.99609375$, $R^2 = 1$ for 2014). The regression analysis proved that vegetation condition depends on surface water arising from rainfall. The results indicate that the whole of Nkonkobe Local Municipality is susceptible to drought with villages in south eastern part being most vulnerable to droughts due to high sensitivity and low adaptive capacity.

Declaration by candidate

I, **Martin Munashe Chari**, the undersigned candidate, hereby declare that the content of this dissertation is my original work and has not been formerly submitted to any other university for an award of a qualification either in part or in its entirety.

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Signature Date

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- Statistics South Africa (StatsSA), Eastern Cape Socio-Economic Consultative Council (ECSECC) and Quantec for demographic data.
- My parents for encouragement and support throughout the years.

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Dedication

I dedicate this project to my parents and siblings; Noel, Melissa and Ashley.

Acronyms

StatsSA – Statistics South Africa

CSIR – Council for Scientific & Industrial Research

DEA - Department of Environmental Affairs

CoGTA - Cooperative Governance and Traditional Affairs

ADM - Amathole District Municipality

HSRC - Human Sciences Research Council

IPCC - Intergovernmental Panel on Climate Change

OECD - Organization for Economic Cooperation and Development

ECSECC - Eastern Cape Socio-Economic Consultative Council

1 INTRODUCTION

1.1 Background

The study focused on the use of Geographical Information Systems (GIS) and remote sensing data in assessing the vulnerability of resource-poor households to risks associated with climate variability in the Nkonkobe Local Municipality in the Eastern Cape Province of South Africa.

According to FAO (2007), climate refers to average weather over time for a specific region. Climate variability is the way climate fluctuates yearly above or below long-term average weather conditions. It differs from climate change in that climate change is defined as long-term continuous change (increase or decrease) to average weather conditions or the range of weather. Climate variability determines the future livelihoods of households and climate is always expected to vary over time (Davis, 2011). The IPCC (2007a) defines "climate change" as "a change in the state of the climate that can be identified by changes in the mean and / or the variability of its properties, and that persists for an extended period, typically decades or longer". Climate variability can be influenced by natural functioning of climate systems or by human activities, the latter being of more concern since they can be regulated. A report by Lavell *et al.* (2012) defines disasters as severe alterations in the normal functioning of a community or a society due to hazardous physical events interacting with vulnerable social conditions, leading to widespread adverse human, material, economic, or environmental effects that require immediate emergency response to satisfy critical human needs and that may require external support for recovery.

Natural climate deviations may possibly be associated to the channel of seasons at altered times of the year. Global climate similarly fluctuates on spans of many centuries. Milankovitch cycles provide a description of fluctuations in the earth's orbit around the sun, the angle (or tilt) of the earth's axis and variations in the axis of rotation of the earth (Davis, 2011). All three cause prolonged periods of cooler (and drier) or warmer (and wetter) conditions for the global climate system. Variations in sea-surface temperatures and the interchange of moisture and energy between the ocean and atmosphere over the Pacific Ocean basin result in variations which affect the global climate system (Davis, 2011). These cyclic variations are indicative of periodic fluctuations in the global climate system in response to wide-ranging human activities and natural factors (IPCC, 2007). Rebuilding of environmental and climatic trends during the recent historical past offers opportunities for better understanding of climate change processes (Hamandawana *et al.* 2008) in order to enhance our capacities to adapt to the exigencies of unprecedented changes in climatic conditions.

Adaptation is extensively acknowledged as a dynamic constituent of any strategic reaction to climate change (Gbetibouo, 2009). The degree to which a system is impacted by climate change depends on its adaptive capacity. The placement of well-versed adaptation strategies planned to augment human capacities to handle the adverse effects of climate variability is critical since adoption of effective strategies requires official acknowledgement of the non-transient character of the current trend of climatic change (Hamandawana, 2007). Africa is perceived to be the most vulnerable continent to climate change due to low adaptive capacity and multiple stresses (CSIR, 2010). Southern Africa is one of the most susceptible regions to climate change with rural communities being affected worst due to low levels of adaptive capacity (IPCC, 2007). Resource-poor households are usually situated within rural areas which are susceptible to drought (HSRC Report, 2012).

Climate change increases the susceptibility of households to disasters such as droughts which pose threats to food and water security. The assessment of local-level vulnerability to climate change has become an imperative subject in climate change adaptation. Maps depicting climate change "hotspots" have been issued with increasing regularity in recent years by researchers, advocacy groups, and Non-Governmental Organizations (NGOs) (de Sherbinin, 2014). By identifying likely climate change impacts and conveying them in a map format with strong visual elements, hotspots maps can help to communicate issues in a manner that may be easier to interpret than text (de Sherbinin, 2014).

Climate variability can have an adverse effect on the well-being and livelihood of millions of people hence should be considered into national social and economic development efforts both at the policy and practical levels (Wongbusarakum & Loper, 2011). Climate variability is likely to challenge sustainable development, intensify poverty, and defer or avoid the apprehension of the

Millennium Development Goals (Wongbusarakum & Loper, 2011). Building adaptive capacity and resilience to climate-related risks is essential in order to assist in meeting the Millennium Development Goals (MDGs) set by the United Nations in year 2000 which address issues such as poverty alleviation, hunger, access to water and human health (Anju, 2007). Climate variability results in extreme temperatures which lead to increased rates of evaporation hence less availability of surface water and lowering of water tables. Climate variability alters precipitation patterns resulting in unexpected low or high rainfall with the former often leading to drought and reduced crop production as people will not be aware of the right time to grow crops while the latter can induce severe flooding (Anju, 2007).

In South Africa, recent observations over the 43 years before 2003 point to a steady increase in temperatures by an average of 0.13°C per decade (Kruger & Shongwe 2004). This increase is expected to continue, with projections estimating increases by 1.2°C by 2020, 2.4°C by 2050 and 4.2°C by the year 2080 while rainfall is projected to reduce by 5.4%, 6.3% and 9.5% by 2020, 2050 and 2080 respectively. These scenarios are an example of climate projections which are an indicative of climate variability in the entire country.

In vulnerability assessments of resource-poor households to droughts, indices are often used due to their ability to distinguish vegetation and moisture conditions more precisely. Various studies (Tucker, 1980; Kogan, 1997; McVicar & Bierwirth, 2001; Ji & Peters, 2003; Song *et al.* 2004; Vicente-Serrano *et al.* 2006; Jain *et al.* 2009) have portrayed NDVI to be advantageous in drought assessment. Although NDVI is very capable in drought assessment, its partial capability in estimating vegetation water condition is often affected by other variables. The restrictions of NDVI are: a) diverse plant types have their particular association of chlorophyll content and vegetation water state, b) a reduction in chlorophyll content does not infer a decline in vegetation water condition, whereas a reduction in vegetation water condition does not include a decline in chlorophyll content (Thomas *et al.* 2004). NDWI is a more sensitive indicator for drought monitoring than NDVI because it is prejudiced by both dryness and wilting in the vegetation canopy (Xu, 2006). NDWI has more ability to detect and monitor the moisture condition of vegetation canopies over large areas as compared to other indices (Xiao *et al.* 2002; Jackson *et al.* 2004; Maki *et al.* 2004; Chen *et al.* 2005; Delbart *et al.* 2005).

The recent (2011) Department of Environmental Affairs (D.E.A.) report on South Africa's communication under U.N.F.C.C.C. describes South Africa as a country with a semi-arid and warm climate on average with most regional and local climatic conditions being attributed to strong gradients in temperature and rainfall. The spread of aridity makes South Africa's susceptibility to increased water scarcity a critical vulnerability (DEA, 2011). Because agriculture is directly dependent on climate variables such as precipitation and temperature, it is deemed South Africa's most vulnerable sector to climate variability (Turpie & Visser, 2013). Although human livelihoods in South Africa are often unambiguously related to the climate of their respective geographical locations (CSIR, 2010), human activities and ignorance of the climate change phenomenon have increasingly come to be recognized as being responsible for intensifying climate variability (Madzwamuse, 2010).

Although the Western Cape and Gauteng provinces of the country have the lowest vulnerability indexes to climate variability related problems due to high levels of infrastructure development, high literacy rates, and low shares of agriculture in total Gross Domestic Product (GDP), the Limpopo, Eastern Cape and KwaZulu-Natal Provinces are highly vulnerable to climate variability related problems due to their high dependency on rain-fed agriculture, densely populated rural areas, large numbers of small-scale farmers, and high rates of land degradation (Gbetibouo *et al.* 2010).

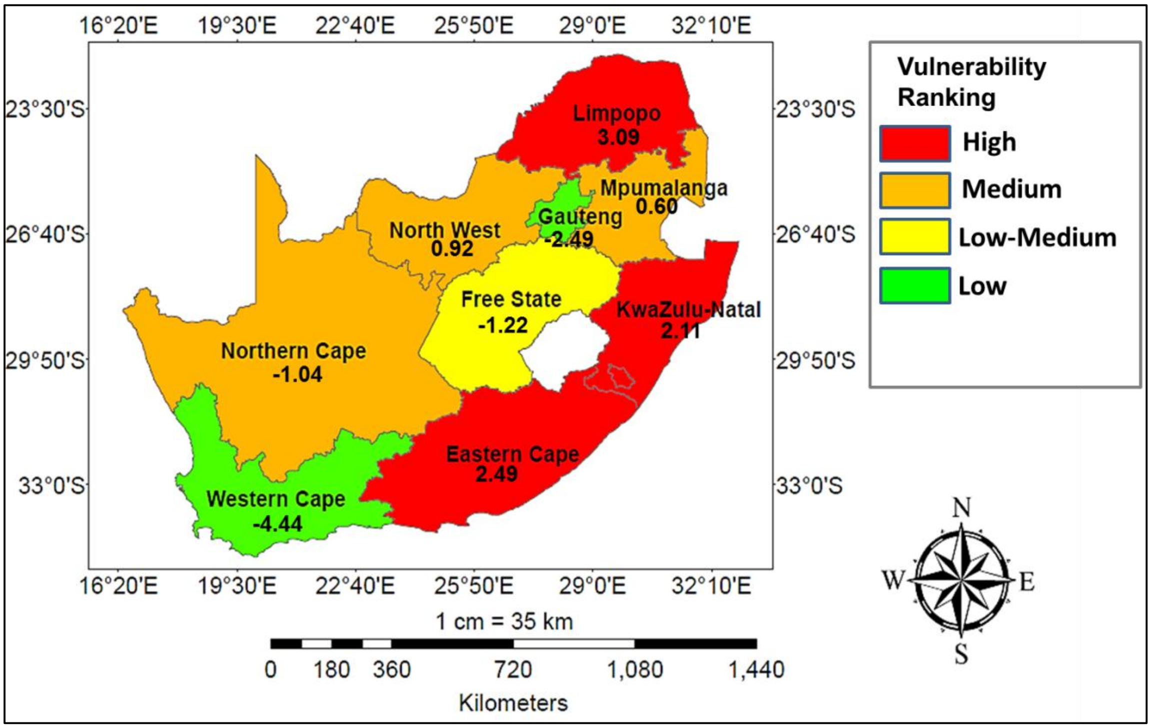


Figure 1: Vulnerability ranking in South Africa

Source: Adapted from Gbetibouo & Ringler, 2009

The high vulnerability of most communities to climate change related problems in the Eastern Cape Province (Figure 1) is a result of high incidences of poverty since the majority of these people are heavily dependent on rain fed agriculture, livestock production and government social grants for their livelihood (Gbetibouo & Ringler 2009; Zhou *et al.* 2013; Ndhleve *et al.* 2014). Proximity to the ocean also contributes to the susceptibility of a region to climate variability (Ndhleve *et al.* 2014), hence the scenario of the Eastern Cape Province. Although the Eastern Cape Province has the highest proportion of unutilized land, it is on record as one of the country's most degraded areas and also one of the worst affected by food insecurity (Bank & Minkley, 2005).

Although the Eastern Cape Province has the highest proportion of unutilized land, it is on record as one of the country's most degraded areas and also one of the worst affected by food insecurity (Bank & Minkley, 2005). The tracts of land lying fallow could be productive if the environmental and social effects of climate variability do not continue to put agriculture at risk (Ndhleve *et al.* 2014).

Amathole District Municipality (DM) occupies the central coastal portion of the Eastern Cape Province and is made up of seven local municipalities one of which is Nkonkobe Local Municipality (LM). According to the South African classification of district municipalities, Amathole DM is classified as a C2 category municipality because of its rural character, low urbanization rate, and limited budget capacity (ADM IDP, 2012–2017). These characteristics make this area extremely vulnerable to climate variability related problems. Nkonkobe LM falls under the B3 category (which is dominated by small towns (Turpie & Visser, 2013; Monkam, 2014) none of which is large enough to serve as a core. These towns are situated in regions where poverty, unemployment and low standards of living prevail (CoGTA, 2009). Nkonkobe LM has a vulnerability score of 4 on a scale ranging from 1-5, with 5 being the most vulnerable to the impacts of climate change and variability and vice versa (Turpie & Visser, 2013).

In 2004, the Eastern Cape Province was one of South Africa's six provinces that were declared a disaster area due to drought with the entire country experiencing three types of droughts comprising reduction in water resources, significant reduction in rainfall and, reduced crop yields and livestock numbers during the same period (IFRC, 2004). The magnitude and severity of the 2004 drought became evident in Nkonkobe Local Municipality when 1063 farmers submitted applications for drought relief support (ADM, 2004).

In July 2009, the Amathole District Municipality which contains Nkonkobe, Amahlathi, Mbhashe, Nxuba and Great Kei Local Municipalities was declared a disaster area owing to persistent drought conditions in the region. Although some good rains were received in selected parts of the district, rainfall in most areas was below average. Severe drought conditions were experienced in the Bedford, Adelaide towns of Nxuba Local Municipality, and Dutywa town of Mbhashe Local Municipality while dam levels in Hogsback (under Nkonkobe Local Municipality), Cathcart (under Amahlathi Local Municipality), Kei Mouth and Cintsa East (under Great Kei Local Municipality), went critically low (ACN, 2010; ADM IDP, 2011/12).

1.1.1 Climate of Nkonkobe Local Municipality

The climate of Nkonkobe Local Municipality is semi-arid. Long term rainfall averages range from 601mm – 800mm/annum. The annual rainfall regime is characterized by a bimodal seasonal distribution with monthly averages ranging from a minimum of 20.9 mm in the dry winter month of July to a maximum of 70.3 mm in the wet summer of month of January. The wet summer season begins in October and ends in April; the dry winter season covers the remaining months of the year.

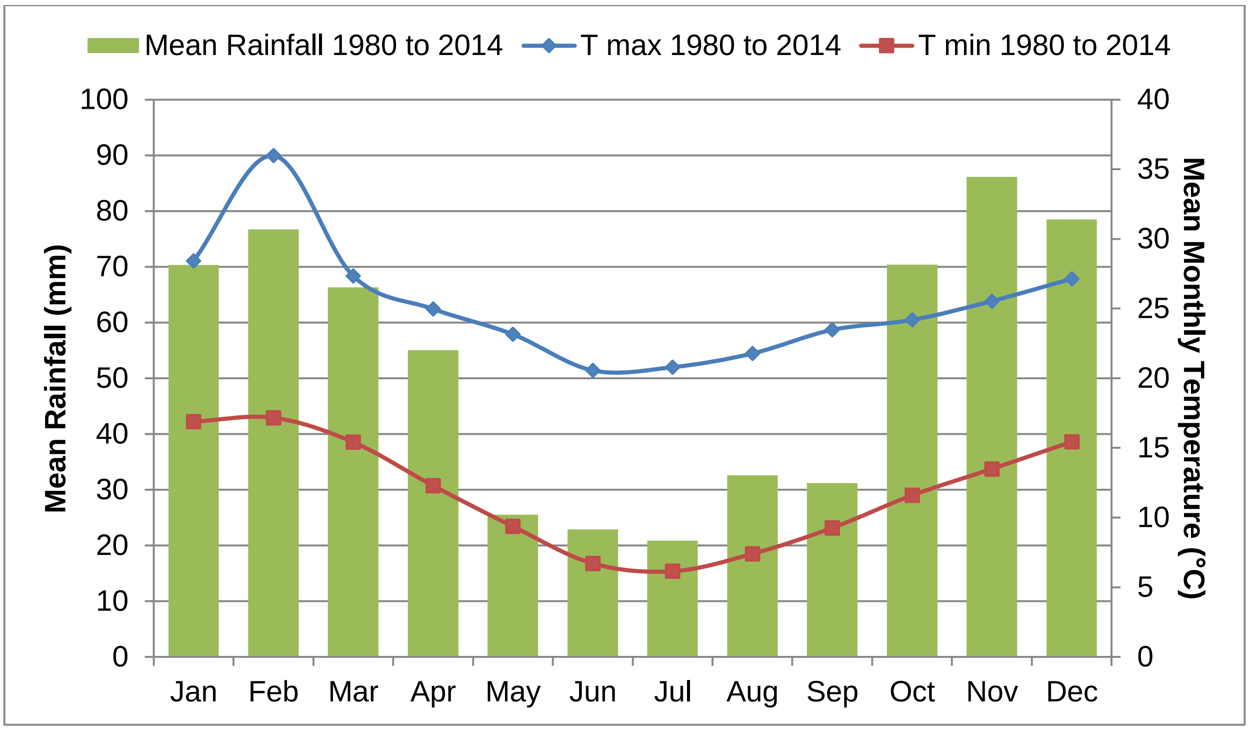


Figure 2: Long term monthly climatology of rainfall totals and monthly averaged minimum and maximum temperatures.

Source of figures: South African Weather Services (SAWS)

Mean monthly temperatures range from 6.2 °C to 20.8 °C in July (coldest winter month) and from 17.2 °C to 36.0 °C in February (hottest summer month). An analysis of historical rainfall data acquired from South African Weather Services shows that in the past 30 years, Nkonkobe Local Municipality experienced droughts in 1980, 1982, 1987, 1992 and 1997 with mean annual precipitation averaging less than 500mm which is below the expected mean annual precipitation of 601mm – 800mm (Eastern Cape Provincial Spatial Development Plan, 2010). Hence, this aridity makes the municipality vulnerable to adverse effects of climate change. These scenarios have posed a serious problem by compromising the abilities of local communities to adapt to the adverse effects of climate change by inducing scarcities in the availability of basic requirements notably food and water and recurrent occurrence of disastrous floods.

In recent years it has been shown that climate variability is linked to disasters affecting households with the resource poor ones being more vulnerable. Vulnerability can be assessed using the Human Development Index (HDI) which indicates the status of a place in terms of development. The index can take any value between 0 and 1, places with an index over 0.800 being part of the high Human Development Group and places between 0.500 and 0.800 are part of the medium and places below 0.500 are part of the low HDI group according to the United Nations' HDI report of 2012. The HDI for Nkonkobe LM is based at 0.60 which is still very low (Nkonkobe Municipality IDP, 2012-2017). This ranking suggests that Nkonkobe LM is still a less developed municipality hence more vulnerable to disasters associated with climate variability due to inadequate adaptive capacity. This limitation provides part explanation of why this municipality was deemed suitable for intensive investigation of the impacts of climate variability on the livelihoods of resource-poor households. The majority of the population in Nkonkobe LM is highly dependent on agriculture and natural resources whose performance and availability is substantially influenced by rainfall and precipitation patterns. The following Fig. 1 illustrates the exact spatial location of Nkonkobe LM within the Eastern Cape Province of South Africa.

1.1.2 The national and sub-national climate variability vulnerability nexus

South Africa's disasters, food and water insecurities are, in many instances, analyzed from an aggregated level giving rise to poorly targeted policy interventions. An identification of vulnerable households is critical in the formulation of well-targeted adaptation and mitigation policies and strategies. There are few studies that have analyzed the vulnerability at village level, where the policies are supposed to make a difference. This has been acknowledged by the National Disaster Management Framework (2005) which states that one of the challenges that hamper the effectiveness of the functioning of the disaster risk management is the lack of data on vulnerability studies. When a climate-change disaster strikes, the first point of call is at the local municipalities and as such municipalities are the first point of call. Therefore municipalities need to be able to know and understand who is most vulnerable when a disaster such as drought or flooding occurs.

The mapping of climate variability is becoming increasingly popular due to the need for spatial rendering of geographically heterogeneous determinants of vulnerability and their interactions (Preston *et al.* 2011). Vulnerability mapping assists in promoting spatial planning (Clark *et al.* 1998; NRC, 2007a) and plays a role in educating the public about climate variability and the processes by which it may interact with coupled human or environmental systems (Preston *et al.* 2009).

In this study, vulnerability assessment of households was assessed using a GIS based mapping approach because it allows for the presentation of identified areas containing households most vulnerable to climate variability related disasters in a strong visual output format which assists in communicating issues in a way that is easier to interpret than text. Remote sensing indices were employed in the study due to their ability to detect state of vegetation and moisture conditions on the ground hence contributing greatly in drought monitoring. GIS captures subnational variation in vulnerability mapping by linking spatial data layers where each layer is converted to a unitless scale and aggregated with the other layers to reflect levels of vulnerability (de Sherbinin, 2014). In this approach, most vulnerable areas (hotspots) emerge from the spatial analysis, being revealed through the integration of spatial layers. GIS provides maps for decision-making and support, which allows overlaying of different kinds of information that may not be normally linked (Kaiser *et al.* 2003).

1.2 Statement of problem

The main problem is closely related to the manner in which climate variability threatens human livelihoods. In the Nkonkobe municipality, the main disaster associated with climate variability is drought. This susceptibility prompted to this study will assess household vulnerability to drought in order better understand the different ways in which affected communities can adapt to precarious climatic conditions.

Climate variability increases the susceptibility of households to disasters such as droughts which pose threats to food and water security. There are few studies that have analyzed the vulnerability, in context of drought hazard, at household level, where policies are supposed to make a difference. The recurrent droughts in Nkonkobe Local Municipality during the recent past argue for an organized household vulnerability assessment in order to identify those areas which are more vulnerable to droughts at present and in the future. This scenario justifies why there is a need for an objectively informed mapping approach to identify households that are vulnerable to climate variability-driven drought risks. This identification is important because it assists the planning process in formulating and implementing appropriate adaptive strategies.

1.3 Objectives

1.3.1 Primary objective

The main objective of the study is to assess the extent to which resource-poor villages in the Nkonkobe municipality are vulnerable to climate variability-driven drought risks using remotely sensed data and GIS based mapping approach.

1.3.2 Specific objectives

The specific objectives of this study are to:

- Assess the exposure of resource-poor households to droughts.
- Assess the sensitivity of resource-poor households to droughts.
- Assess the adaptive capacity of resource-poor households to droughts.
- Investigate changes in vegetation cover and moisture content associated with climate variability-related droughts for the past 29 years i.e. 1985 – 2014.
- Identify areas facing high drought risk by linking satellite data and thematic information.

1.4 Research questions

To achieve the objectives of the study, the following research questions will be used:

- How exposed are resource-poor households to droughts?
- How sensitive are resource-poor households to climate change?
- How resource-poor households are able to cope up with drought?
- Is the link between land surface water and vegetation cover related to droughts?
- How suitable can vulnerability be evaluated by a combination of satellite and meteorological data?

1.5 Hypotheses

1.5.1 Major hypothesis

The major hypotheses which was formulated to guide this investigation is that:

- Climate variability has had and continues to have adverse effects on the livelihoods of people notably resource-poor communities in the Nkonkobe Local Municipality.

1.5.2 Specific hypotheses

The specific hypotheses on which this study is premised are that:

- There has been high vulnerability to drought due to limited adaptive capacity within the municipality.
- Resource-poor households with high sensitivity are not necessarily vulnerable to climate change related drought.
- Exposure and sensitivity together narrate the potential impact which climate variability can have on households.
- The link between land surface water and vegetation cover is related to droughts.
- The combination of satellite, meteorological and thematic information assists in better evaluation of vulnerability to drought.

1.6 Justification and limitations of the study

1.6.1 Justification of the study

The study has potential contribution to the South African Risk and Vulnerability Atlas (SARVA) project and Global Change Research Programme (GCRP) by availing information that is potentially capable of enhancing the capacities of: a) affected households to cope with the adverse effects of climate variability and b) the planning process to formulate objectively informed intervention strategies. The South African Risk and Vulnerability Atlas (SARVA) project is a flagship science-into-policy initiative of the Department of Science and Technology's Global Change Grand Challenge which provides up to date information for key sectors to support strategy development in the areas of risk and vulnerability.

Drought is considered by many to be the most complex and least understood of all hazards, affecting more people than any other hazard (UNSO, 1999). It is hoped that this study will promote drought awareness and encourage pro-active management of drought as opposed to the static reactive management approach often employed by most farming communities. When local-level vulnerability mapping case studies (that is Nkonkobe LM) are combined with regional-level case studies (that is Eastern Cape Province), there is increased potential to capture factors and processes operating and inter-acting at different spatial scales and at variable levels of magnitude and/or intensity (O'Brien *et al.* 2004). The combination of the two different levels of vulnerability mapping also enhances understanding of how local-level decisions are shaped by influences at the provincial, national or international levels (O'Brien *et al.* 2004). Using GIS modelling will help in the identification of spatial locations of areas where policy intervention is mostly needed e.g. access to irrigation and alternative crops thereby providing valuable guidance to decision-makers and investors.

There is a need for spatial information in assessing the vulnerability of households to disasters associated with climate variability. This information can be conveniently presented in the form of maps which show areas vulnerable to the adverse effects of climate variability. Although such maps are generally available at the national scale level, the available maps need to be updated by incorporating up-to-date climate indicators. The work done by Tralli *et al.* (2005) in modelling and deriving geospatial information of natural disasters for decision support illustrates that GIS augments the assessment and collation of information on disasters. GIS modelling is unaffected by disasters on the ground and provides unbiased and timely information on different components of the disaster management cycle (Navalgund *et al.* 2010). GIS is suitable for this investigation because it allows the integration of spatial data in analyzing disasters related to climate variability.

1.6.2 Limitations of the study

The limitation for this study is that the graphical climate projections that were used in assessing the exposure to climate change are generalized for the whole municipality rather than for different parts within the municipality due to the presence of only one weather station (Fort Beaufort) with long-term historical weather data.

1.7 Organization of the dissertation

This subsection provides an overview of how the remaining 6 chapters of this study (Chapters 2 – 6) are organized.

Chapter 2 provides a comprehensive review of the literature with emphasis being placed on: natural and natural drivers of climate variability, South Africa’s present day climate, the vulnerability framework that was used to guide this investigation, drought indices and climate projections.

Chapter 3 provides a detailed and illustrated description of the study area for the research and an overview of the materials and methods that were used in this investigation with the latter providing a detailed description of how vulnerability assessment was conducted. The accuracy assessment techniques used are specified.

Chapter 4 presents the results of this study. The outcomes of the research are presented in form of graphs, pictorial forms (maps) with brief statements attached to each graph or picture.

Chapter 5 offers discussion of the results and the valid statistical procedures used to test significance of results are explained with emphasis on demographic data, NDWI and NDVI. The conclusion for the study is revealed based upon the analyzed results.

Chapter 6 highlights the suggested suitable recommendations and policies that can be implemented to curb vulnerability to droughts. The conclusion of the study is also provided.

2 LITERATURE REVIEW

2.1 Conceptual framework introduction

The alleviation of the adverse effects of disasters necessitates significant facts concerning the disaster in real time. Furthermore, the probable likelihood and monitoring of the disaster entails prompt and continuous data as well as information generation or collecting. Since disasters causing massive societal and fiscal interferences typically distress outsized extents or regions and are associated with global change, it is not possible to efficiently gather constant data on them using controversial approaches. Remote sensing and GIS technologies compromise exceptional potentials of gathering the vital information. This is due to the capability of technologies to gather data at global and local scales promptly and cyclically in a digital form for easy data manipulation. An outstanding communication medium is delivered by remote sensing and GIS technology.

2.1.1 What is climate variability?

Climate varies over time and these changes happen both naturally, as essential parts of the functioning of the global and regional climate systems, and as well as in reaction to further influences owing to anthropogenic factors (Davis, 2011).

Normal weather differences may be related to the channel of periods at altered intervals of the year, or annually. The purported Milankovitch cycles define variations in the earth's trajectory around the sun, the angle (or tilt) of the earth's axis and changes in the axis of rotation of the earth. All three result in prolonged times of cooler (and drier) or warmer (and wetter) conditions for the global climate system (Davis, 2011).

On inter-annual spans, the most significant example of natural climate variability is the El Niño-Southern Oscillation (ENSO) phenomenon (Figure 3).

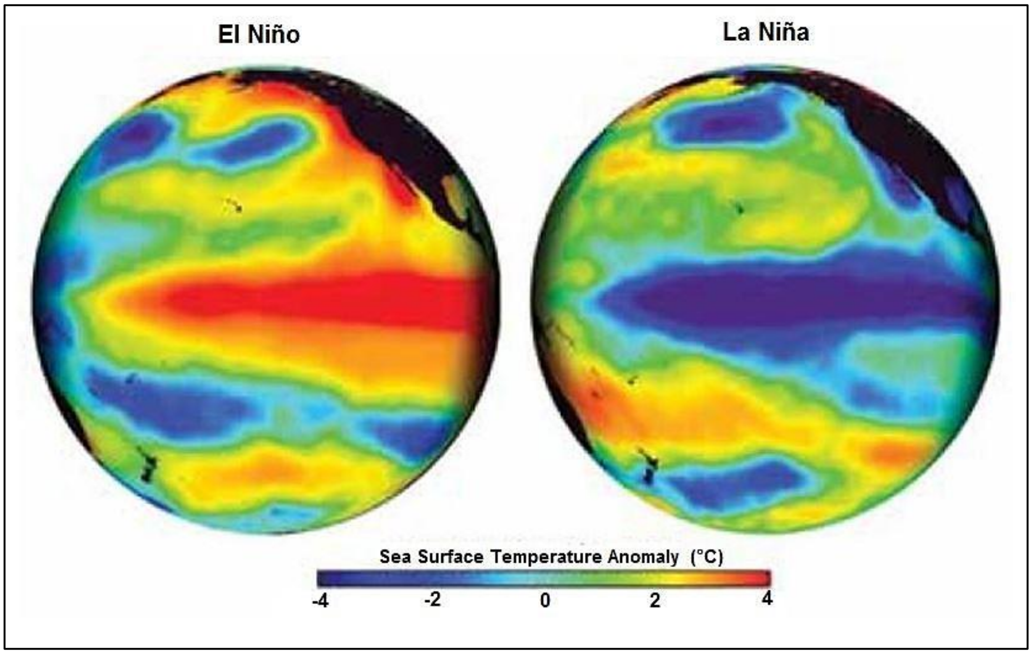


Figure 3: Patterns of sea-surface temperature during El Niño and La Niña episodes. The colors along the equator show areas that are warmer or cooler than the long-term average. Image courtesy of Steve Albers, NOAA and ClimateWatch Magazine
Source: http://www.oar.noaa.gov/climate/t_observing.html

El Niño denotes to the large-scale phenomenon linked to a solid warming in sea-surface temperatures across the central and east-central equatorial Pacific Ocean that has essential significances for weather around the globe. An El Niño event occurs every three to seven years. The ENSO cycle is characterized by spatially coherent and strong variations in sea-surface temperatures, rainfall, air pressure and atmospheric circulation across the equatorial Pacific and around the globe (Davis, 2011). La Niña, on the other hand, refers to the periodic cooling of sea-surface temperatures in the central and east-central equatorial Pacific Ocean. La Niña is the cold phase of the ENSO cycle. These changes in tropical rainfall affect weather patterns throughout the world. For example, over southern Africa, El Niño conditions are commonly connected with below-average rainfall years over the summer rainfall regions, while La Niña conditions are linked to above-average rainfall conditions. Deviations in sea-surface temperatures and the interchange of moisture and energy between the ocean and atmosphere over the Pacific Ocean basin result in variations which affect the global climate system. The impacts of ENSO variability on southern African climate are provided by Davis (2011).

2.1.2 South Africa's present day climate

The precipitation and climate of South Africa is one of extreme variation. Seasonal rainfall percentage deviations since 1960 prove extensive instabilities about the long-term average and it is in this framework that large rainfall shortages must be evaluated. Between July of 1960 and June of 2004, there have been 8 summer-rainfall seasons where rainfall for the entire summer-rainfall area has been less than 80% of normal. A shortfall of 25% is usually deemed as a severe meteorological drought but it can be safely assumed that a deficit of 20% from usual rainfall will result in crop and water shortfalls in many regions accompanied by societal and economic adversity (http://www.weathersa.co.za/learning/climate-questions/36-what-kind-of-droughts-does-south-africa-experience).

2.1.3 Defining drought

Drought assessments are significant due to their impact on humanity and the economy of any country. Drought remains a catastrophic natural occurrence which contrasts from other natural risks in its slow accumulating process and its unknown initiation and ending (Stone & Potgieter, 2008). Although drought has many descriptions, it originates from a deficit of precipitation over a prolonged period of time, typically a season or more. This deficit results in a water scarcity for some activity, crowd or ecological region. Drought is furthermore associated to the scheduling of rainfall. Other climatic aspects such as high temperature, high wind and low relative humidity are regularly connected to drought.

National Commission on Agriculture (1976) broadly classified droughts into the following three types.

- Meteorological drought: It is a situation when there is a significant decrease in rainfall from the normal over an area.

- Hydrological drought: Meteorological drought, if prolonged, results in hydrological drought with marked depletion of surface water and consequent drying up of inland water bodies such as lakes, reservoirs, streams and rivers and fall in level of water table.
- Agricultural drought: It occurs when soil moisture and rainfall are inadequate to support crop growth to maturity and cause extreme crop stress leading to the loss of yield.

Apart from the droughts defined by National Commission on Agriculture, socioeconomic drought is also defined. Socioeconomic drought occurs when physical water shortages start to affect the health, well-being and quality of life of the people or when the drought starts to affect the supply and demand of an economic product (Kogan, 1997). However this study seeks to specifically focus on meteorological droughts. Drought severities are usually determined using drought indices thus aiding in policy-making.

2.2 Vulnerability conceptual framework

The theory of vulnerability has been an influential investigative tool for unfolding the state of susceptibility to harm and marginality of both the physical and social system from adverse effects of climate change, and for guiding policy-makers of actions to enhance well-being through the reduction of climate risks (Adger, 2006).

The work done by the United Nations Environment Programme (UNEP) in reviewing the various concepts of vulnerability, methodologies for vulnerability assessment, and recent work on vulnerability assessment and indices provides evidence that there are various definitions of vulnerability used by international organizations depending on their role or field of influence (UNEP, 2002). An explanation of vulnerability by Adger (2006) also supports that the definitions for vulnerability mostly depend on the disciplines of their origin. Performing a vulnerability assessment to climate risks requires the articulation of a comprehensible definition of vulnerability. The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as the susceptibility of a system to be adversely affected by climate change and variability (IPCC, 2014).

A vulnerability assessment identifies who, what is exposed, and sensitive to climate variability and change. A vulnerability assessment takes into account the factors that make human livelihoods susceptible to harm, that is, access to natural and financial support; ability to self-protect; support networks (UNDP, 2010). Hence, since this study seeks to assess vulnerability of households to climate variability-driven disasters, vulnerability can be defined as the extent to which human livelihoods are prone to and unable to cope with the adverse impacts of climate variability (that is droughts). In both climate change and variability and disaster risk management context, vulnerability has been expressed as being encompassed by a function of 3 common components namely sensitivity, exposure, and lack of adaptive capacity (Turner, 2003; Gallopin, 2006; IPCC, 2007; IPCC, 2014). This suggests that a system is vulnerable if it is exposed and sensitive to climate change and variability effects and at the same time has only limited capacity to adapt to the change. In reverse, a system is less vulnerable if it is less exposed, less sensitive or has a strong adaptive capacity (Smit *et al.* 1999; Smit & Wandel, 2006).

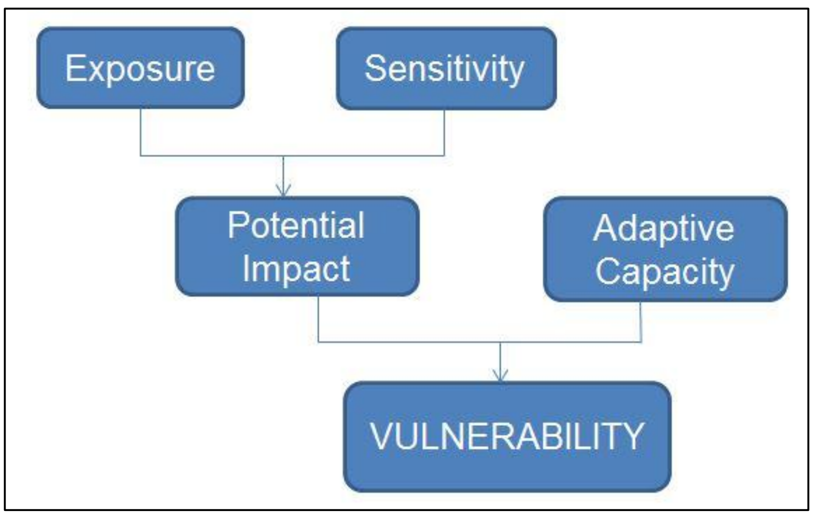


Figure 4: Components of vulnerability

Source: Allen Consulting, 2005

Exposure is a component of vulnerability which means the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected by climate variability (IPCC, 2014). It is the extent to which climate pressure acts on a specific unit of analysis (Heltberg & Bonch-Osmolovskiy, 2011), that is households in this study.

Sensitivity is defined as the extent to which a system will respond, either positively or negatively to variability in climate (Polsky, 2003; O'Brien *et al.* 2004; Füssel & Klein, 2006). The sensitivity of households to climate change and variability reflects the degree to which households are affected, either adversely or beneficially, by climate variability or change. The effect may be direct such as deviation change in crop yield in response to a change in the mean, range or variability of temperature or indirect such as damage caused by an increase in the frequency of coastal flooding due to sea level rise (IPCC, 2007). Sensitivity reflects the responsiveness of a system to climatic influences, and the degree to which changes in climate might affect it in its current form. Thus, a sensitive system is highly responsive to climate and can be significantly affected by small climate changes. Sensitivity can be determined by components like groundwater recharge and occurrence, access to agricultural services and population density.

Exposure and sensitivity together describe the potential impact which climate change and variability can have on a system. Although a system may be considered as being highly exposed and/or sensitive to climate change, it does not always mean that it is vulnerable. This is because neither exposure nor sensitivity account for the capacity of a system to adapt to climate change (i.e. its adaptive capacity), whereas vulnerability is the net impact that remains after adaptation is taken into account (Figure 4). Thus, the adaptive capacity of a system affects its vulnerability to climate change by varying exposure and sensitivity (Yohe & Tol, 2002; Gallopin, 2006; Adger *et al.* 2007).

Adaptive capacity or coping capacity is defined as the ability of people, organizations, and systems, using available skills, resources, and opportunities, to address, manage, and overcome adverse conditions of climate variability (OECD, 2009; IPCC, 2012). Adaptive means ability to sustain risks at a particular point of time and such ability can result from money, deployment of technology, infrastructure or emergency response systems (UNEP, 2002). Adaptive capacity is not only a significant portion of vulnerability assessments; it also motivates and assists the governing of adaptation actions, thus making it a matter applicable to climate policy. Hence the assessment of adaptive capacity provides decision makers on global, countrywide and local level imperative information to improve adaptation policies to climate change (Juhola & Kruse, 2015).

2.2.1 Groundwater occurrence

Groundwater occurrence reveals the presence of water in aquifers. Areas with limited groundwater occurrence are more vulnerable to droughts due to the absence of/ limited water quantities in the aquifers. In the Eastern Cape Province of South Africa, groundwater occurrences are expressed in terms of three aquifer types namely 1) fractured, 2) inter-granular, and 3) inter-granular & fractured. Five borehole yield classes are used which are: 0-0.1l/s, 0.1-0.5l/s, 0.5-2.0l/s, 2.0-5.0l/s and >5.0l/s. When classifying the different regions in terms of 'development potential' the terms extremely low, very low, low, medium and high are used respectively for the aforementioned yield classes (EC Groundwater Plan, 2010).

Extremely low development potential means practically no groundwater can be found in the aquifers and if there is any water, a wind pump or hand pump is needed in order to cater for individual household supplies. In very low development potential regions enough water is expected for both hand or wind pumps and the water can serve small supplies for small communities. Little additional groundwater could be accessible for community gardening or other poverty alleviation activities. Many boreholes will have to be drilled to obtain a yield at the high-end of the range in very low development potential regions.

Low development potential - enough water for either hand or wind pumps, i.e. small supplies for small communities, stock watering or single households can easily be achieved. Additional groundwater for community gardening or other poverty alleviation actions is available. At the high-end of the yield range larger communities from single boreholes and well fields supplying large communities would be possible. However, due to large variability in borehole yields, an appreciable amount of boreholes need to be drilled to obtain a yield at the high-end of the range (EC Groundwater Plan, 2010).

Medium development potential – domestic water supplies for large villages, towns and small-scale irrigation from several boreholes, can be achievable in aquifers with medium development potential. The amount of boreholes to be drilled before high-end yields that can be expected depends on the variability of borehole yields. Well fields and the concomitant benefit for the management of aquifers make the development of groundwater within medium high potential aquifers very attractive. High development potential – Large-scale irrigation, large village and even large town supplies can be obtained from these aquifers (EC Groundwater Plan, 2010).

2.2.2 **Groundwater recharge**

Groundwater recharge is the process by which rain water seeps into groundwater systems, and is calculated as an average over several years. Groundwater recharge is dependent mainly on rainfall and geological permeability, and different areas vary in their ability to recharge groundwater (DWAF, 2005b). The NFEPA (National Freshwater Ecosystem Priority Areas) identifies areas having high groundwater recharge and these can be regarded as strategic water supply areas of the country and less vulnerable to droughts due to abundance of water.

Recharge is ratio of sub-quaternary catchment to primary catchment groundwater recharge. In South Africa, values ≥ 300 indicate high groundwater recharge areas where the sub-quaternary catchment is at least three times more than the average for the related primary catchment (Midgley *et al.* 1994; DWAF, 2005b). High groundwater recharge areas are sub-quaternary catchments where groundwater recharge is three times higher than the average for the related primary catchment. High groundwater recharge areas are not all FEPAs (Freshwater Ecosystem Priority Areas), but the recommendation is that the surrounding land should be managed so as not to adversely impact groundwater quality and quantity. High groundwater recharge areas can be considered as the 'recharge hotspots' of a region. Keeping natural habitat in areas intact and healthy is precarious to the running of groundwater dependent ecosystems, which can be in the abrupt locality, or far removed from the recharge area (Nel *et al.* 2011).

Currently in South Africa, high groundwater recharge is determined as follows according to DWAF (2005) and Nel *et al.* (2011): the map of high groundwater recharge areas is derived using groundwater resource assessment data, available at a resolution of 1 km x 1 km (DWAF, 2005) which is based on the Chloride Mass Balance provided by Lerner *et al.* (1990). A GIS model is established, which replicates natural processes of direct groundwater recharge (DWAF, 2005). The model is calibrated and refined according to known recharge values at several sites across the country, as well as expert knowledge. Groundwater recharge (mm per year) for each 1 km x 1 km cell is expressed as a percentage of the mean annual rainfall (mm per year) for that cell. This gives a relative idea of where the proportionally highest recharge areas are in the country, compared to using absolute numbers (mm per year). Percentage recharge for each sub-quaternary catchment is expressed as the percentage recharge for the relevant primary catchment to identify areas where groundwater recharge is at least three times more than that of the primary catchment.

2.3 Drought indices

A drought index value can be defined as an individual number used for decision-making policies. Typically, drought indices are continuous functions of precipitation, stream discharge, temperature or other quantifiable variables. Rainfall data is extensively used to compute drought indices due to availability of long-term rainfall archives. Although rainfall data alone might not reveal the scale of drought-linked circumstances, it can serve as a logical solution in data-poor areas. Although there are many drought indices that have been developed by researchers, only a reduced number are being used operationally in most countries.

From the IPCC (2012) report, the confidence levels of patterns in drought progression since the 1950s are medium to low, often owing to the numerous regions where evidence is unreliable or inadequate. The reason for the irregularities is how outcomes contrast depending on model and dryness indices used. Hence it is of prior significance to comprehend the numerous indices, models and reacting parameters used in drought analyses, alongside their rewards and drawbacks. A short narrative on drought indices which are convened according to the surface of information used in their formulation such as hydrological, agricultural, and meteorological is revised in the following sub-section.

2.3.1 Dry Index (DI)

The Dry Index (DI) gives the relationship between temperature and precipitation of a region and is given by

$$DI = 56 \times \log (120 \times T)/P$$

Where T is annual average temperature in 0C and P is the annual average precipitation in mm. The index is positive for dry climatic regions and negative for moist climates. A region is classified as arid extreme if; DI > 72, arid moderate if DI is between 50-71 and arid mild if DI < 50 (Nagarajan, 2003). However, the dry index only indicates the relationship between temperature and rainfall without indicating the state of vegetation on the ground.

2.3.2 Standardized Precipitation Index (SPI)

The SPI was designed by Colorado State University (McKee *et al.* 1993) in a bid to advance drought detection and monitoring proficiencies. SPI allows quantification of the rainfall shortfall for numerous time frames, replicating the impact of rainfall shortage on the availability of several water supplies. They calculated the SPI for 3-, 6-, 12-, 24-, and 48-month time frames to reveal the temporal behavior of the impact. The SPI is calculated by taking the difference of the precipitation from the mean for a specific time scale, then dividing it by the standard deviation. The strength of SPI lies in its capability to be calculated for a variety of time scales. The disadvantage of SPI is that values based on preliminary data may change.

2.3.3 Normalized Difference Vegetation Index (NDVI)

There are two common groups of vegetation indices namely ratios and linear combinations, both of which exploit the surface-dependent and/or wavelength-dependent features. Ratio vegetation indices may be the simple ratio of any two spectral bands, or the ratio of sums, differences or products of any number of bands. Linear combinations are orthogonal sets of *n* linear equations calculated using data from *n* spectral bands (Jackson & Huete, 1991).

When light collides to a surface, some is reflected, some is transmitted and the remainder is absorbed. The virtual quantities of reflected, transmitted and absorbed light are a function of the surface and diverge with the wavelength of the light. For instance, the majority of light striking soils is either reflected or absorbed, with very little being transmitted and relatively being transmitted and relatively little change with the wavelength (Jackson & Huete, 1991). With vegetation, however, most of the light in the near-infrared (NIR) wavelengths is transmitted and reflected, with little absorbed, in contrast to the visible wavelengths were absorption is predominant, with some reflected and little transmitted.

The following Figure 5 depicts the reflectance spectra for bare soil, bare wet soil and a full-cover wheat canopy. The vertical dashed lines labelled ‘red’ and ‘near infrared’ delineate the wavelength intervals representative of Bands 3 and 4 of the Thematic Mapper (TM) on Landsat 4 and 5, and Bands 2 and 3 of the high resolution visible (HRV) sensors on the French satellites SPOT 1 and 2. Horizontal solid lines labelled A-F indicate the average reflectance within the waveband for the soil and wheat targets. If a wheat field is to be monitored, early in the season only bare soil will be observed by the sensor (Jackson & Huete, 1991).

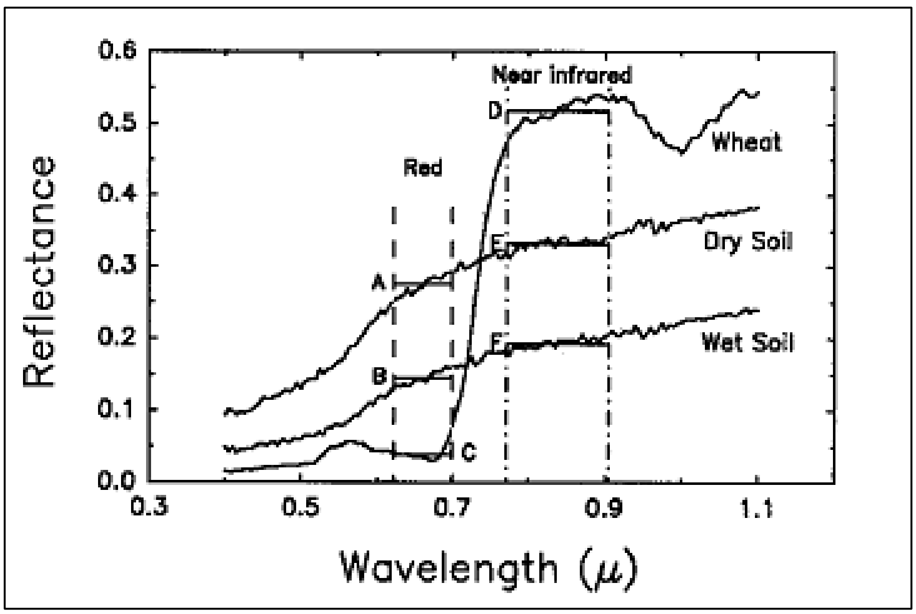


Figure 5: Reflectance spectra for wheat, dry bare soil, and wet bare soil. Vertical dashed lines indicate the appropriate band widths of the red and NIR bands of the Landsat TM

Source: Jackson & Huete, 1991

The most commonly used index for drought monitoring is NDVI, whose values range between -1 to +1. A large NDVI index corresponds to areas of high evapotranspiration rates that represent dense vegetative cover, permeable soil and substantial soil moisture. A small index value corresponds to areas having minimal evapotranspiration that represents bare ground or little vegetation, relatively impermeable soils and minimal soil moisture (Nagarajan, 2003). The expression for calculating NDVI is,

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

Where NIR and R, are the reflectance in near infrared and red regions of an electromagnetic spectrum.

When doing a simple visual analysis of NDVI one can use the "Image Analysis" in ArcGIS but if doing some serious change detection studies then it is better to go from Digital Numbers (DNs)->Radiance->TOA Reflectance->Atmospheric Correction steps. Reflectance values should be used to calculate the NDVI rather than DN values, or else the results will be not correct.

The Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and the Normalized Difference Drought Index (NDDI) are the practical remote sensing indices for drought assessment. The NDDI is a combination of NDVI and NDWI. Other commonly used vegetation indices associated with remote sensing data are Difference Vegetation Index (DVI), Ratio Vegetation Index (RVI), Perpendicular Vegetation Index (PVI), Soil Adjusted Vegetation Index (SAVI), Transformed Soil Adopted Vegetation Index (TSAVI), Weighted Difference Vegetation Index (WDVI), Vegetation Condition Index (VCI), Transformed Vegetation Index (TVI) and Green Vegetation Index (GVI) (Kasturirangan, 1996).

2.3.4 Palmer Drought Severity Index (PDSI)

Palmer (1965) developed a soil moisture algorithm (a model), which uses precipitation, temperature data and local available water content. Many United States government agencies and states depend on the Palmer index to prompt drought relief programs. The index is based on the supply-demand concept of the water balance equation, taking into account more than only the precipitation deficit at specific locations (Palmer, 1965).

The objective of the PDSI was to provide a measurement of moisture conditions that were standardized so that comparisons using the index could be made between locations and between months. The PDSI is a meteorological drought index which reacts to weather conditions that have been irregularly dry or irregularly wet.

When conditions change from dry to normal or wet, for example, the drought measured by the PDSI ends without taking into account streamflow, lake and reservoir levels, and other longer-term hydrologic impacts (Karl & Knight, 1985). The PDSI is a two layer model and the following table 1 shows Palmer classifications of drought.

Table 1: Palmer classifications

Palmer Classifications	
4.0 or more	extremely wet
3.0 to 3.99	very wet
2.0 to 2.99	moderately wet
1.0 to 1.99	slightly wet
0.5 to 0.99	incipient wet spell
0.49 to -0.49	near normal
-0.5 to -0.99	incipient dry spell
-1.0 to -1.99	mild drought
-2.0 to -2.99	moderate drought
-3.0 to -3.99	severe drought
-4.0 or less	extreme drought

Source: http://drought.unl.edu/Planning/Monitoring/Comparisonof IndicesIntro/ Palmer Drought Severity Index.aspx

The PDSI is computed based on precipitation and temperature data, as well as the local Available Water Content (AWC) of the soil. From the inputs, all the basic terms of the water balance equation can be determined, including evapotranspiration, soil recharge, runoff, and moisture loss from the surface layer. Human impacts on the water balance, such as irrigation, are not considered. Palmer (1965) and Alley (1984) provide complete descriptions of the equations on water balance.

Alley (1984) and Karl & Knight (1985) provide a comprehensive insight into the limitations of the PDSI. However, numerous scholars have offered supplementary restrictions of the Palmer Index. McKee *et al.* (1995) suggested that the PDSI is designed for agriculture but does not accurately represent the hydrological impacts resulting from longer droughts. Also, the Palmer Index is applied within the United States but has little acceptance elsewhere (Kogan, 1995) and one explanation for this is provided by Smith *et al.* (1993), who suggested that it does not do well in regions where there are extremes in the variability of rainfall or runoff such as in Australia and South Africa were given.

Another weakness in the PDSI is that the "extreme" and "severe" classifications of drought occur with a greater frequency in some parts of the country than in others (Willeke *et al.* 1994). "Extreme" droughts in the Great Plains occur with a frequency greater than 10%. This limits the accuracy of comparing the intensity of droughts between two regions and makes planning response actions based on certain intensity more difficult. Apart from climatological parameters, physical parameters like canopy-air temperature differences have also been used for assessing the stress degree days to indicate the impact of drought.

The drawback of the PDSI is that Palmer values may lag emerging droughts by several months; less well suited for mountainous land or areas of frequent climatic extremes; complex—has an unspecified, built-in time scale that can be misleading (McKee *et al.* 1995).

2.3.5 Surface Water Supply Index (SWSI)

The Surface Water Supply Index (SWSI) was developed by Shafer & Dezman (1982) to supplement the Palmer Index for moisture conditions across the state of Colorado. The Palmer Index is basically a soil moisture algorithm regulated for comparatively consistent regions, but it is not intended for large topographic variations across a region and it does not justify for snow accumulation and subsequent runoff. Shafer & Dezman (1982) designed the SWSI to be an indicator of surface water conditions and described the index as "mountain water dependent", in which mountain snowpack is a major component.

The aim of the SWSI was to include both hydrological and climatological structures into a single index value approximating the Palmer Index for each major river basin in the state of Colorado (Shafer & Dezman, 1982). These values would be standardized to allow comparisons between basins.

Four inputs are required within the SWSI: snowpack, streamflow, precipitation, and reservoir storage. SWSI represents water supply conditions unique to each basin or water requirement of each basin. Hence inter-basinal comparisons are not possible. Since SWSI is dependent on the season, it is calculated with only snowpack, precipitation, and reservoir storage in the winter. During the summer months, streamflow replaces snowpack as a component within the SWSI equation (http://drought.unl.edu/Planning/Monitoring/ComparisonofIndicesIntro/SWSI.aspx).

Monthly precipitation data are collected and summed for all rain gauge stations; reservoir and stream flow measuring stations. The summed up components are normalized using frequency analysis gathered from a long term dataset. The probability of non-exceedence i.e. the probability that subsequent sums of that component will not be greater than the current sum is determined for each component based on the frequency analysis. Each component has a weight assigned to it. Depending on its typical contribution to the surface water with in that basin and these weighted components are summed to determine SWSI. It ranges between -4.2 and +4.2 (Nagarajan, 2003). The disadvantage of SWSI is that changing a data collection station or water management requires that new algorithms be calculated, and the index is unique to each basin, which limits inter-basin comparisons.

2.3.6 Crop Moisture Index (CMI)

The Crop Moisture Index (CMI) was a development by Palmer (1968) from techniques during the calculation of the Palmer Drought Severity Index (PDSI). CMI uses a meteorological method to monitor week-to-week crop conditions. Since the PDSI monitors long-term meteorological wet and dry spells, the CMI was intended to assess short-term moisture conditions across major crop generating areas. Because it is planned to monitor short-term moisture conditions impinging an evolving crop, the CMI is not suitable for long-term drought-monitoring.

Since the CMI is designed to monitor short-term moisture conditions affecting a developing crop, it is not a good long-term drought monitoring tool. The CMI's rapid response to changing short-term conditions may provide misleading information about long-term conditions. For example, a beneficial rainfall during a drought may allow the CMI value to indicate adequate moisture conditions, while the long-term drought at that location persists (http://drought.unl.edu/Planning/Monitoring/ComparisonofIndicesIntro/CMI.aspx).

Another characteristic of the CMI that limits its use as a long-term drought monitoring tool is that the CMI typically begins and ends each growing season near zero. This limitation prevents the CMI from being used to monitor moisture conditions outside the general growing season, especially in droughts that extend over several years. The CMI also may not be applicable during seed germination at the beginning of a specific crop's growing season.

2.3.7 Normalized Difference Water Index (NDWI)

Though vegetation indices were established to extract the plant signal only, the soil background, moisture condition, solar zenith angle, view angle, as well as the atmosphere, alter the index values in complex ways (Jackson & Huete, 1991). From Gao (1996), the NDWI is a more recent satellite-derived index from the NIR and short wave infrared (SWIR) channels that reflects changes in both the water content (absorption of SWIR radiation) and spongy mesophyll in vegetation canopies. Various studies (Xiao *et al.* 2002; Jackson *et al.* 2004; Maki *et al.* 2004; Chen *et al.* 2005; Delbart *et al.* 2005) have illustrated the usage of NDWI calculated from the 500-m SWIR band of MODIS to detect and monitor the moisture condition of vegetation canopies over large areas.

McFeeters' NDWI is a water index which is designed from (Green - NIR)/ (Green + NIR), where Green and NIR are the reflectance of the green and NIR bands (McFeeters, 1996). McFeeters' NDWI is incapable to fully distinct built-up features from water features. To report this problem, the altered NDWI (Xu's NDWI) was advanced, which is designed from (Green -SWIR)/ (Green + SWIR), where SWIR is the reflectance of the SWIR band (Xu, 2006).

2.4 Climate modeling conceptual framework

This section provides an insight into the regional climate change projections in order to provide decision-makers with a better appreciation of the kinds of the predicted changes, and also ways to incorporate this information when articulating and employing suitable climate change adaptive policies. Since climate change projections are probability-based, they cannot be deemed to be absolute predictions. The modelling of risk exposure outcomes in predictions of the likelihoods of forthcoming climate circumstances which are not absolute forecasts. Since climate the models are becoming progressively refined, forthcoming modelling is probable to produce diverse and more perfect outcomes than the presently obtainable.

Dynamic climate models have become the principal implements for the prediction of forthcoming climate change, at both the global and regional scales. The laws of physics applied to the earth system form the basis of the dynamic models. The laws constitute a set of complex partial differential equations when conveyed in scientific formula (Engelbrecht *et al.* 2011). Global Climate Models, statistical downscalings and dynamical downscalings all indicate an upsurge in probable temperatures.

The application of Global Climate Models (GCMs) is relatively beneficial in evolving our appreciation of the dynamical mechanisms prevailing hydro-climatic variability (Hoerling & Kumar, 2003; Schubert *et al.* 2009; Seager, 2007). GCMs assist in observation of droughts on decadal basis (Mishra & Singh, 2011). The work of Herweijer *et al.* 2006 and Seager *et al.* 2005 support that GCMs are generally capable to reproduce perceived or estimated patterns of drought with extraordinary reliability. Dynamically-downscaled climate projections deliver information on temperature, rainfall and weather extremes for three time periods which are 2011-2040, 2041-2070, and 2071-2100.

According to the DEA (2013) report, the Long Term Adaptation Scenario (LTAS) Phase 1 climate trends and scenarios work settled an agreement on the range of probable climate scenarios for three time-periods for South Africa at national and sub-national scales under a range of global emissions scenarios. The time-periods considered were 2015 to 2035 (centered on ~2025, so-called short-term) in addition to the previously followed approach of exploring climate change over several decades into the future (centered on ~2050 (medium-term) and ~2090 (long-term)). These developments were advanced through local and international climate modelling expertise using both statistical and dynamical downscaling methodologies based on outputs from IPCC AR4 (A2 and B1 emissions scenarios) and IPCC AR5 (RCP 8.5 and 4.5 Wm-2 pathways) (DEA, 2013). These represent an unmitigated future energy pathway (unconstrained, A2 and RCP8.5) and mitigated future energy pathway (constrained, B1 and RCP4.5, or emissions scenarios equivalent to CO^2 emission levels stabilizing between 450 and 500ppm) (DEA, 2013).

The LTAS also reexamined observed climate trends (1960–2012) and current climatology for South Africa and matched these with expected trends by using a subset of the models (DEA, 2013). This reexamination of observed climate trends is preliminary effort to ascertain possible strengths and weaknesses in modelling approaches employed so far to provide a qualitative basis for evaluating the credibility of future projections, and to guide efforts to address potential shortcomings. The Conformal Cubic Atmospheric Model (CCAM) is a variable resolution global model which reproduces the mean periodic precipitation patterns and has been used for a number of years for dynamic climate downscaling, mainly over Australian region. CCAM is a hydrostatic model, with two-time level semi-implicit differencing which employs semi-Lagrangian horizontal advection with bi-cubic horizontal interpolation (McGregor, 1996), in conjunction with total-variation-diminishing vertical advection.

2.4.1 Representative concentration pathways (RCPs)

RCPs are scenarios that include time series of emissions and concentrations of the full suite of greenhouse gases (GHGs) and aerosols and chemically active gases, as well as land use/land cover (Moss *et al.* 2008). The word representative signifies that each RCP provides only one of many possible scenarios that would lead to the specific radiative forcing characteristics. The term pathway emphasizes that only the long-term concentration levels are of interest, but also the trajectory taken over time to reach that outcome (Moss *et al.* 2010). RCPs are designed to facilitate the interactions with climate models by including geospatially resolved emissions and land-use data (Rasch, 2012).

The RCPs are used for climate modelling and research and describe four possible climate futures, all of which are considered possible depending on how much greenhouse gases are emitted in the years to come. The four RCPs: RCP2.6, RCP4.5, RCP6, and RCP8.5, are named according to radiative forcing target level for year 2100 relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W/m^2, respectively) (Moss *et al.* 2008). The radiative forcing estimates are based on the forcing of greenhouse gases and other forcing agents. The forcing levels are relative to pre-industrial values and do not include land use (albedo), dust, or nitrate aerosol forcing (Van Vuuren *et al.* 2011).

2.4.2 The Coupled Model Intercomparison Project (CIMP)

The CIMP was initiated in 1995 by the JSC/CLIVAR Working Group on Coupled Models (a part of the World Climate Research Program) with an aim of providing climate scientists with a database of coupled GCM simulations under standardized boundary conditions. The CMIP investigators use the model output in efforts to ascertain why various models give diverse output in reaction to the same input, and also to ascertain characteristics of the simulations in which agreements in model predictions occur. However, in cognizance with advancements in technology the project has also been upgraded, with the fifth phase (CIMP5) being the most recent (http://cmip-pcmdi.llnl.gov/history.html).

CIMP5 uses the RCPs to characterize possible trajectories of climate forcing over the 21st century (Field *et al.* 2014). The first model output from CIMP5 became available for analysis in February 2011 (http://cmip-pcmdi.llnl.gov/cmip5/). CMIP5 endorses a standard set of model simulations in order to:

- determine how realistic the models are in simulating the recent past,
- deliver projections of future climate change on two time scales, near term (out to about 2035) and long term (out to 2100 and beyond), and

- comprehend some of the factors accountable for variances in model projections, including quantifying some key feedbacks such as those involving clouds and the carbon cycle (http://cmip-pcmdi.llnl.gov/cmip5/).

CMIP5 regional climate changes are generally similar to previous generation CMIP3 model results but however CMIP5 models provide: more simulations, higher spatial resolution, more developed process representation and daily output is more available. CMIP5 representation of short term climate variability is somewhat improved over CMIP3 (Taylor *et al.* 2012). In South Africa, the CIMP5 data has been extensively used in climate research organizations such the Climate System Analysis Group.

2.4.3 Projections: Early century

In an Eastern Cape Province case study, two GCMs were used to generate climate scenarios downscaled to the Fort Beaufort study location for 2 RCPs; 4.5 and 8.5. The GCM control periods used are provided in APPENDIX section under Annex 1.The climate projections clearly showed agreement in an increase in temperatures for the early and mid-21st century relative to the baseline, with higher temperature increase further into the century than earlier. Rainfall projections were however uncertain across all scenarios with no clear indication of whether rainfall will increase or decrease.

The following Figure 6 shows the expected increase from baseline to early 21st century future in minimum and maximum temperatures across all 10 GCMs. Figure 7 shows that under RCP4.5, monthly changes range on average from +0.4 ^{o}C to above +1.2 ^{o}C for both minimum and maximum temperatures. Monthly GCMs projections differ by less than 1.2 ^{o}C (10th to 90th percentile) for minimum temperatures and less than 1.5 ^{o}C for maximum temperatures, which translates to a strong agreement in projections.

The overall message is an apparent increase in temperatures, across the year, for both minimum and maximum temperatures. Minimum temperatures increase shows some sign of seasonality with high (with wider range) increase inter-seasons (March-April and October) and low increase in winter (June). This message does not appear significantly with maximum temperatures.

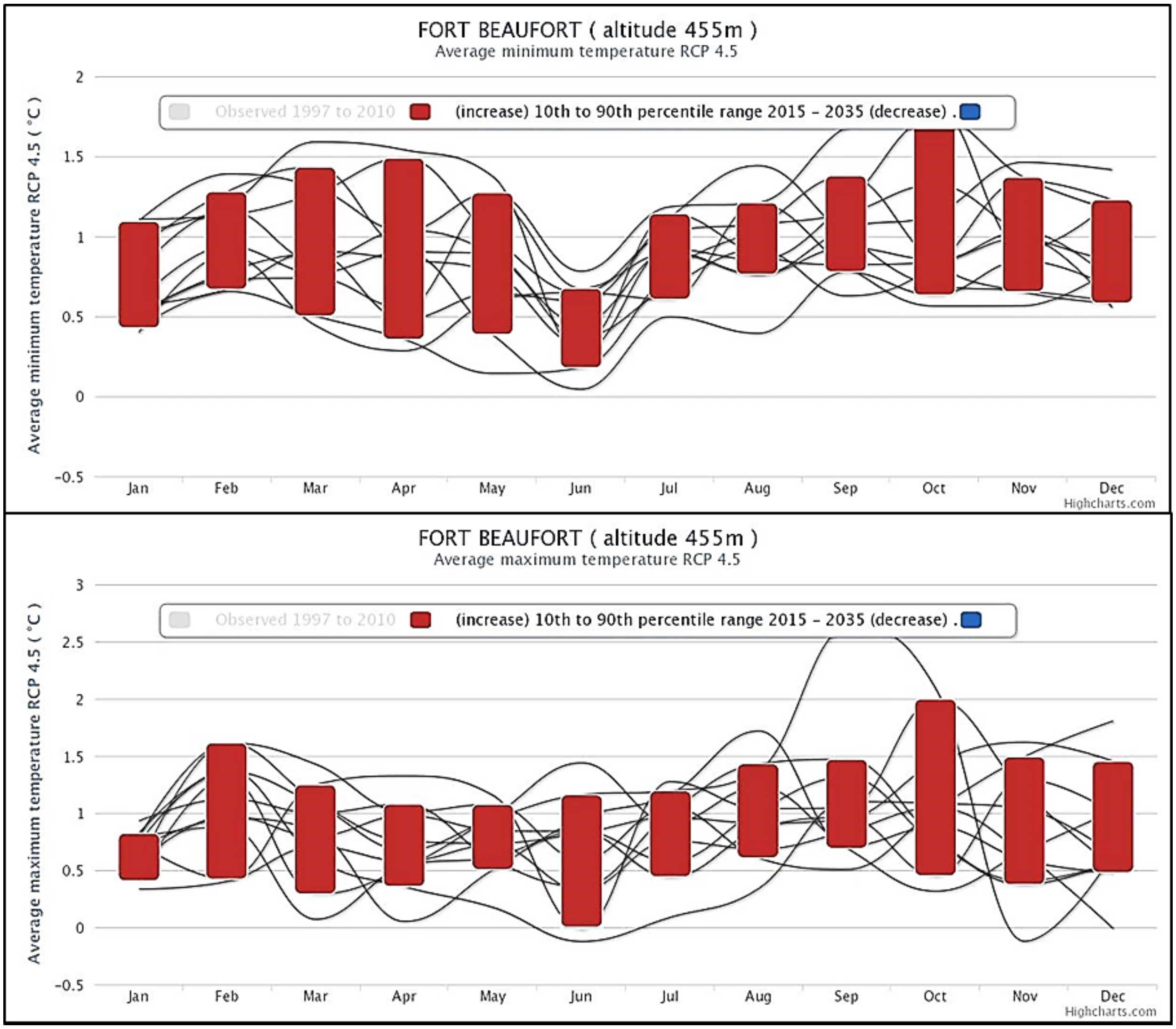


Figure 6: Range of projected minimum (top) and maximum (bottom) temperature changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP4.5

Source: FFC, 2014

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models project the future changes.

Figure 7 show that under RCP8.5, monthly change averages range from +0.6 °C to +1.3 °C for minimum and from +0.3 °C to above +1.1 °C maximum temperatures. Monthly GCMs projections differ less than 0.8 °C (10th to 90th percentile) for minimum temperatures and less than 1.1 °C for maximum temperatures, which translate a strong agreement in projections towards increase (except for 2 GCMs in April for maximum temperatures). Both minimum and maximum temperature increases show a sign of seasonality with high increase from mid-winter until end of summer season (July to March) and low increase spring (April to June).

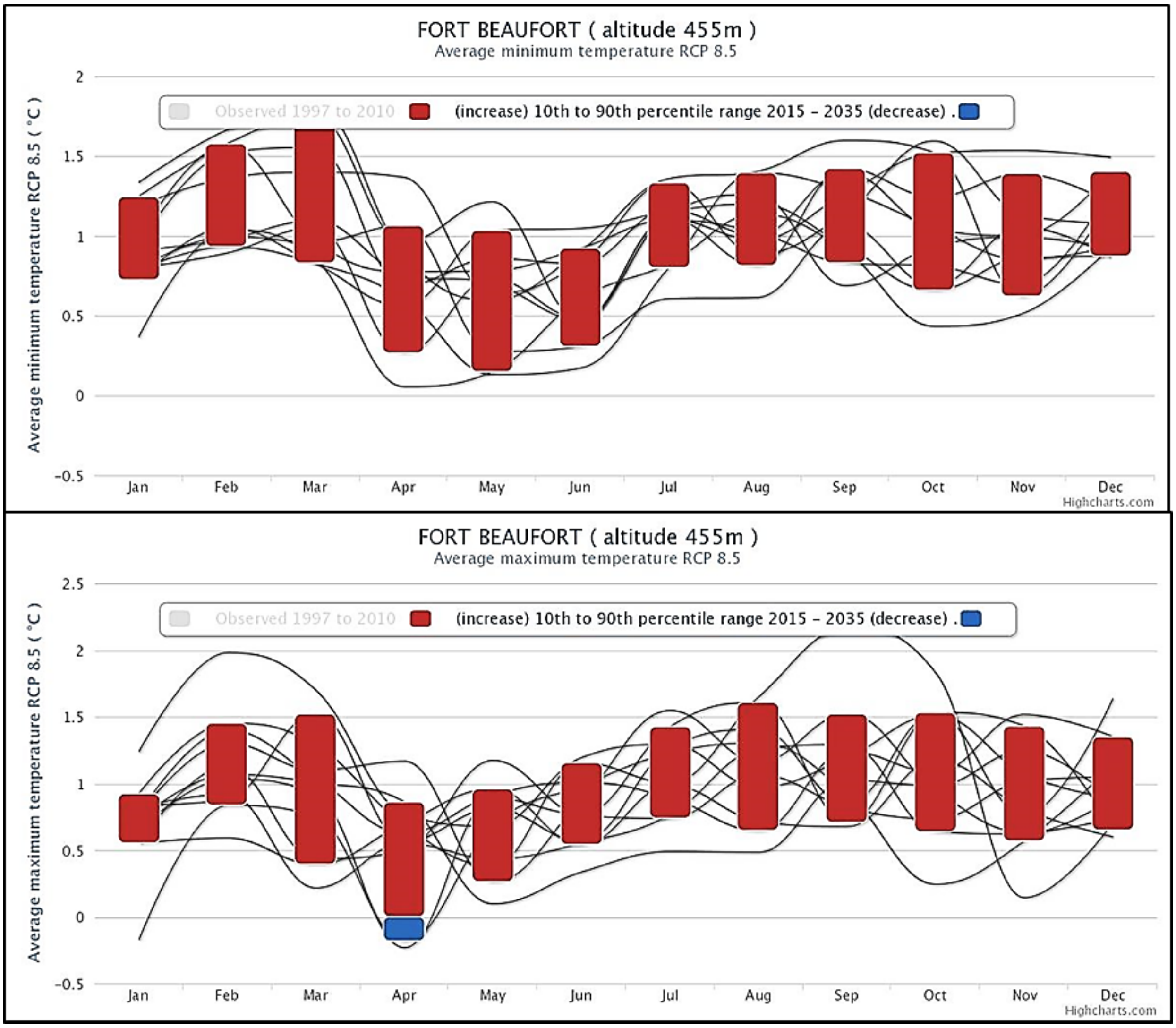


Figure 7: Range of projected minimum (top) and maximum (bottom) temperature changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP8.5

Source: FFC, 2014

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models (intentionally not named) project the future changes. Figure 8 illustrates the monthly rainfall changes across the year. The projections vary from large range of projections (-32 to +14 mm in January) to small ranges (-2 to +7 mm in August).

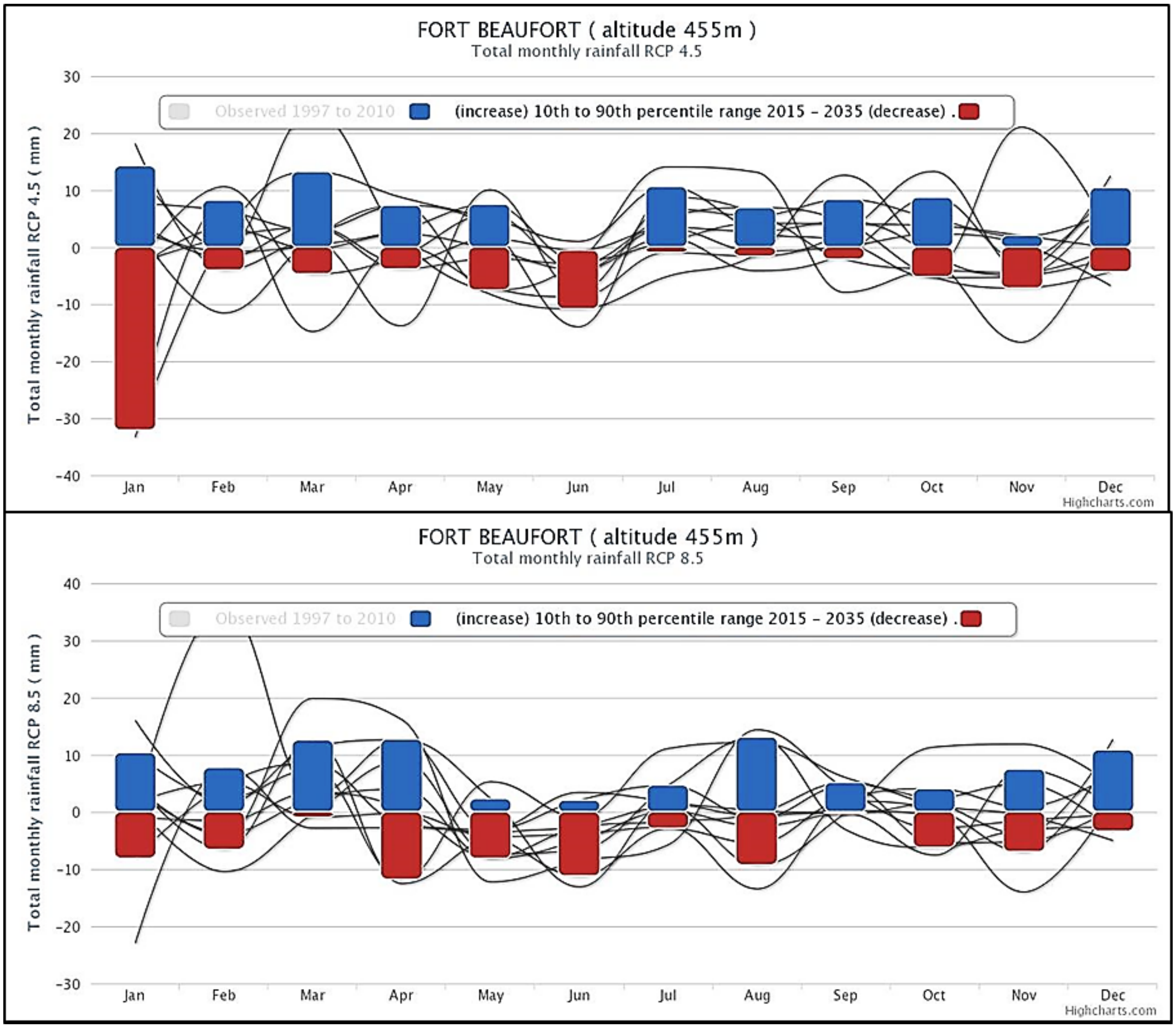


Figure 8: Range of projected rainfall changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP4.5 (top) and RCP8.5 (bottom)

Source: FFC, 2014

Although those ranges translate changes compared with the baseline, the different change directions (increase vs. decrease) and the accuracy of GCMs to represent baseline period give no clear message about rainfall projection.

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models (intentionally not named) project the future changes.

2.4.4 Projections: Mid-century

Figure 9 shows the expected increase from baseline to mid-century future in minimum and maximum temperatures across all GCMs. Under RCP4.5, monthly change averages range from +1.1 ^{o}C to above +1.7 ^{o}C for minimum and maximum temperatures. Monthly GCMs projections differ by less than 1.2 ^{o}C (10th to 90th percentile) for minimum temperatures and less than 1.4 ^{o}C for maximum temperatures, which translate a strong agreement in projections. The overall message is a clear and confident increase of temperatures, all across the year, for both minimum and maximum temperatures. There is no clear signal of seasonality.

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models (intentionally not named) project the future changes.

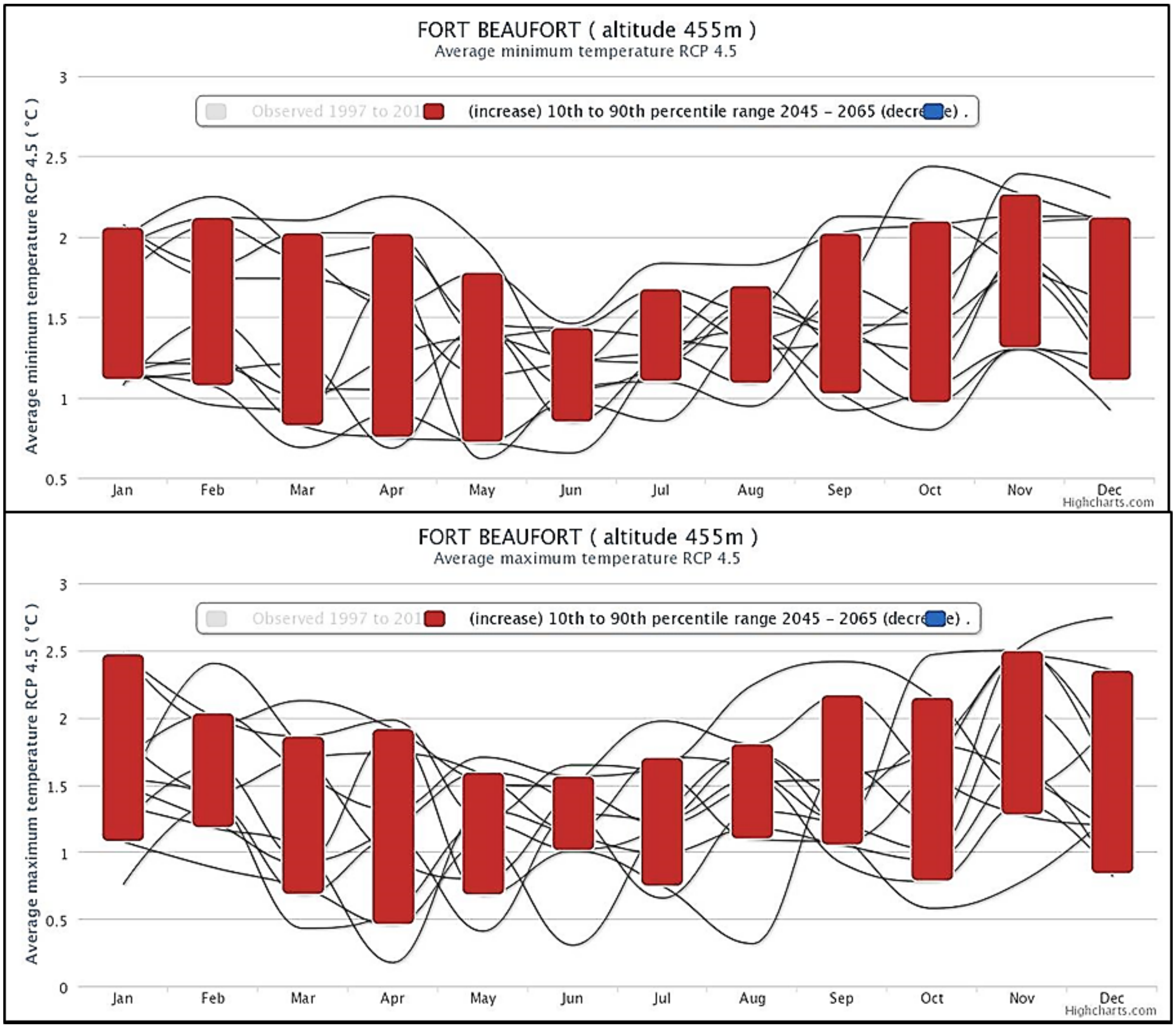


Figure 9: Range of projected minimum (top) and maximum (bottom) temperature changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP4.5

Source: FFC, 2014

Under RCP8.5 (Figure 10), monthly change averages range from +1.7 ^{o}C to above +2.4 ^{o}C for both minimum and maximum temperatures. Monthly GCMs projections differ by 2.7 ^{o}C (10th to 90th percentile) for minimum temperatures and less than 1.1 ^{o}C for maximum temperatures, which translate a stronger agreement regarding maximum temperatures projections. The overall message is a clear increase in temperatures, all across the year, for both minimum and maximum, but no clear signal of seasonality.

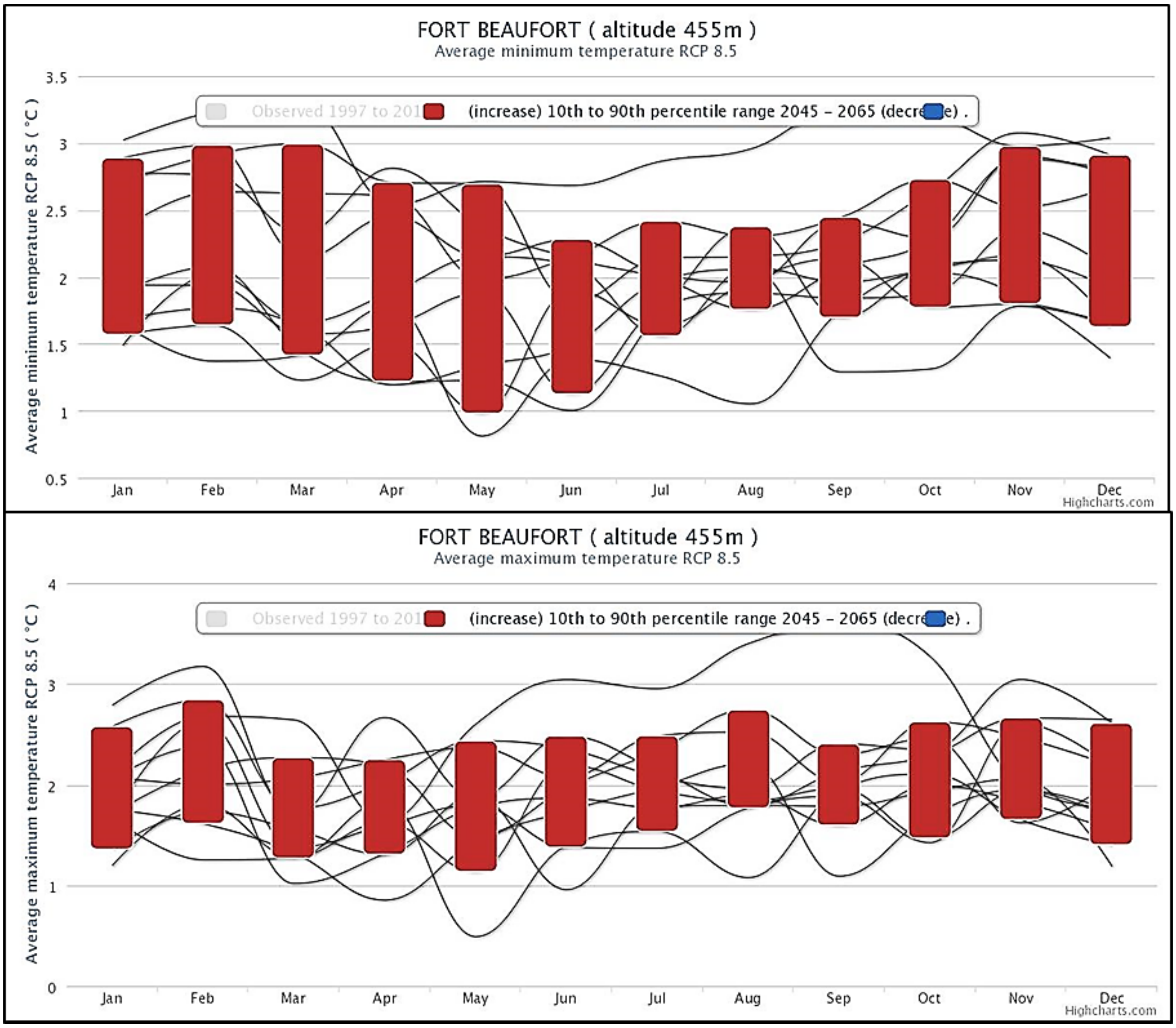


Figure 10: Range of projected minimum (top) and maximum (bottom) temperature changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP8.5

Source: FFC, 2014

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models (intentionally not named) project the future changes.

Figure 11 illustrates the monthly rainfall changes across the year. The projections vary from large range of projections (-20 to +5 mm in January) to smaller ranges (-5 to +5 mm in October). Although those ranges show some changes from baseline, the various projections (increase vs. decrease) produce no clear message about rainfall whether rainfall will increase or decrease.

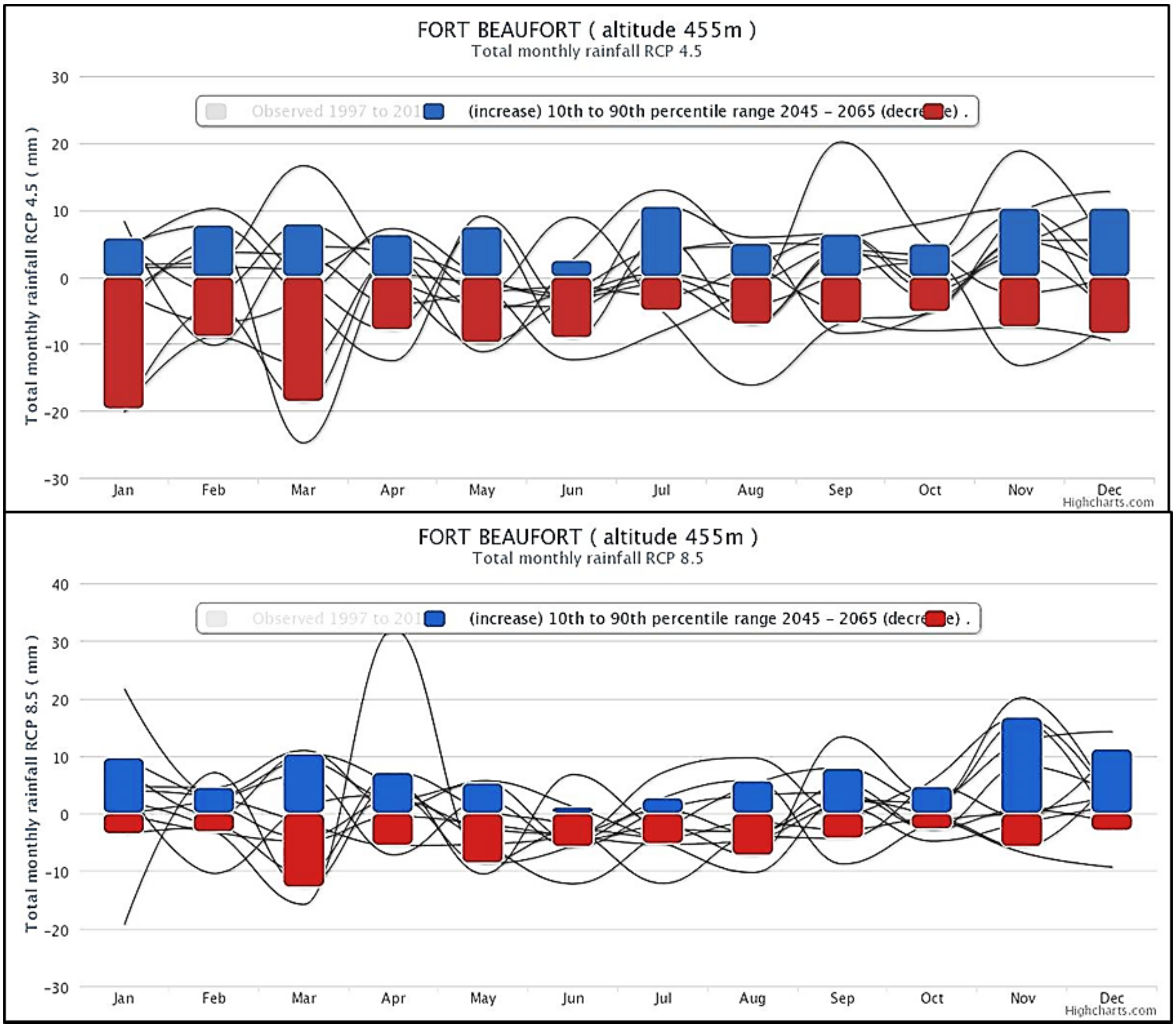


Figure 11: Range of projected rainfall changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP4.5 (top) and RCP8.5 (bottom)

Source: FFC, 2014

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models (intentionally not named) project the future changes.

2.5 Drought risk assessment using a remote sensing and GIS approach

GIS incorporates spatial and statistical tools to answer 'who, where and why' questions about vulnerable households to the adverse effects of climate variability. Although in most vulnerability assessment scenarios the data produced is usually integrated in tabular, graphical and chart presentations, maps are more advantageous since they present data in an easily accessible, readily visible and eye-catching manner.

Maps created using GIS can join information from different sectors to provide an immediate comprehensive picture of the geographical distribution of vulnerable households at sub-national level. By providing a visual overview of the major issues affecting food security and vulnerability of households to climate variability, the maps highlight gaps and shortfalls in information and thus areas needing attention. A GIS-based approach is helpful for highly disaggregated data in performing vulnerability assessments because it can easily perform statistical analysis as well as graphic and geographic presentations (UNEP, 2002).

2.5.1 Why Landsat images?

- Freely available online from United States Geological Survey (USGS) website
- Represents high-resolution (30 m) instantaneous acquisitions that are less affected by sub-pixel cloud contamination, spatial compositing, and mixed pixels (Hall *et al.* 2006).
- Landsat does not suffer as much from sensor degradation due to its on-board calibration achieving an accuracy of ±5% (Chander & Markham, 2003).

2.5.2 **Past studies based on remote sensing and GIS**

Various vulnerability assessment studies (Jain *et al.* 2009; Abson *et al.* 2012; Sharma & Jangle, 2012) have been carried out using remote sensing and GIS-based methodologies within their vulnerability frameworks and these have proved the value of the application of remote sensing and GIS in mapping of households vulnerable to climate risks.

The work done by Jain *et al.* (2009) in the identification of drought-susceptible zones using NOAA AVHRR satellite data in Rajasthan and Gujarat provinces in India produced results of drought and NDVI analysis showing that the vegetation condition can be used as an sign for evaluating the drought situation of a region. Jain *et al.* (2009) also supports that Standard Precipitation Index (SPI) is one of the drought indices that remain extensively used by decision makers for computing most kinds of drought events. The benefit of this index is that it offers spatial and temporal illustrations of historical drought. But in order to better comprehend the spatial behavior of droughts, study of satellite data is essential. However, calculation of the SPI for drought-monitoring processes requires precipitation data and gathering of this data is very challenging, time consuming and costly for a large area whereas satellite data are readily available with high spatial coverage and at low cost. Satellite data can be downloaded for free from the internet.

The application of Principal Component Analysis (PCA) by Abson *et al.* (2012) for information-rich socio-ecological vulnerability mapping in Southern Africa presented a 'proof of concept' analysis of socio-ecological vulnerability for the Southern Africa Development Community (SADC) region using both PCA and traditional normalization based techniques for generating spatially explicit, aggregated socio-ecological vulnerability indices.

The vulnerability indices are based on published biophysical and socio-economic data and mapped at a 10 arc minute resolution. The resulting PCA based vulnerability maps indicated the regional spatial variability of four statistically independent, unique components of socio-ecological vulnerability, providing more information than the single index produced using a normalization/summation approach. Such uncorrelated, information-rich vulnerability indices represent a potentially useful policy tool for identifying areas of greatest concern in terms of both the relative level, and the underlying causes and impacts of, socio-ecological vulnerability to environmental changes across broad spatial scales.

The limitation of using PCA approach in vulnerability mapping is that it is mainly suitable for regional level (such as international or provincial level) rather than local level (that is village level) vulnerability mapping. A PCA does not provide weightings regarding the relative importance of each of the indicators in the resulting aggregate indices since each indicator is treated as equally important as a driver of vulnerability. Therefore, a PCA based approach to vulnerability mapping does not provide absolute measures of vulnerability; rather it indicates the different spatial patterns of relative vulnerability relating to spatially co-occurrences of individual drivers of vulnerability (Abson *et al.* 2012). There is need to carefully consider scale when using PCA to generate aggregate vulnerability indices. The application of PCA may not be appropriate in creating aggregate vulnerability indices in systems where the particular drivers of vulnerability are to be of paramount importance (Abson *et al.* 2012), hence PCA not suitable for this study since drivers of vulnerability are of paramount importance.

Sharma & Jangle (2012) used a GIS platform in mapping the vulnerability of village households to climate risks in Ahmednagar (in Maharashtra) and Vaishali (in Bihar) districts in India. A multi-stage stratification sampling technique was applied to determine the villages within the study area to be included in the survey and identify the number of households to be interviewed in each of the villages. The vulnerability map produced assisted in identifying the areas that might be worst affected in case of climate variability related disasters. Adaptive capacity was highest in Vishanpaidu village of Bidupur amongst 52 villages under study because of high social capital, high penetration of health insurance and reasonable income diversification and literacy rate. Sensitivity was highest for Chaklewadi and Bhose villages of Karjat block in Ahmednagar district due to the high number of households that use unsafe water sources and also without a toilet facility. It was also portrayed that a considerable number of the households in these villages are depending on rain-fed agriculture and livestock as a key income source. From exposure mapping, it was observed that Hajipur and Bidupur blocks within Vaishali district has very high chances of drought and floods hence more vulnerable to climate risks. Resultant vulnerability maps after combining exposure, sensitivity, and adaptive capacity using ArcGIS software revealed highest vulnerability to climate risks for Imaidpur Sultan in Hajipur district. Although the sensitivity of the village was medium, low adaptive capacity and high exposure caused high vulnerability to climate variability risks.

Drought research by Gao *et al.* (1996) revealed that in order to enrich the information attained from the NDWI, the index must be applied together with another indicator that reflects more information on rainfall and soil moisture to find out the vegetation response. NDWI has been utilized to detect and control the moisture states of flora canopies from the work of Xiao *et al.* (2002) in the characterization of forest types in Northeastern China using multi-temporal SPOT-4 vegetation sensor data. Gu *et al.* (2007) experimented with the NDWI as a drought indicator and discovered that the values showed a more rapid response to drought condition than NDVI. Due to the higher sensitivity of NDWI to soil moisture content, vegetation cover and leaf moisture content, it is deemed proficient in the area of stress (Tychon *et al.* 2007). However, the pitfalls of NDWI are in its proneness to soil background effects on the partial vegetation cover. Drought and water stress are not the only factors that can result in a decrease in the NDWI values or anomalies. Changes in land cover or pest and diseases can also be accountable for deviations of the indication (Gao *et al.* 1996).

2.6 Synoptic overview of conceptual framework

For vulnerability assessment in this project a 4-step approach GIS based methodology similar to Sharma & Jangle (2012) will be adopted, with the differences being in the identification of indicators and secondary data. The methodology will be adopted because of: a) its assessment of vulnerability of households at local-level (that is village level) rather than regional-level (that is provincial level) which is similar to the scope of this study b) most indicators that were identified for assessing adaptive capacity, sensitivity and exposure are also relevant in Nkonkobe Local Municipality e.g. percentage of households not using irrigation practices c) its ability to allow quantification of vulnerability to enable a more accurate vulnerability assessment, hence better targeted policy interventions d) researcher’s familiarity with ArcGIS software used for the vulnerability mapping. Using GIS at a local level is believed to concurrently deal with the planning content, answer the questions asked of the geo-information, and also address and satisfy the local stakeholders' underlying interests, thus it is deemed to be both efficient and effective (McCall, 2003).

Satellite data processed into the NDVI can be used to designate insufficiencies in precipitation and reveal drought patterns temporally and spatially, thereby helping as a pointer of local drought patterns. Vulnerability assessment is a crucial component for decision-making processes because it updates decision makers and simplifies their decision-making processes (Senbetacc, 2009). Data and sampling assumptions will be used to suit the population data to the appropriate statistical test. The Landsat imagery will be atmospherically corrected first prior to NDWI and NDVI calculations and simple linear regression model will be applied on the NDWI - NDVI results.

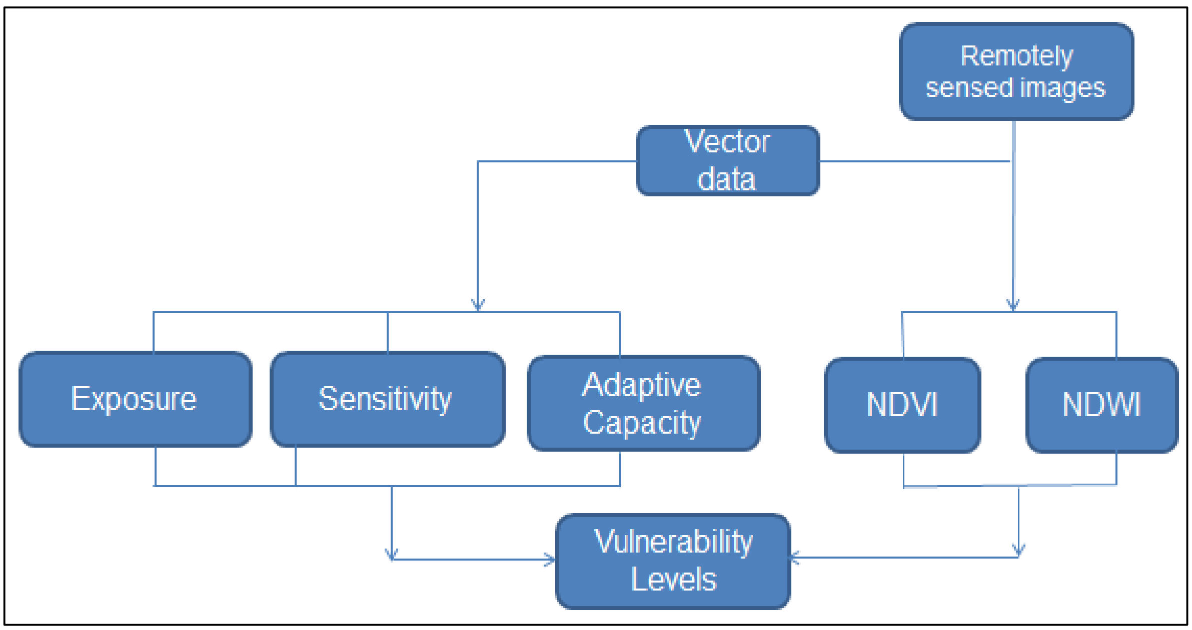
Therefore, it is of prior importance to understand climate change and variability impacts so that appropriate long-term climate change and variability adaptability measures can be implemented which will assist in reduced human vulnerability to disasters. This study addresses an important topic on climate change and vulnerability assessments given the huge costs and time required to map these issues at smaller household or village scales. The exploring of cheaper, innovative Remote Sensing and GIS applications to investigating vulnerability and adaptive capacity at household level hastens the understanding of where government should channel more resources to alleviate suffering.

3 MATERIALS AND METHODS

3.1 Introduction

The primary data collected were multi-temporal Landsat images which were pre-processed and clipped to study area in ArcGIS 10.1 software environment. Secondary data were demographic data which were overlaid in ArcGIS weighted sum analysis to determine vulnerability levels and then inter-linked with vegetation indices derived from the Landsat images.

The research methodology comprised of assessment of vulnerability levels, determination of drought hazard and drought risk assessment (Figure 12).



NDVI – Normalized Difference Vegetation Index

NDWI – Normalized Difference Water Index

Figure 12: Summary of materials and methods

The work done in past vulnerability assessment studies (O'Brien *et al.* 2004; Heltberg & Bonch-Osmolovskiy, 2011) illustrates that in order to quantify vulnerability; a 4-step approach is applied. Quantification of vulnerability allows for a more comprehensive statistical analysis hence more accurate results. In the 4-step approach vulnerability is a function of three components, namely exposure, sensitivity, and adaptive capacity (O'Brien *et al.* 2004; Heltberg

& Bonch-Osmolovskiy, 2011), which are calculated individually and then in the fourth step, the calculated variables are aggregated to determine the vulnerability.

The weights for the indicators were obtained from the Nkonkobe Integrated Development Plan (IDP) for 2012 - 2017 and judgment by experts conversant with the subject.
The primary datasets were the Landsat images downloaded from USGS website.

3.2 Study Area

The following Figure 13 depicts the location of Nkonkobe Local Municipality in the Eastern Cape Province of South Africa. Nkonkobe municipality is a countryside municipality which constitutes 16% of the surface area of Amathole District Municipality (Nkonkobe Municipality IDP, 2012-2017), covers an area of approximately 3 725 km^2 and has a population density of 43 people per square kilometer (Amathole District IDP, 2012-2017).

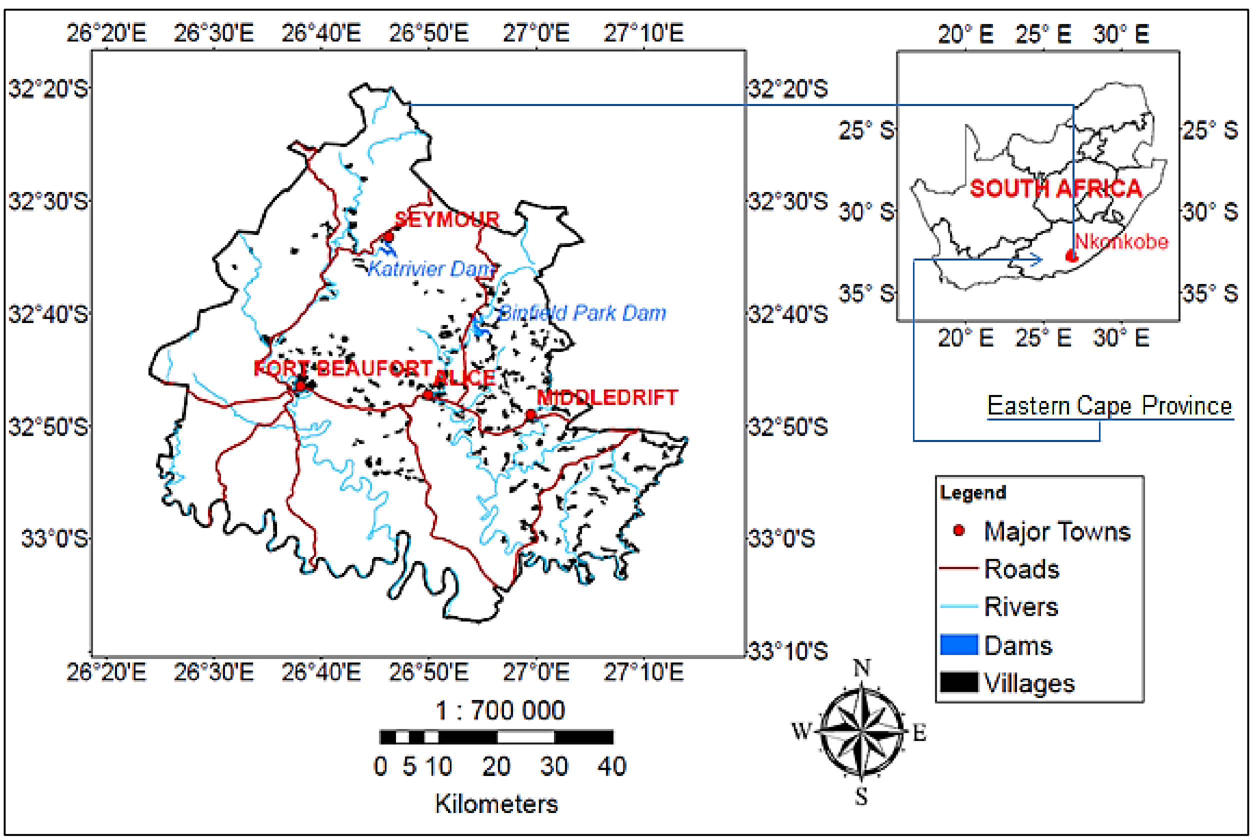


Figure 13: Location of Nkonkobe Local Municipality in the Eastern Cape Province, South Africa

Established in the year 2000, Nkonkobe Municipality is the second largest municipality in the Amathole District Municipality in the Eastern Cape Province of South Africa. Nkonkobe is made up of Alice, Middledrift, Fort Beaufort, Hogsback and Seymour/Balfour which are recognized as disestablished Transitional Local Councils (TLCs). Urbanization is mainly in Alice and Fort Beaufort. An estimated 74% of people living within the municipality are poor. The majority of the population (72%) resides in both villages and farms and 28% resides in urban settlements (Nkonkobe Municipality IDP, 2012-2017). This implies that the municipality is rural and therefore its service delivery systems should empower mainly the rural communities.

The climate varies from “arid and semi-arid moderate midlands”, to “arid and semi-arid cold high lying land”. Minimum temperatures are recorded to be 0.1˚C - 2˚C in the northern region and 6.1˚C - 8˚C in the southern region. Maximum temperatures are recorded to be 0˚C - 18˚C in the northern region and 21.9˚C - 24˚C in the southern region (SDF, 2010). The northern mountainous regions of the Nkonkobe Local Municipality have the highest rainfall, recording figures greater than 800mm per annum, whereas the southern regions record the lowest rainfall with figures of 500-599mm per annum. The soils in the area are mainly derived from the Beaufort and Molteno series of the Karoo sequence. Most of the soils are shallow, poorly developed and rocky. Alluvium occurs in the river terraces. No mineral deposits occur in the region but building stone and gravel can be obtained.

The larger portion of the Nkonkobe Municipality land is exploited for subsistence agriculture, while the western region has the highest potential for commercial agriculture. Nkonkobe LM has a dispersed settlement pattern where pockets of developed urban centers are surrounded by scattered undeveloped rural villages, which implies great costs to fulfill every basic human right to basic infrastructure and services (Nkonkobe SDF, 2010-2013). The population of Nkonkobe is said to be declining and one of the contributors is suspected to be the HIV/AIDS pandemic. The population of Nkonkobe has been growing just under -1.0% (Nkonkobe IDP, 2011).

The municipality prides itself as it is home to three educational institutions Fort Hare University; Lovedale FET College and Fort Cox Agricultural Collage. The Human Development Index

(HDI) for Nkonkobe Municipality is at 0.60 (Nkonkobe IDP, 2011). This shows that the levels of human development are still very low. The income distribution pattern in the district shows that the majority of the people are living in poverty. 81% of households earn less than R1 500 per month (Nkonkobe IDP, 2011).

Due to the rural nature of the Nkonkobe Local Municipality, subsistence agriculture (both crop and livestock production), is the main form of primary industry and is producing 30% of food needs despite the fact that there is a lot of arable land. In the past 12 years, the agricultural sector has been in a state of decline (Nkonkobe SDF, 2010). Commercial agriculture is mostly practiced in the Kat River Basin due to the favorable soils and adequate water supply. Citrus productions in this river basin, as well as forestry in the northern and western parts of the Nkonkobe Local Municipality are the main forms of economic agricultural activity. Other parts if the rural areas are used for subsistence farming.

3.3 Criteria for choosing Landsat images

- All parts of South Africa wet-season is from September to April, except for Cape Town where it rains June-July (South Africa Weather Service).
- From Average Temperatures and Precipitation 1980-2014 for Nkonkobe Local Municipality, the months chosen were March and April, since they are preceded by good rates of precipitation and average temperatures.
- Cloud cover less than 10%

Table 2: Landsat images that were used for NDVI and NDWI calculations

Instrument	Date	Cloud Cover	Spatial resolution	Temporal resolution
Landsat MSS	21/03/1985	0%	57m	14 days
Landsat TM	28/01/1995	0 %	57m	14 days
Landsat ETM+	04/03/2005	0%	30m	14 days
Landsat 8	21/03/2014	0.06%	30m	14 days

Source: http://earthexplorer.usgs.gov/

The following table 3 indicates the Landsat spectral bands and their applications in remote sensing.

Table 3: Landsat spectral bands and their principal uses

Band	Spectral region	Use/Application
1	Blue	Useful for discriminating soil/ vegetation, forest mapping and identifying man-made features. Bathymetric mapping. Useful for coastal water mapping
2	Green	Shows vegetation through its ability to detect greenness.
3	Red	Absorbs chlorophyll and it is good in vegetation differentiation. Also useful in Geological mapping
4	Near infra-red	Useful for crop identification. This is very good at mapping and analysing vegetation.
5	Shortwave Infrared	Sensitive to turbidity, (amount of water in plants). Good in soil moisture and mineralogy studies.
6	Thermal	Measure the amount of heat emitted from surface. Useful in thermal mapping, vegetation studies and fire monitoring.
7	Mid Infrared	useful for measuring the moisture content of soil and vegetation; helps differentiate between snow and clouds
8	Panchromatic	Used to sharpen images,

Source: Hamandawana, 2009; Hassan, 2011; Lillesand *et al.* 2004

3.3.1 Image pre-processing

Reclassification was performed on the Landsat images so that all 0 values are mapped to "NoData" using reclassify tool in ArcGIS spatial analyst so as not to calculate reflectance or vegetation indices on the sections where data is missing.

Reclassification of Digital Numbers (DNs) for Red and Near Infra-Red band images was done by reclassifying zero values to NoData using a Python conditional statement in ArcGIS Raster calculator. Cells with value = 0 in a Landsat image indicates missing data. The zero values from the multi-temporal Landsat imagery were reclassified using the following expression:

```
Con("LE71700832005063ASN00_B3.TIF">=1,"LE71700832005063ASN00_B3.
TIF")
```

Where LE71700832005063ASN00_B3.TIF is a Landsat filename in the python expression.

For example, before reclassification of the Landsat 1995 image, cell values ranged 0 – 277(Figure 14).

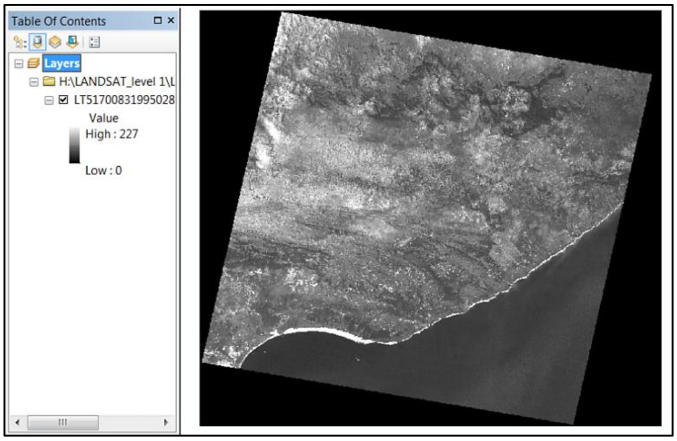


Figure 14: Landsat image before reclassification

After the reclassification of the Landsat 1995 image cells values ranged 1 - 255 (Figure 15).

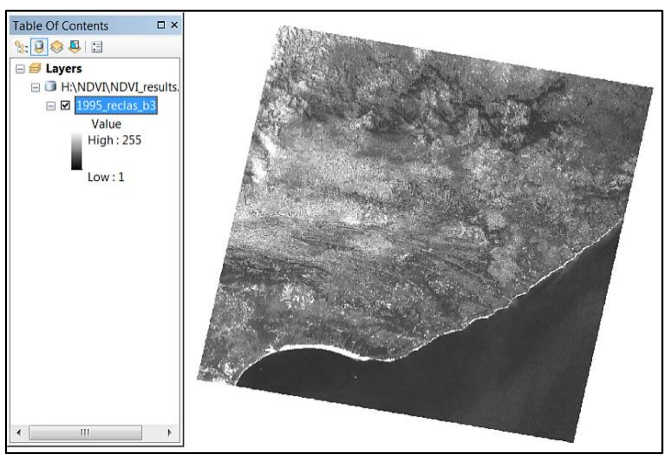


Figure 15: Landsat image after reclassification

The multi-temporal Landsat images were clipped to the Nkonkobe Local Municipality boundary so as to reflect the area of interest for the study. The ArcGIS clip tool from the Raster Processing tools was used for the clipping. Secondary data were: rainfall and temperature data were obtained from SAWS (South Africa Weather Service), census data from Stats SA as illustrated in the following table 4.

Table 4: Secondary input data

Input data	Source	Format	Details
Rainfall (daily)	SAWS	MS Excel	From 1985 to 2014 (29 years) at municipal level.
Temperature (Daily minimum and maximum)	SAWS	MS Excel	From 1985 to 2014 (29 years) at municipal level.
Literacy level in Nkonkobe municipality	Stats SA	MS Excel	At village level
Access to water	StatsSA	MS Excel	At village level
Households with alternative income sources	Stats SA	MS Excel	At village level
Villages not using irrigation practices	GeoTerraImage	Shapefile	At village level
Groundwater occurrence	Department of Water Affairs	Shapefile	
Groundwater recharge	Department of Water Affairs	Shapefile	
Rural population density	Stats SA	Shapefile	At village level

3.4 Determining vulnerable villages to drought

The 4 step approach was carried out as follows:

1. Identification of indicators and assessing adaptive capacity assessment. From Heltberg & Bonch-Osmolovskiy (2011) adaptive capacity is regarded as an outcome of wealth, levels of social capital, education, and presence of alternative livelihood options. The following indicators were used to assess the adaptive capacity:

   i. Access to water (A).

   ii. Literacy level in the municipality (B): this specified the degree of disaster awareness within the households at ward level.

   iii. Villages with alternative income sources (C): this indicator was used to give surety of how capable households have adapted by expanding their sources of income.

   Basing on the above indicators:

   $$\text{Adaptive capacity} = (A + B + C)/\ 3$$

2. Identification of indicators and assessing of sensitivity. According to Sharma & Jangle (2012), sensitivity is a result of the susceptibility of population, assets and livelihoods that are prone to risk. Regions which encounter identical exposure may have varying vulnerability as a result of ineradicable susceptibility. The following parameters were identified and estimated using field calculator of ArcGIS 10.1. An overlay analysis operation was performed on the parameters in order to assess sensitivity. The indicators were:
   i. Villages not using irrigation practices (A).
   ii. Groundwater occurrence (B).
   iii. Groundwater recharge (C): High groundwater recharge areas were considered as the 'recharge hotspots' of the region.
   iv. Rural population density (D).

   Therefore basing on the above indicators sensitivity was calculated as:

   $$\text{Sensitivity} = (A + B + C + D)/\ 4$$

3. Identification of indicators and assessment of exposure. The indicators which were used in assessment of exposure were:
   i. Projected total monthly rainfall for 2015 - 2035 (A): This was based on historical trends of total monthly rainfall (1980– 2000).
   ii. Projected average maximum monthly temperature for 2015 - 2035(B): This was based on historical trends of average maximum monthly temperature (1980 – 2000).
   iii. Projected average minimum monthly temperature for 2015 - 2035(B): This was based on historical trends of average minimum monthly temperature (1980 – 2000).

   Therefore from the above indicators, exposure of Nkonkobe municipality was illustrated in form of graphs for rainfall and temperature across 10 different statistically downscaled CMIP5 GCMs for RCP8.5. Fort Beaufort was used as a reference weather station since it is the main collecting point of climate data within the municipality.

4. Determination of vulnerability:

   The determination of villages most vulnerable to drought was deduced from the linkage of the exposure, sensitivity and adaptive capacity assessments. The adaptive capacity map was linked with sensitivity map but however for the exposure component, linkages could not be carried out for specific villages or wards since the climate projections were for the whole municipality and only one weather station (Fort Beaufort) is being used as a climate reference station. Hence the graphical output for exposure was used to provide an indication of future climate projections for the whole municipality.

3.5 NDVI and NDWI calculations

Landsat images were radiometrically, and geographically-corrected, and formatted to fit in an 8-bit number (ranges from 0-255). Data in such a format is referred to as digital number (or DN data). Before it can be used to calculate vegetation indices, the data must be converted to reflectance, a physical measurement. Reflectance calculated from Landsat data are a so-called "top of atmosphere" (TOA) measurement.

Reclassified Digital number (DN) images were converted to radiance images using the methods provided by Chander *et al.* 2009 as in the following equation.

$$L_\lambda = (gain_\lambda \times DN) + bias_\lambda$$

Where $gain_\lambda$ and $bias_\lambda$: Band specific number

L_λ: Radiance [Watts/ (m^2*µm*ster)]

DN: Landsat digital number data

Gain and bias values for different bands from different Landsat images are provided by Chander *et al.* 2009. Radiance images were converted to reflectance images by the following formula in Raster Calculator.

$$R_\lambda = \frac{\pi \times L_\lambda \times d^2}{E_{su,\lambda} \times \sin(\theta_{SE})}$$

Where L_λ : Radiance [Watts/ (m^2*µm*ster)]

R_λ: Reflectance [unitless ratio]

d: earth-sun distance [in astronomical units]

$E_{su,\lambda}$: Band-specific radiance emitted by the sun

θ_{SE} : Solar elevation angle

The Julian day calendar (Table 13 in Annex 3) was used to deduce Days of Year (DOYs). The DOYs were used to derive Earth-sun distances as provided by Chander *et al.* 2009 (illustrated in Table 12 in Annex 2).

Chander *et al.* 2009 provide values for Band-specific radiance emitted by the sun. An example of expression used to convert the 2005 radiance image to reflectance:

```
(3.141592654 * "2005_rad_b4" * Square (0.9915781)) / (1039 * Sin (45.78082517 * 3.141592654/180))
```

The reflectance images were corrected so as to remove negative values produced during radiance-reflectance conversion. The correction was done on the 1995, 2005 and 2014 images since the 1985 already had reflectance greater than or equal to zero. The Con (,) statement in Raster Calculator was used as in the following expression:

```
Con("2005_ref_b3" < 0,0,"2005_ref_b3")
```

(meaning: if value of 2005_ref_b3 < 0, set value = 0, if not, keep same value)

NDVI was determined by the following ratio:

NDVI = (NIR - R) / (NIR + R)   (Tucker, 1980)

Where, NIR; Near Infra-red, R is Red. In case of Landsat 8, the near infrared band is band 5 and the red band is band 4.

NDVI was calculated using the following expression in Raster Calculator:

```
(Float("con_2005_ref_b4_Clip")-Float("con_2005_ref_b3_Clip1"))/
(Float("con_2005_ref_b4_Clip")+Float("con_2005_ref_b3_Clip1"))
```

The NDWI was calculated for Landsat TM and ETM images using the following NDWI formula modified by Xu (2006) because the modified NDWI prevents the extracted water information a region from mixing with built-up land noise hence the case of the study area.

NDWI = (G - SWIR) / (G + SWIR)   (Xu, 2006)

where SWIR; Short wave Infra-red (band 5) and G is Green band (band 2). For Landsat MSS 1985 image, NDWI is calculated as (G - NIR)/ (G + NIR), where G (band 2) is green and NIR is near infra-red band (band 4). The following expression is an example that was used in Raster Calculator:

```
(Float("con_1995_ref_b2_Clip")-Float("con_1995_ref_b5_Clip"))/
(Float("con_1995_ref_b2_Clip")+Float("con_1995_ref_b5_Clip"))
```

For Landsat 8, green band (Band 3) and the SWIR1 band (Band 6) of the OLI (Operational Land Imager) sensor were used for NDWI since they are the best indicator for land surface water mapping (LSWM) and also completely separate built-up features from water features as provided by Du *et al.* (2014).

3.6 Accuracy assessment techniques

3.6.1 Exposure accuracy assessment

The climate projections were already accurate since they were constructed from 10 different statistically downscaled CMIP5 GCMs for RCP4.5 and RCP8.5.

3.6.2 Adaptive capacity accuracy assessment

The demographic data from three data providers (ECSECC, Quantec and StatsSA) was analyzed at municipal level rather than village-level because organizations such as ECSECC used in the comparison only retain the data at municipal and provincial level. Since the indicator data (literacy level, income, water access, age profile) is collected simultaneously, a test for one selected indicator will serve as a benchmark about the comparison for the other demographic indicators.

Demographics are statistical data linking to the population and precise groups surrounded by it. The choice of indicators for a vulnerability assessment for a large region (municipal or provincial level) is dependent on the type and level of demographic data available from data providers such as StatsSA (Statistics South Africa). StatsSA is the national statistical service of South Africa, with the goal of producing timely, accurate, and official statistics in order to advance economic growth, development, and democracy.

Demographic data from different data providers can be checked for accuracy using statistical methods such as t-Tests and Analysis of Variance (ANOVA) which are based on comparison of population means. Both these tests are based on comparison of means between variables. If the variables to be compared are only two, then a t-Test applies. If the variables are greater than or equal to three, then ANOVA test is applied (Glenberg, 1996; Crawley, 2014).

While the t-test is extensively used for statistical hypothesis tests, one key restriction is that the t-test can be used to compare the means of only two groups at a time. Scientists regularly need to relate the means of three or more collections. The statistical hypothesis test used to compare the means of three or more groups is the analysis of variance (ANOVA) (http://web.grinnell.edu/courses/bio/S08/bio-252-02/ANOVA_prob_set.pdf). ANOVA is a statistical technique for comparing means for multiple (usually ≥ 3) independent populations. Although the idea of ANOVA is to compare 2 or more means, it does this by comparing variances (Crawley, 2014). Normality amongst groups is checked using:

- assumptions about population
- histograms for each group
- normal quantile plot for each group

With such small data sets, there really is not good way to check normality from data, but we make the common assumption that physical measurements of people tend to be normally distributed. A detailed and illustrated outline on how the single factor ANOVA is calculated on data is provided by Faraway (2002) and Crawley (2014). When assumptions for the independent-sample single-factor ANOVA cannot be met, an alternative procedure is the nonparametric Kruskal-Wallis *H* test. However, if the population is a dependent-sample then the nonparametric Friedman *Fr* test is used as an analogue for the dependant-sample ANOVA (Glenberg, 1996). In order to establish a suitable statistical method for comparing the means from the three data providers, the data was first checked whether it met the assumptions of an ANOVA test or not using the procedures provided by Glenberg (1996). However, the data met the assumptions of the nonparametric Kruskal-Wallis *H* test which was employed in this study. The test was run on the objective of assessing the adaptive capacity of resource-poor households.

The Kruskal-Wallis *H* test is a non-parametric test which the assumptions of the independant one-way ANOVA cannot be met. The *H* test is an extension of the rank-sum test, and like the rank-sum test the null hypothesis is about the population distributions, not a specific population parameter. Although the null hypothesis may be rejected due to a variety of differences between the populations, the test is most sensitive to differences in the population central tendencies.

The Kruskal-Wallis *H* test sampling assumptions are as follows:

a) The samples from the *k* populations must be independent of each other.
b) Each of the samples must be obtained using independent (with-in sample) random sampling. If random assignment is used instead of random sampling, then the additional assumption of the randomness of biological systems should be made.
c) If $k = 3$ then all samples should have at least five observations. If $k > 3$ then all samples should have at least two observations.

The data assumption is that the data must be ordinal, interval, or ratio.

The following is the hypotheses used for the *H* test:

H_o: The populations have identical distributions

H_1: The null is wrong

The test statistic is determined as follows:

$$H = \frac{12\text{SST}}{N(N+1)} \text{ with } k-1\ df, \quad SST = \sum \frac{(Ti)^2}{n_i} - CM, \quad CM = \frac{N(N+1)^2}{4}$$

Where T_i = total of the ranks in the *i*th sample; n_i = number of observations in the *i*th sample; N = total number of observations.

For the sampling distribution, all *N* scores are firstly ranked, and then *SST* is calculated as in ANOVA, but the ranks are used in place of the original scores. When H_o is correct, the most likely values for *H* are around $k-1$. When H_1 is correct, the most likely values for *H* are much greater than $k-1$.

The decision rule is established as: Reject H_o if $H \geq \chi^2_\alpha\ (k-1)$, where $\chi^2_\alpha\ (k-1)$ is the value of the χ^2 statistic with $k-1df$ that has α of the distribution above it. *H* is sampled and computed in order to decide and draw conclusions. Rejection of H_o most likely reflects a difference in the population central tendencies. If H_0 is rejected, the protected rank-sum test can be used to compare specific populations (Glenberg, 1996).

After performing the Kruskal-Wallis *H* test, the p-value is computed. The p-value is a probability that measures the evidence against the null hypothesis. P-value is used to determine whether any of the differences between the medians are statistically significant. Lower probabilities provide stronger evidence against the null hypothesis (Townend, 2002). The null hypothesis states that the population medians are all equal. Usually, a significance level (denoted as α or alpha) of 0.05 works well. The following interpretations are used for the p-value:

- If p-value $\leq \alpha$ then the differences between some of the medians are statistically significant. When the p-value is less than or equal to the significance level, you reject the null hypothesis and conclude that not all the group medians are equal.
- If p-value $> \alpha$ then the differences between the medians are not statistically significant. When the p-value is greater than the significance level, you do not have enough evidence to reject the null hypothesis that the group medians are all equal; hence there will be a need to verify that a test has enough power to detect a difference that is practically significant. The verification can be accomplished by using a larger sample or increasing the significance level (Townend, 2002).

3.6.3 Atmospheric correction for Landsat data

When relating bio-physical measurements extracted from one image (such as biomass) with same bio-physical information extracted from other images acquired on varying dates, it is vital that the remote sensor data be atmospherically adjusted. The work done by Jensen *et al* (2002) in computing NDVI derived from Landsat data so as to measure vegetation biomass and functional health in many decision-support systems such as Famine Early Warning System and Livestock Early Warning System supports that erroneous NDVI estimates can result in the loss of livestock and human life. Contributions from the atmosphere to NDVI are significant and can amount to 50 percent or more over thin or broken vegetation cover. Therefore it is necessary to remove the deleterious effects of the atmosphere in remotely sensed data that are used to compute NDVI estimates.

In order to obtain accurate NDVI values that are more representative, the top of the atmosphere values (TOA) has to be corrected and this can be computed by use of the algorithm developed by Chavez (1996). The following equation was used:

$$\rho surf = \frac{\pi(Lsat - Lp)d^2}{E_o \cos\theta_z T_z} \quad \text{: Chavez, (1996)}$$

Where; $Lsat$ = radiance at sensor, d =Earth-Sun distance, E_o = Spectral solar irradiance on top of the atmosphere, θ_z =Solar Zenith Angle, T_z=Atmospheric transmissivity between sun and surface Lp = irradiance resulted from interactions of the electromagnetic radiance with the atmospheric components (molecules and aerosols) that can be obtained as:

$$Lp = (Lmin - L1\%)$$

Where; $Lmin$ is irradiance that corresponds to digital count value for the sum of all pixels with digital counts lower or equal to this value of 0.01% of all the pixels from the image and is expressed as:

$$L1\% = \frac{0.01*(E_o \cos\theta_z T_z)}{\pi d^2}$$

The spectral solar irradiance for the Landsat TM and ETM+ quantities applied were obtained from Qinqin *et al*. (2010) as shown in the following table 5:

Table 5: Solar irradiance for TM and ETM+ sensors (E_o) ($Wm^{-2}x\mu m$)

Band	1	2	3	4	5	7
TM4	195.8	182.8	155.9	104.5	21.91	7.457
TM 5	195.7	182.9	155.7	104.7	21.93	7.452
ETM+	1969	1840	1551	1044	225.7	82.07

Source: Qinqin *et al.* 2009

3.6.4 Landsat imagery correction for negative values from radiance-reflectance conversion

The Landsat reflectance images were corrected using a Python Con (,) statement so as to remove negative values produced during radiance-reflectance conversion since the negative value would produce inaccurate NDVI and NDWI results. The correction was done on the 1995, 2005 and 2014 images since the 1985 already had reflectance greater than or equal to zero. The Con (,) statement in Raster Calculator was used as in the following expression:

```
Con("2005_ref_b3" < 0,0,"2005_ref_b3")
```

(meaning: if value of 2005_ref_b3 < 0, set value = 0, if not, keep same value)

3.6.1 Simple linear regression trend analysis for NDWI-NDVI relationships

Regression analysis is a statistical method that tries to explore and model the association between two or more variables. Various studies (Fensholt *et al.* 2009; Fensholt & Rasmussen, 2011) have supported the application of a simple linear regression as a model for determining trends in NDVI. Chronological trends in NDWI and NDVI were observed by the application of a simple linear regression model in which NDWI is the independent variable while NDVI is the dependent variable. The principles and assumptions of the model are provided by Montgomery *et al* (2012). The identification of linear trends depends on the averages and variances (SD = standard deviation) of the two variables as well as their covariance (Cov). The r-value is defined as:

$$r = \frac{Cov(X,Y)}{SDx \times SDy} \quad \text{(Montgomery } et\ al. \text{ 2012)}$$

The simple linear regression analysis provides a simple, strong, way to examine and discover tong-term trends in NDVI. Furthermore, in using a linear model, resulting gradient and intercept values reported on a pixel level can simply be linked since they relate to the same model. A more flexible approach, allowing for non-linear temporal development of NDVI would make comparisons between pixel/areas and between different time series challenging. Using a linear model, non-linearity of the progression of vegetation greenness over time will cause r-values to be minor (Fensholt *et al.* 2009). Thus, the results of the simple linear trend technique are easy to understand and associate between data sets. Although the absolute value of r-value provides an index of the strength of the linear relationship, they have no direct interpretation. Hence R^2 can give a precise interpretation in terms of variances: the correlation squared is proportion of Y variance associated with X variance. When $R^2 = 1$, this illustrates a perfect linear relationship between Y and X (Glenberg, 1996).

4 RESULTS

4.1 Adaptive capacity assessment in Nkonkobe Local Municipality

4.1.1 Access to water

Figure 16 affects the resilience of communities by influencing the availability of basic needs.

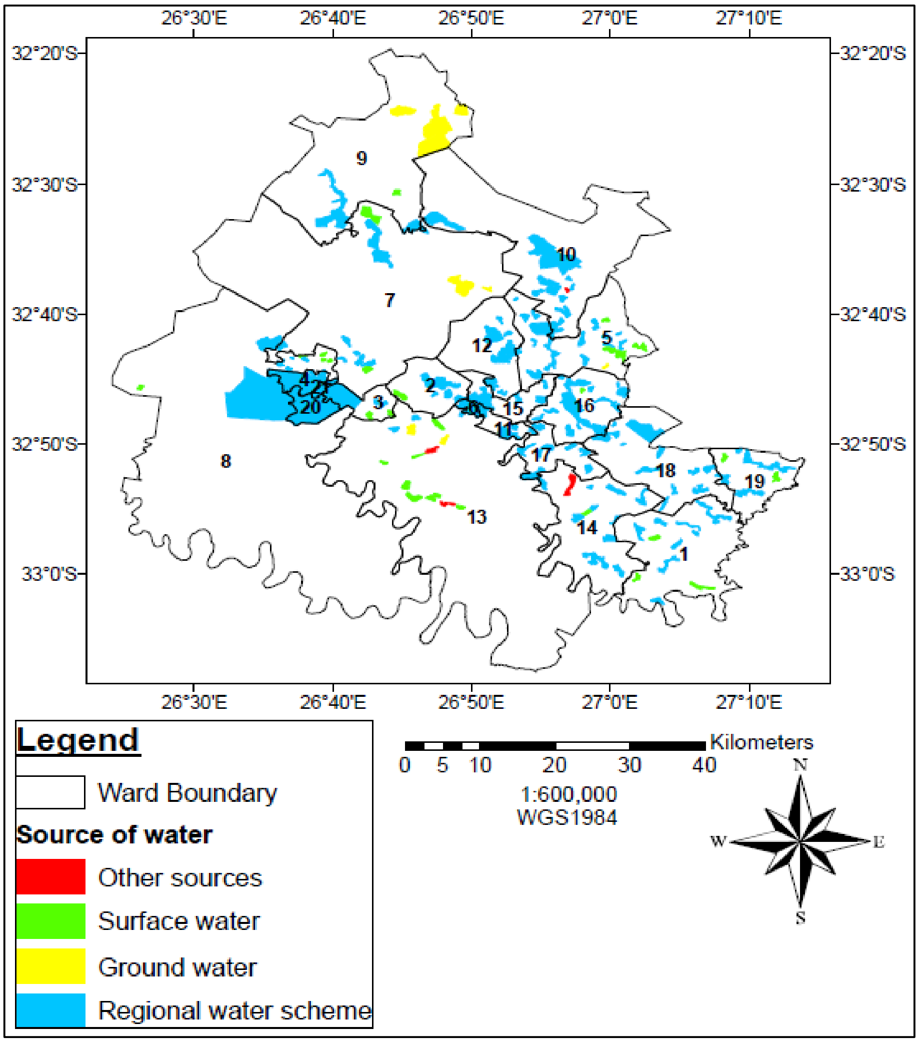


Figure 16: Access to water in Nkonkobe Local Municipality

– Ward 13 is most underdeveloped in terms of water access due to limited availability of regional water schemes. Four villages Mmangweni in ward 10, Allandale in ward 13, Mavuvumezini – in ward 14 and Mpozisa in ward 13 are severely water stressed and get water from non-natural other sources comprising water vendors and water tankers.

4.1.2 Literacy levels

Figure 17 indicates degree of disaster awareness within the households.

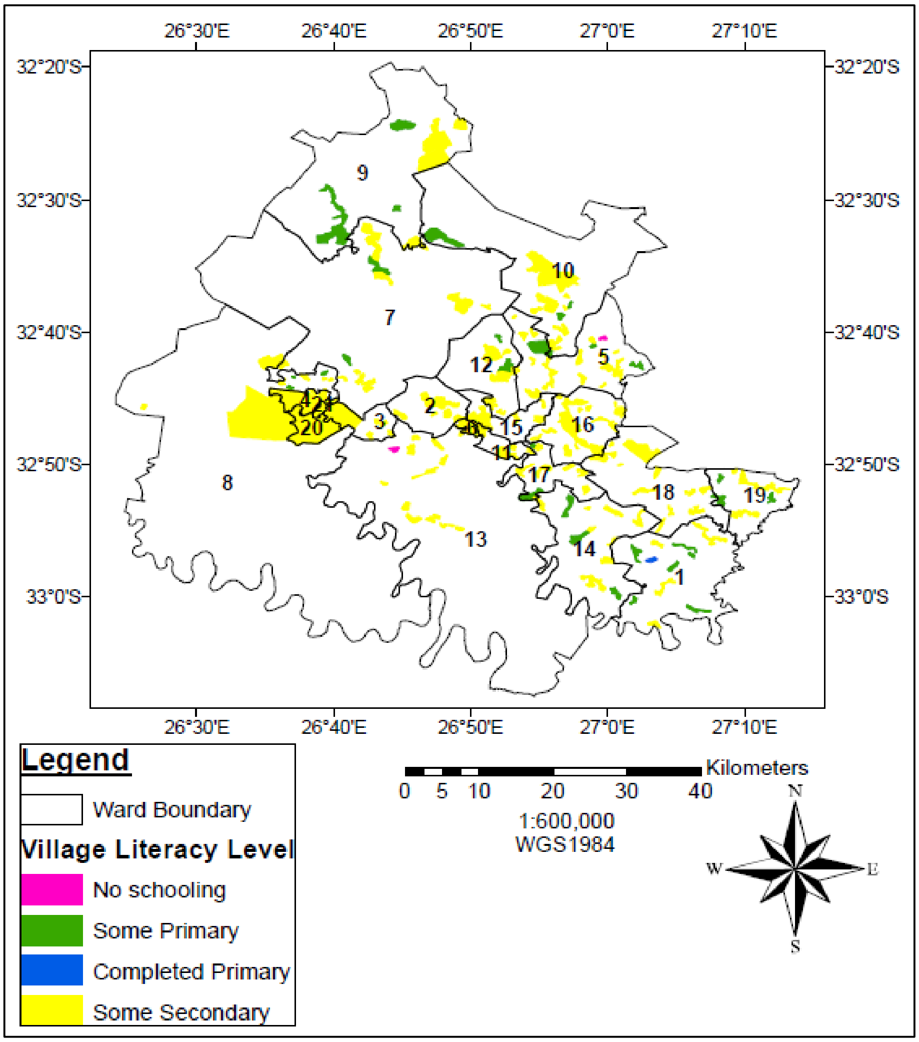


Figure 17: Literacy levels in Nkonkobe Local Municipality

- 2 villages: Mdeni B in ward 5 and Lebanon in ward 13 (pink color) have the majority of people with no schooling and need the greatest attention concerning schooling.
- Green shaded areas represent villages where most people have attended primary school but remain unaware of climate change issues.
- The majority of the villages in the municipality have most people having attended secondary school (yellow shaded areas) hence in these areas people are mostly likely to be aware of climate change and can be easily taught if not aware.

4.1.3 Village income levels

Figure 18 indicates villages with and without income with the latter less being unlikely to have access to credit and poorly resilient to most shocks linked to climate change.

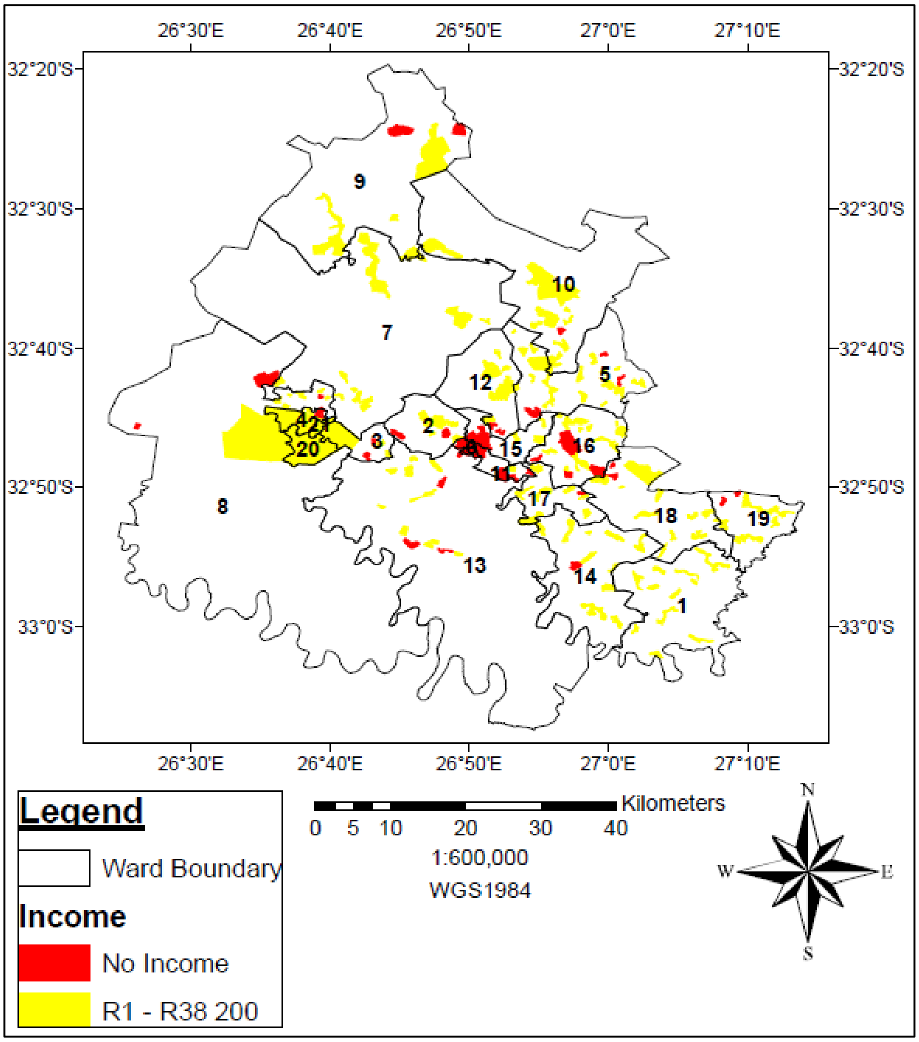


Figure 18: Village income levels in Nkonkobe Local Municipality

- Villages deemed as the poorest in the municipality are mostly in wards 6, 11, 15, 16 and 13 where the majority of people have no income.

4.1.4 Determination of resilience by age profiles

The following figure 19 was based on the reasoning that children and old people have low resilience by virtue of being economically inactive compared to their economically active counterparts of intermediate age.

Age profiling was done as follows, on the basis of the categorization provided by Nkonkobe Integrated Development Plan (IDP) for 2012 – 2017:

- 0-14: child,
- 15-39: young/ intermediate age and,
- 40+: old.

The intermediate age group has high resilience (Score of 0) due to the majority of people having employment and also aware of climate change.

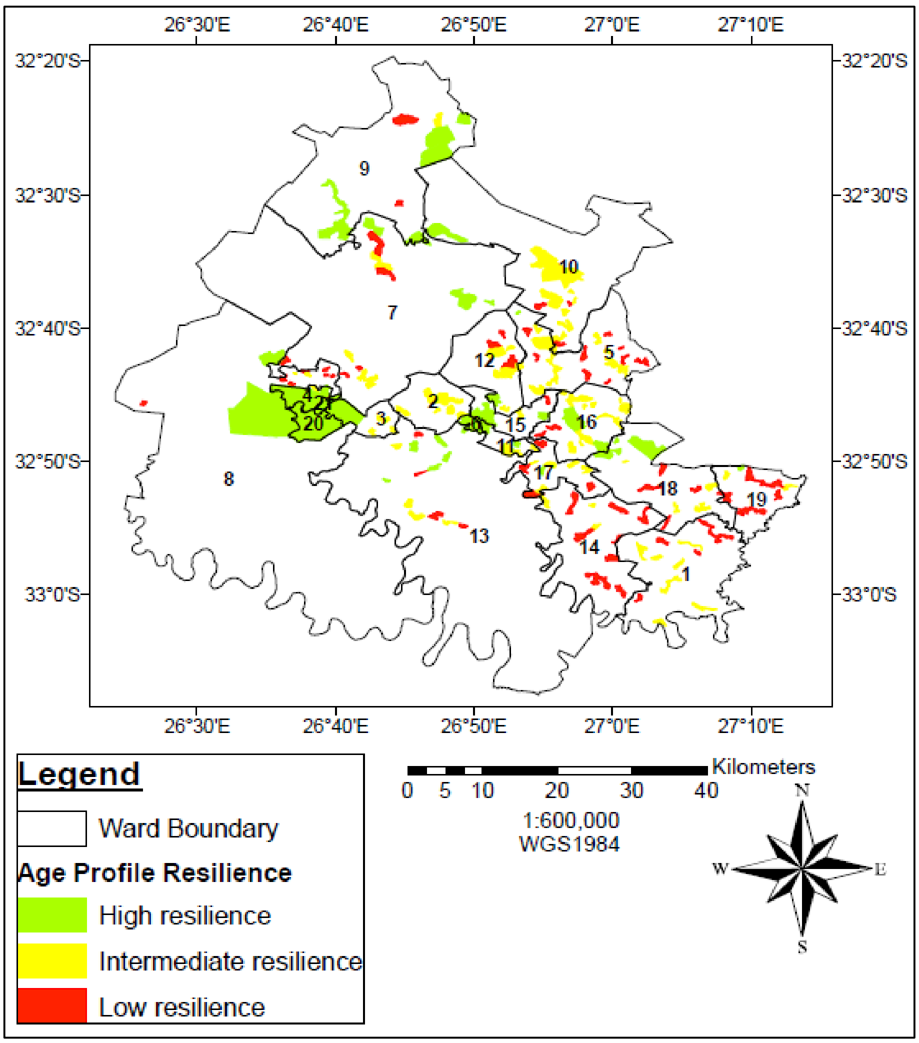


Figure 19: Determination of resilience by population age profiles in Nkonkobe Municipality

- The wards with high numbers of villages with low resilience to climate change are wards 5, 14, 17, 18 and 19.

– The less resilient villages mainly have high populations of children, high population of old people and low populations of people in the intermediate age.

Table 6: Resilience rankings

Village age population	Resilience Score	Resilience ranking
0-14 > 15-39 < Over 40	2	Low
0-14 > 15-39 > Over 40	1	Medium
0-14 < 15-39 < Over 40	1	Medium
0-14 < 15-39 > Over 40	0	High

4.1.5 Adaptive capacity in Nkonkobe Local Municipality

The following Table 7 describes low-medium-high adaptive capacity. Basing on the demographic indicators, overall adaptive capacity score of 0 means low adaptive capacity and a score of 2 is high adaptive capacity.

Table 7: Evaluation of adaptive capacity

Water access	Literacy level	Income levels	Resilience by age profile	Score
Other Sources	No schooling	No Income	Low	Low
Surface water	Some primary	R1 – R38 000	Medium	Medium
Ground water	Completed primary	No Income	High	Medium
Regional water scheme	Some secondary	R1 – R38 000	Low	High
Other Sources	No schooling	R1 – R38 000	Medium	Low
Surface water	Some primary	No Income	High	Low
Ground water	Completed primary	R1 – R38 000	Low	Medium
Regional water scheme	Some secondary	R1 – R38 000	Medium	High
Regional water scheme	Some secondary	R1 – R38 000	High	High
Surface water	Some primary	No Income	High	Low

Figure 20 was estimated by using data compiled from questionnaire surveys and oral interviews to compile map that captures reported spatial variations in the abilities of individual households to mitigate the adverse effects of climate change. Major towns with in the municipality (Fort Beaufort, Alice, Seymour and Middledrift) are excluded from the study because they contain limited number of resource-poor households and are not rural.

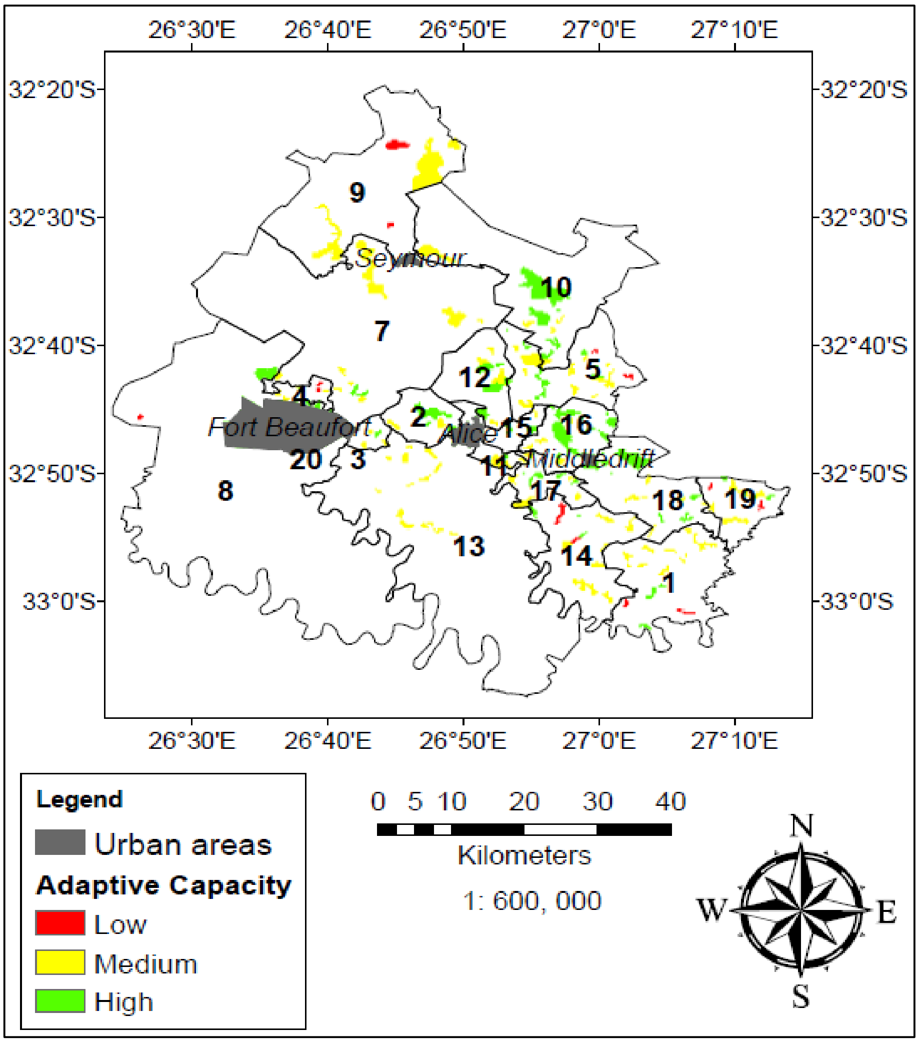


Figure 20: Adaptive capacity map for Nkonkobe Local Municipality

Basing on the indicators used, the assessment reported low adaptive capacities in 14 villages of wards 1, 5, 8, 9, 14 and 19 (Table 8) from a total of 180 villages in the study area.

Table 8: Villages with low adaptive capacity in Nkonkobe municipality

Village	Ward number
Qutubeni	1
Qamdobowa	1
Mdeni B	5
Ndlovura	5
KwaWeza	8
Komkulu B	8
Lower Endwell	8
Cairns	9
Wellsdale	9
Mavuzamezini	14
Ematsamraleni	14
eMgwanisheni	14
Debe valley A	19
Ntonga	19

4.2 Sensitivity assessment in Nkonkobe Local Municipality

4.2.1 Villages not using irrigation practices

Villages without irrigation support are highly sensitive to the adverse effects of climate change such as droughts (figure 21).

Regions practicing subsistence farming (brown-shaded areas) depend on rain-fed agriculture thus being the most sensitive to adverse effects of climate change. This is the case with Nkonkobe Local Municipality as illustrated by the vast brown-shaded areas in the following map (figure 21). The commercial fields, pivots and orchards are dependent on irrigation hence not hindered by climate change.

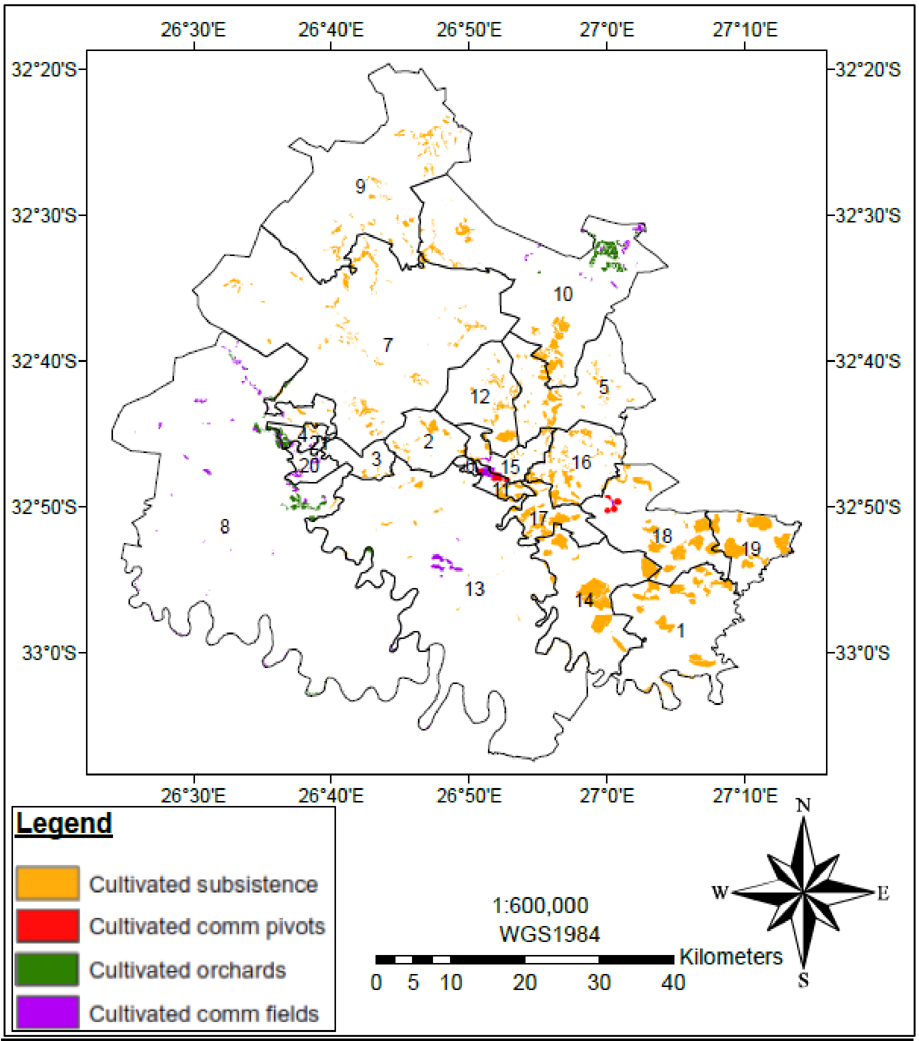


Figure 21: Villages not using irrigation practices in Nkonkobe Local Municipality

Subsistence farming is mostly dominant from the eastern parts, stretching to the south eastern parts of the municipality. The wards dominant in subsistence farming are wards 1, 5, 12, 14, 17, 18 and 19. This is because a larger population of the municipality is situated in these regions and also probably due to better soil quality as compared to the other parts within the municipality.

4.2.2 Groundwater occurrence

Groundwater occurrence was expressed in terms of three aquifer types namely 1) fractured, 2) inter-granular, and 3) inter-granular & fractured as shown in the following figure 22.

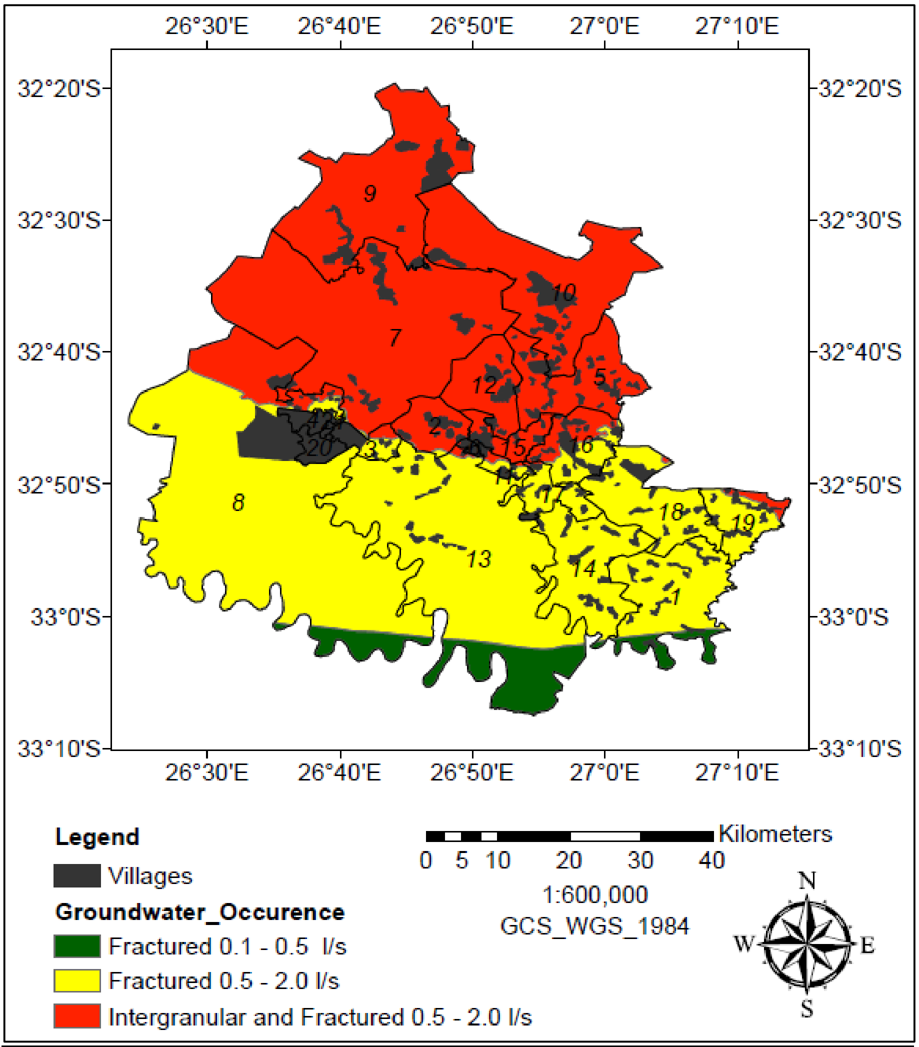


Figure 22: Groundwater occurrence in Nkonkobe Local Municipality

It has been shown from figure 22 that villages in the upper part of the municipality (red shaded area) are situated on aquifers of mostly reasonable groundwater prospects (that is inter-granular and fractured aquifers with median borehole yields of 0.5 – 1.0 L/s). This supports the argument that rolling out better and more reliable groundwater supplies is not primarily a "technical" or hydrogeological issue at all, but many other factors interfere. The red shaded areas have a low development potential (EC Groundwater Plan, 2010), however this is better as compared to the areas with fractured aquifers with borehole yields of 0.1 – 05L/s which is very low development potential. Hence regions with fractured aquifers (yellow and green shaded areas in figure 22) are most sensitive to climate change.

4.2.3 Groundwater recharge

Groundwater recharge provided information on areas identified by National Freshwater Ecosystem Priority Areas (NFEPA) as having high groundwater recharge and these can be regarded as strategic water supply areas of the country (figure 23).

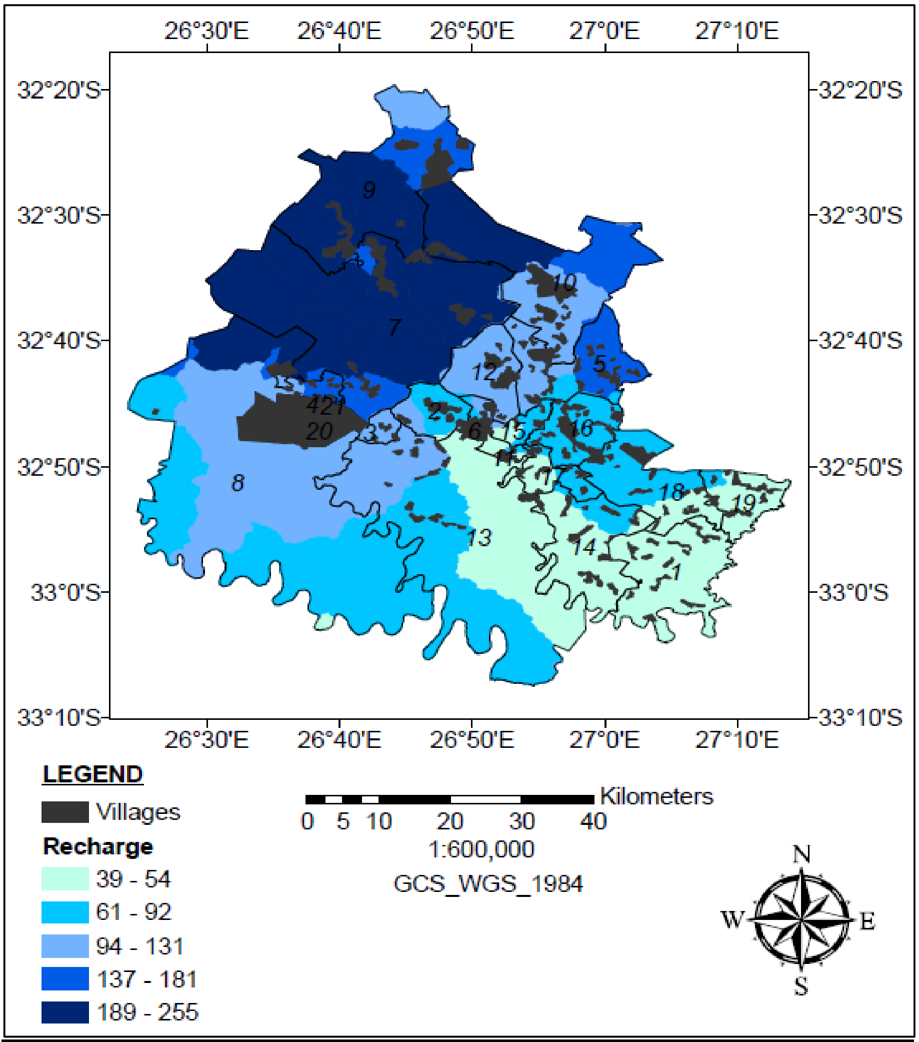


Figure 23: Groundwater recharge in Nkonkobe Local Municipality

Within the municipality regions with recharge values below 137 can be deemed as most sensitive to climate change since it is less than half of the 300 expected by DWAF 2005b report.

4.2.4 Population density per ward

This indicated the number of people residing in any given ward (figure 24).

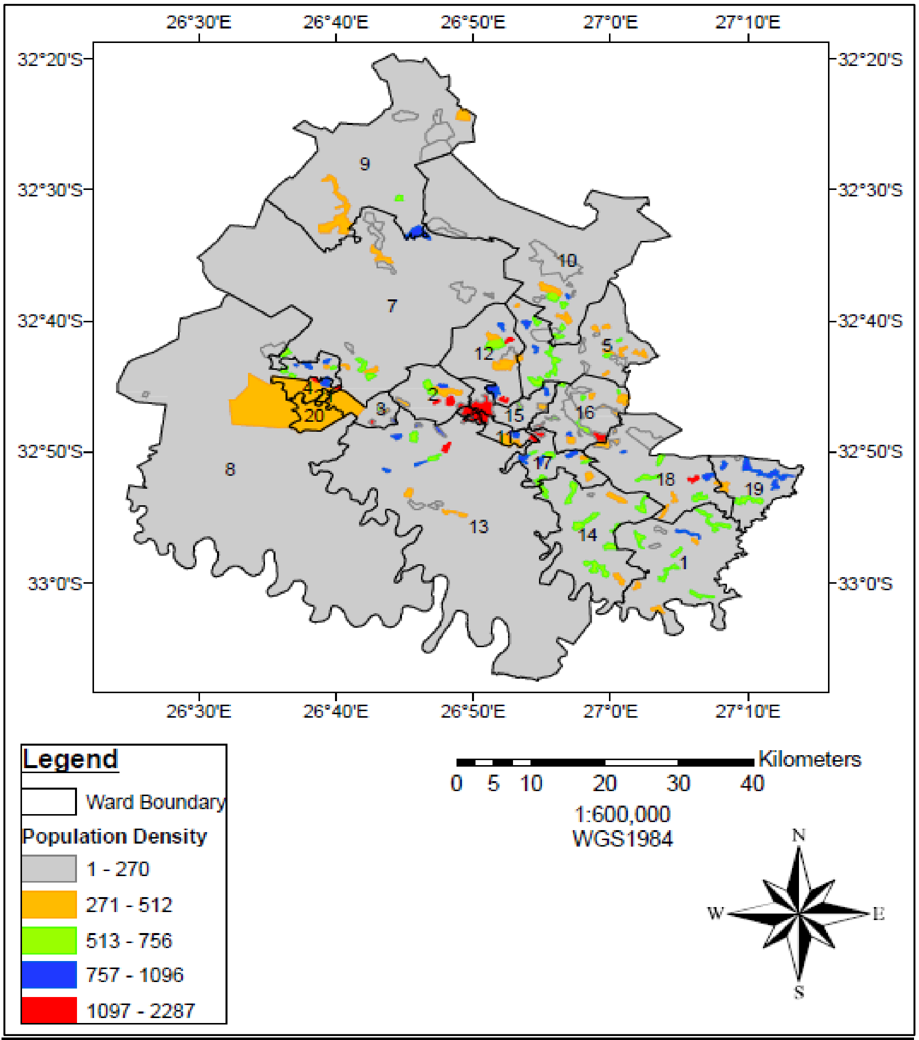


Figure 24: Population density per ward in Nkonkobe Local Municipality

Population density per ward influences sensitivity of a region to climate change. Areas with high population densities per ward (above 513 as shown in figure 24) are most sensitive to climate change due to probable over-exhaustion of natural resources.

4.2.5 Sensitivity to drought in Nkonkobe Local Municipality

The following figure 25 shows the location of villages identified as highly sensitive to climate change basing on the sensitivity indicators.

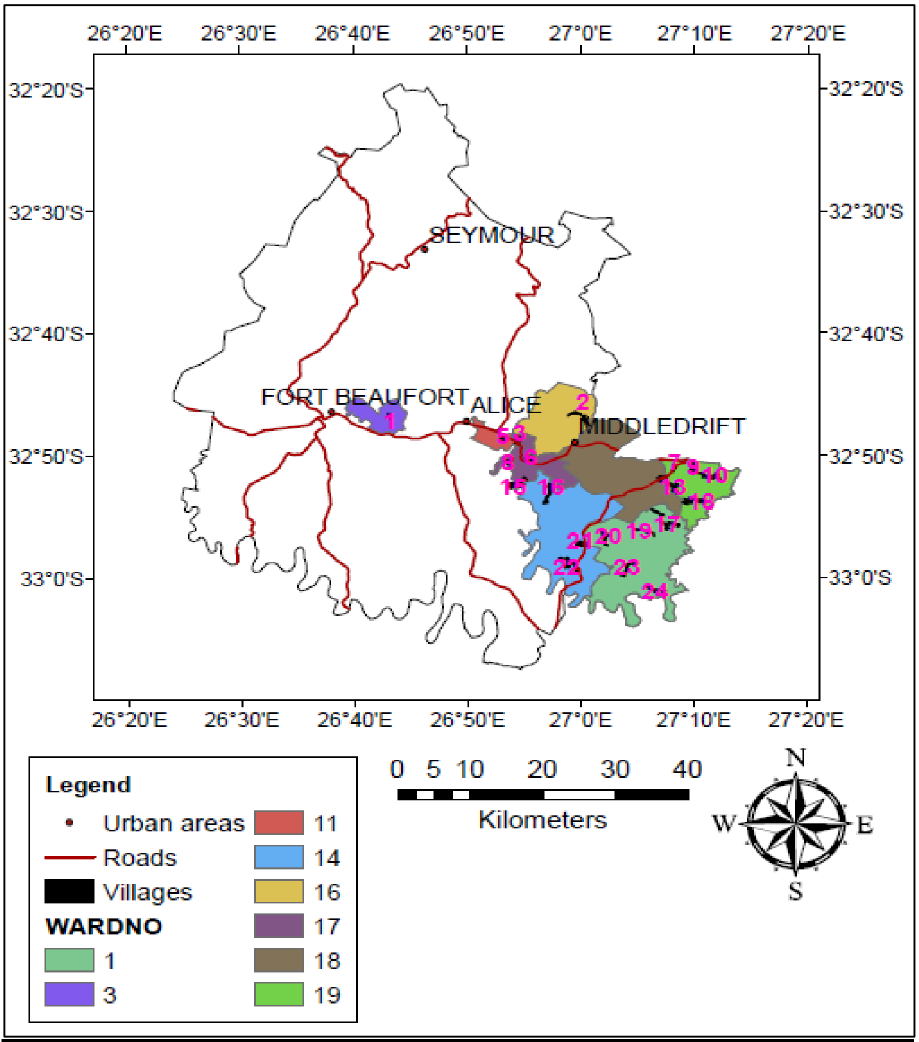


Figure 25: Villages with high drought sensitivity in Nkonkobe Local Municipality

From the assessment, the following table 9 shows 24 villages that were found to be the most sensitive to climate change basing on the indicators. It was observed that the main cause of the sensitivity was situation of villages in regions with very low groundwater recharge and also limited groundwater occurrence (that is regions with fractured aquifers with borehole yields of 0.1 – 05L/s and 0.5 – 2.0L/s).

Table 9: Villages with highest sensitivity to droughts

	Village	Ward number
1	eMxohelo	3
2	Cilidara	16
3	Efama	17
4	Red Hill	11
5	eDrayini	11
6	Ngwenya	17
7	Debe Valley A	19
8	KwaSityi	17
9	Zihlahleni	19
10	Maipase	19
11	Tafeni	18
12	Nduveni	17
13	Lolini	19
14	Singeni	17
15	Esgangeni	17
16	Mavuvumezini	14
17	Mnqaba Kulile	1
18	Xukwane	19
19	Mgxotyeni	1
20	Qibira A	1
21	Ngqolowa B	14
22	Dhlawu	14
23	Zigodlo	1
24	Qamdobowa	1

4.3 Exposure to droughts in Nkonkobe Local Municipality

The exposure of Nkonkobe Local Municipality to droughts was assessed using climate projections for year 2015 – 2035 relative to the historical period 1980 – 2000. The relative climate data was for the Fort Beaufort weather station because it is the only weather station with longest historical period within the municipality.

4.3.1 Projected total monthly rainfall changes

Figure 26 illustrates the monthly rainfall changes across the years 2015 - 2035. The projections vary from large range of projections (-8 to +10 mm in January) to small ranges (0 to +5 mm in September). Although those ranges translate changes compared with the baseline, the different change directions (increase vs. decrease) and the accuracy of GCMs to represent baseline period give no clear message about rainfall projection.

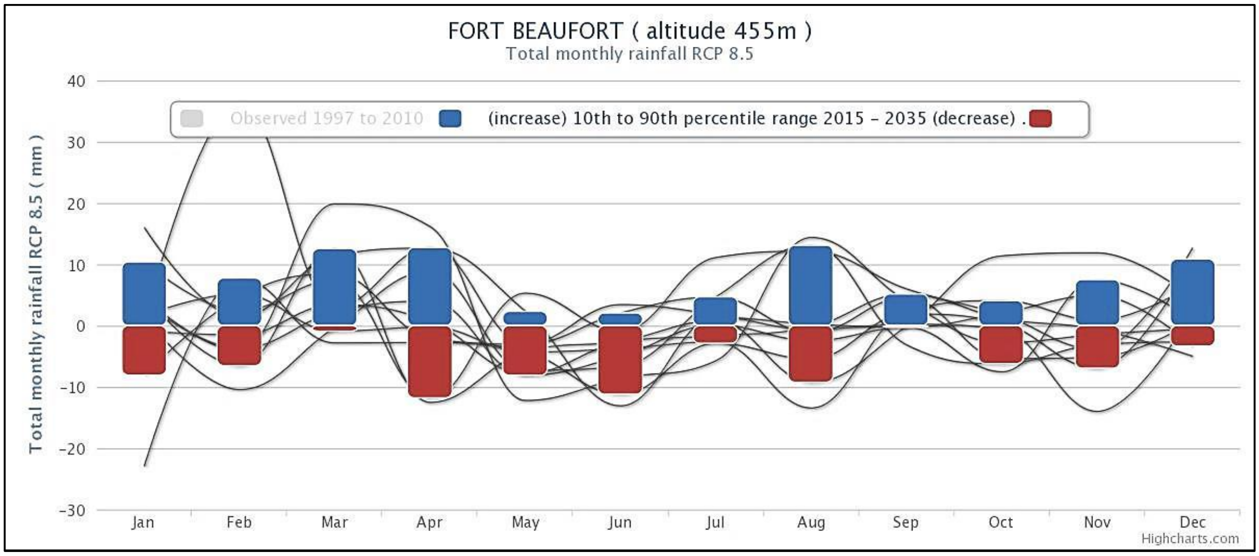


Figure 26: Range of projected rainfall changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP8.5

Source: http://cip.csag.uct.ac.za/webclient2/datasets/south-africa-cmip5

Anomalies are calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models project the future changes.

4.3.1 Projected average maximum temperature changes RCP 8.5

Figure 27 show that under RCP8.5, monthly change averages range from +0.3 ^{o}C to above +1.1 ^{o}C maximum temperatures.

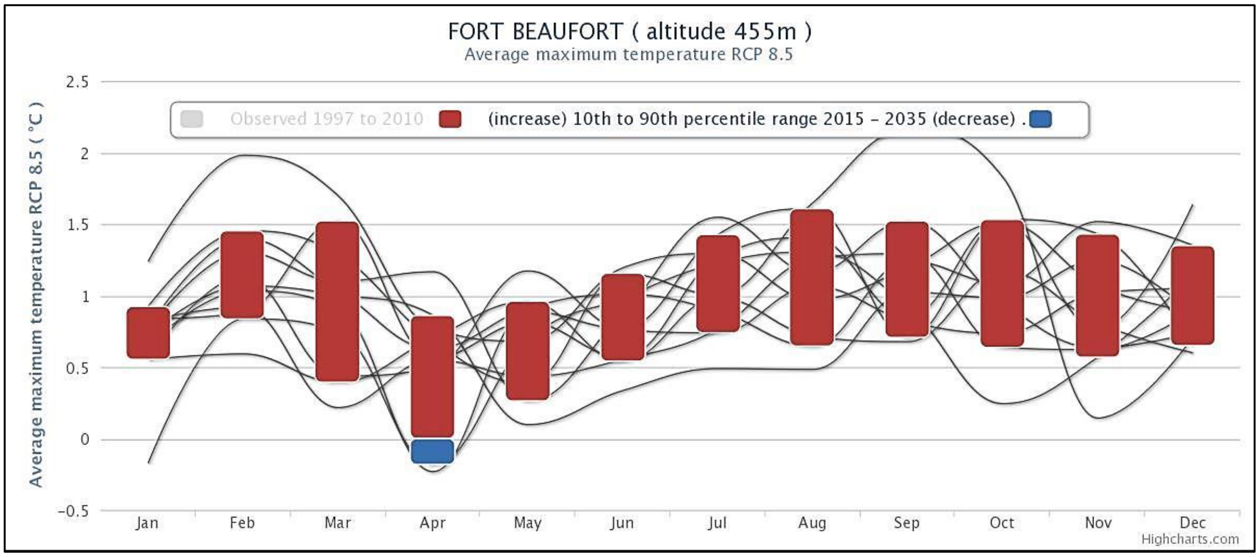


Figure 27: Range of projected maximum temperature changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP8.5

Source: http://cip.csag.uct.ac.za/webclient2/datasets/south-africa-cmip5

Anomalies were calculated relative the historical period 1980 - 2000. The solid bars represent the range between the middle 80% of projected change and so exclude the upper and lower 10% as these are often considered to be outliers. The grey lines show the projected change for each model so it is possible to see how individual models (intentionally not named) project the future changes.

4.3.2 Projected average minimum temperature changes RCP 8.5

Figure 28 show that under RCP8.5, monthly change averages range from +0.6 ^{o}C to +1.3 ^{o}C for minimum temperatures. Monthly GCMs projections differ less than 0.8 ^{o}C (10th to 90th percentile) for minimum temperatures and less than 1.1 ^{o}C for maximum temperatures (Figure 30), which translate a strong agreement in projections towards increase (except for 2 GCMs in April for maximum temperatures). Both minimum and maximum temperature increases show a sign of seasonality with high increase from mid-winter until end of summer season (July to March) and low increase spring (April to June).

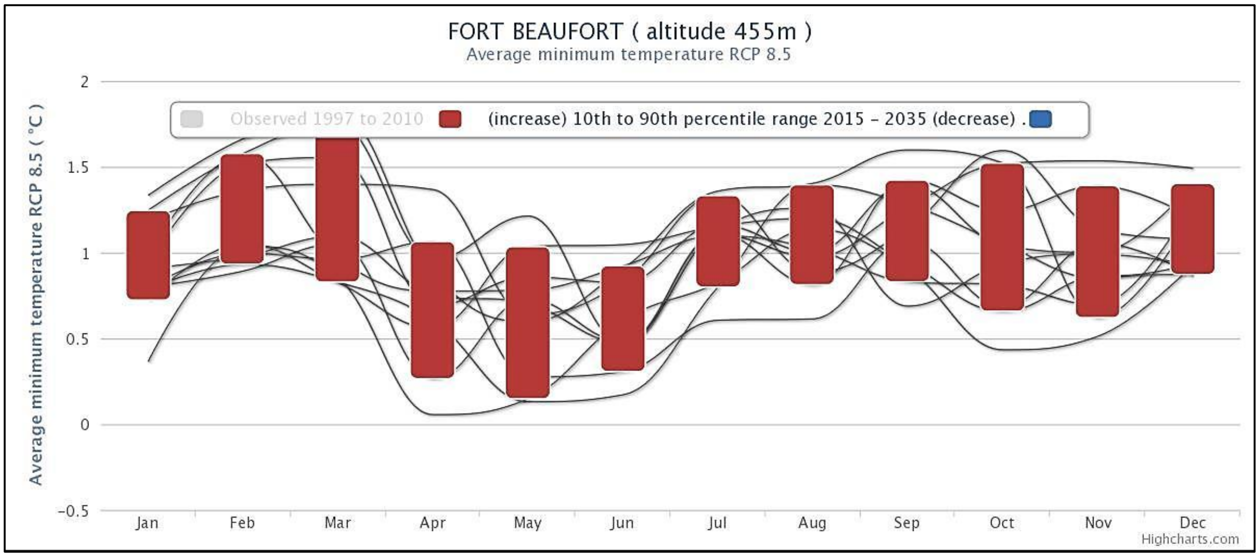


Figure 28: Range of projected minimum temperature changes for Fort Beaufort across 10 different statistically downscaled CMIP5 GCMs for RCP8.5

Source: http://cip.csag.uct.ac.za/webclient2/datasets/south-africa-cmip5

The results of the exposure assessment illustrate that the whole municipality is still exposed to climate change owing to fluctuations in rainfall and temperature for the projected period 2015 - 2035.

4.4 NDVI and NDWI calculations

4.4.1 NDVI 1985

The following figure 29 shows the vegetation health within the municipality in year 1985.

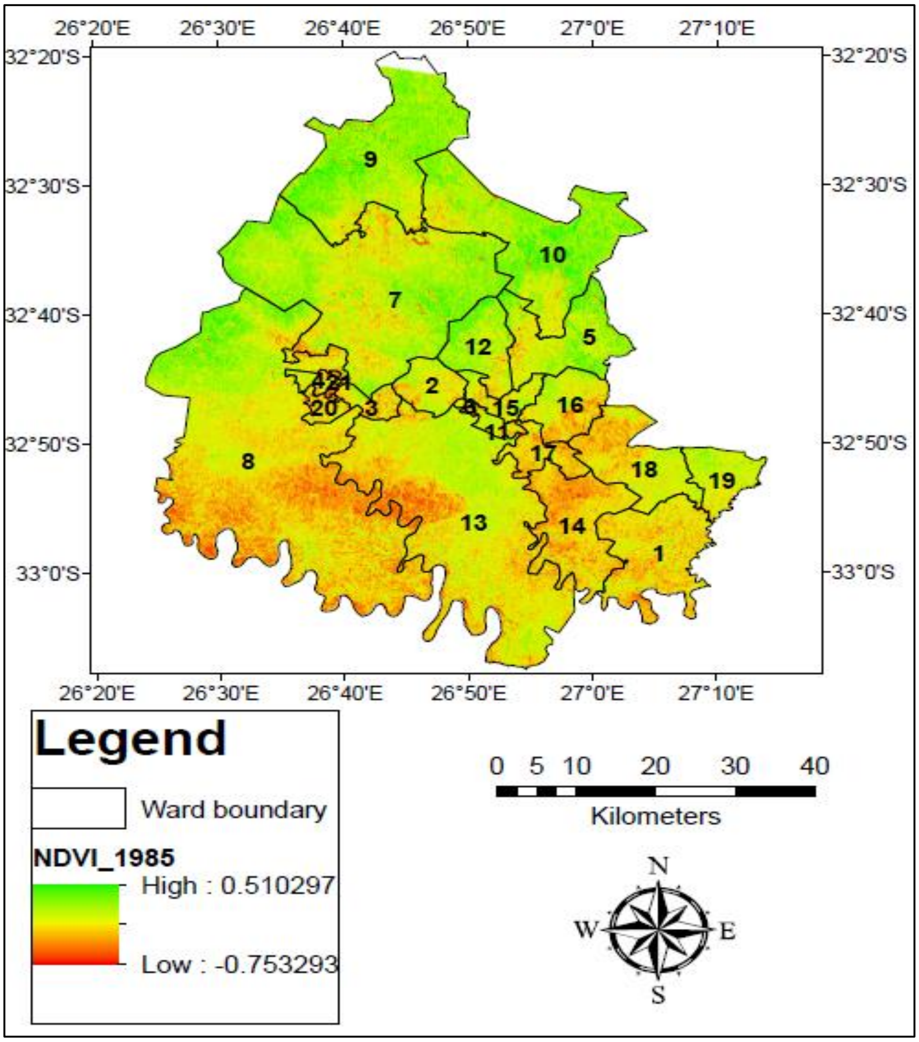


Figure 29: NDVI 1985

The wards in the lower part of municipality had the lowest NDVI values hence less vegetation greenness. The wards were ward 1, 8, 13 and 14 as illustrated in figure 29.

4.4.2 NDVI 1995

Figure 30 shows the vegetation health in Nkonkobe municipality for year 1995.

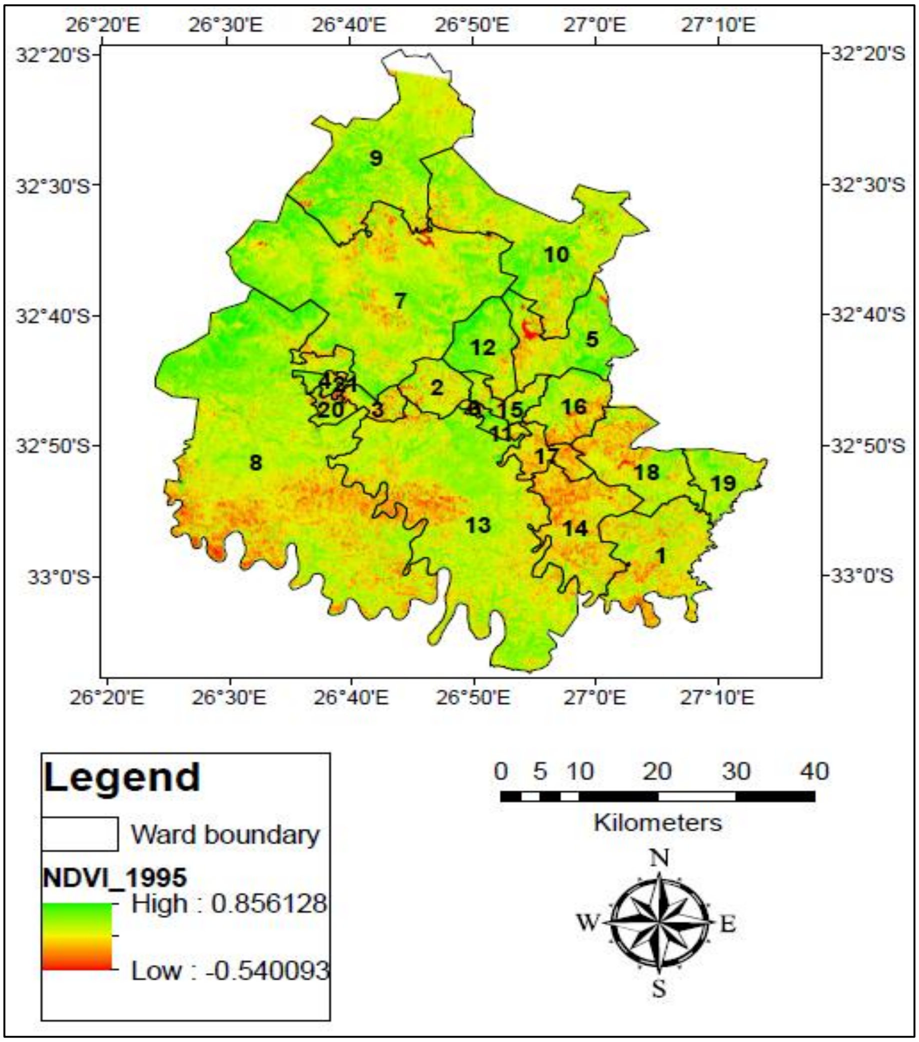


Figure 30: NDVI 1995

In 1995 there was an increase in vegetation greenness as shown in figure 30 by a rise of maximum NDVI value from approximately 0.51 in year 1985 to 0.86 in 1995 (an increase of about 0.35) and also a change of the minimum NDVI value from -0.75 to -0.54. This change could have been resultant from increased rainfall amounts within the 1995 wet-season.

4.4.3 NDVI 2005

The following figure 31 shows the level vegetation cover as computed from Landsat 2005 image.

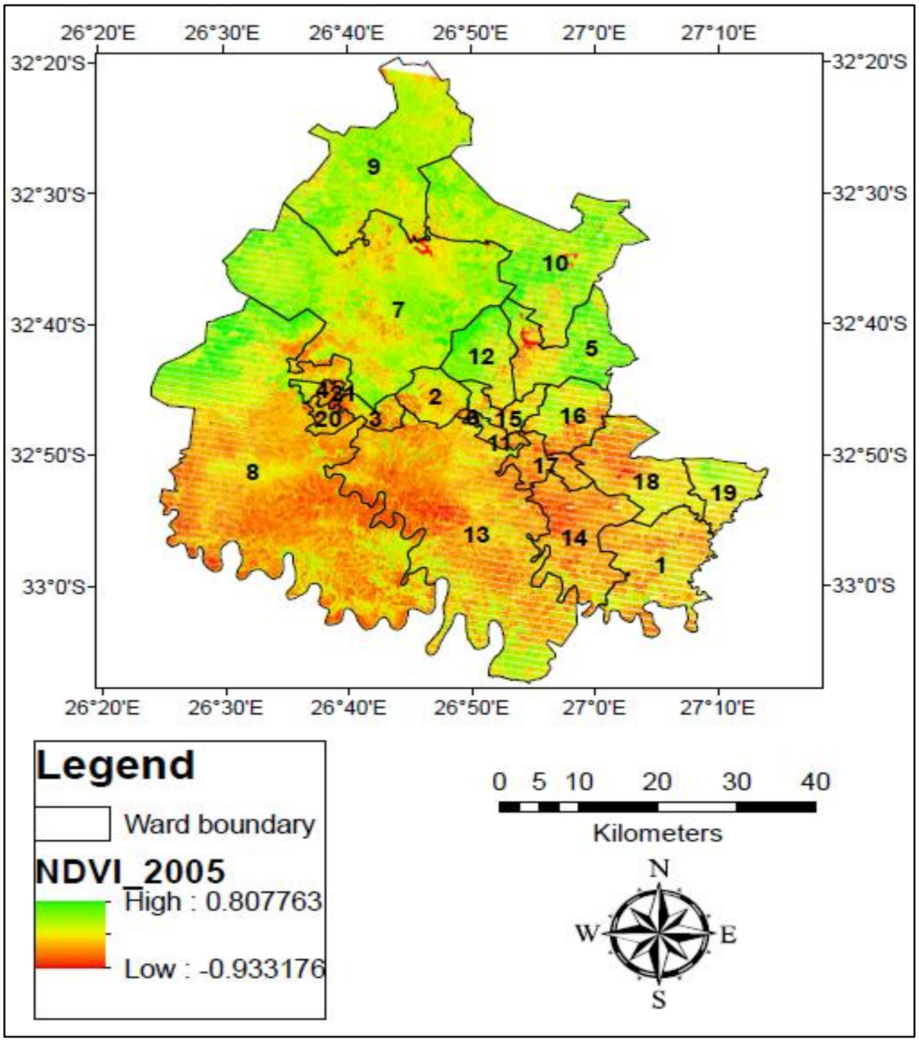


Figure 31: NDVI 2005

In 2005 there was decrease in vegetation greenness especially in the wards situated in the lower parts of the municipality as shown in figure 31. Wards 1, 3, 4, 8, 13, 14, 16, 17, 18, 20, 21 were mostly deficient in healthy vegetation. The maximum NDVI value has decreased by 0.05 and the minimum NDVI value has drastically increased (increase by 0.39) as compared to the 1995. This change could have been resultant from the adverse effects of the 2004 drought which was experienced in the municipality (ADM, 2004).

4.4.4 NDVI 2014

Figure 32 shows the level vegetation health as deduced from Landsat 2014 image. The vegetation health was compared with the previously calculated NDVI for the multi-temporal timescale.

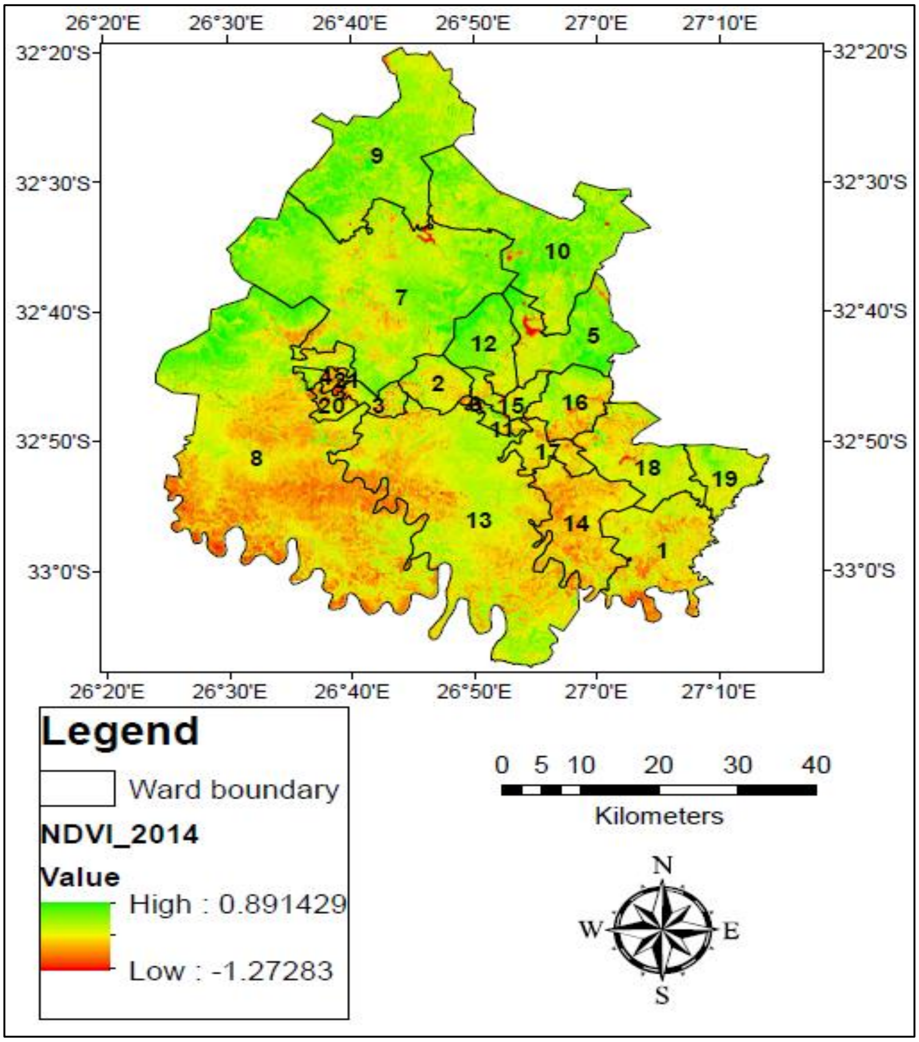


Figure 32: NDVI 2014

In 2014 there was increase vegetation greenness especially in the wards situated in the lower parts of the municipality as shown in figure 32. The lower parts of the municipality still remain outstanding with vegetation stress. The maximum NDVI value has increased by 0.09 and the minimum NDVI value has changed from -0.93 to -1.27. This maximum NDVI change could have been resultant from slight increase in rainfall. The change for the minimum NDVI could have been attributed by spread of bare ground owing to human and animal activities.

4.4.5 NDWI 1985

The following figure 33 portrays the state of distribution of vegetation water content in Nkonkobe Local Municipality in the year 1985.

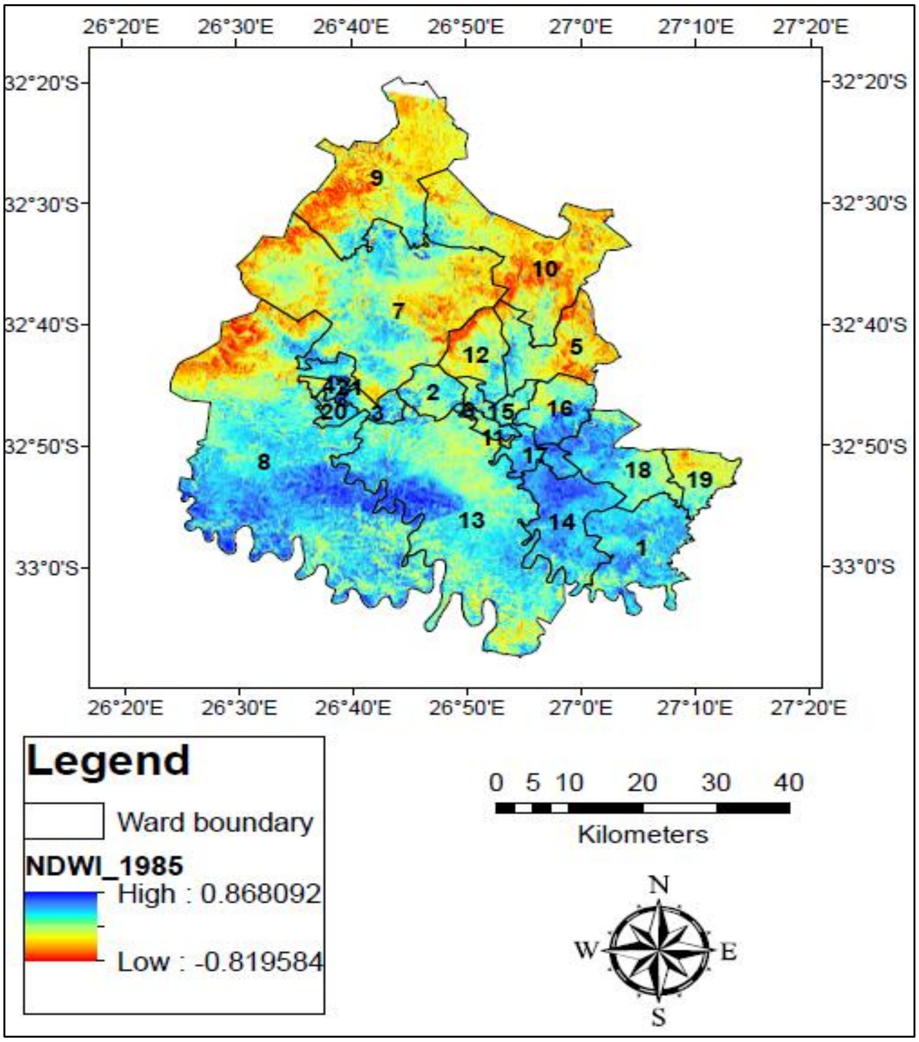


Figure 33: NDWI 1985

The lower half of the municipality had the more regions with the high vegetation water content relative to the regions in the upper half. Almost all wards in the municipality had considerable regions of good vegetation water content (NDWI > 0.5) except for wards 5, 9 and 10.

4.4.6 NDWI 1995

The following figure 34 portrays the state of distribution of vegetation water content in Nkonkobe Local Municipality in the year 1985.

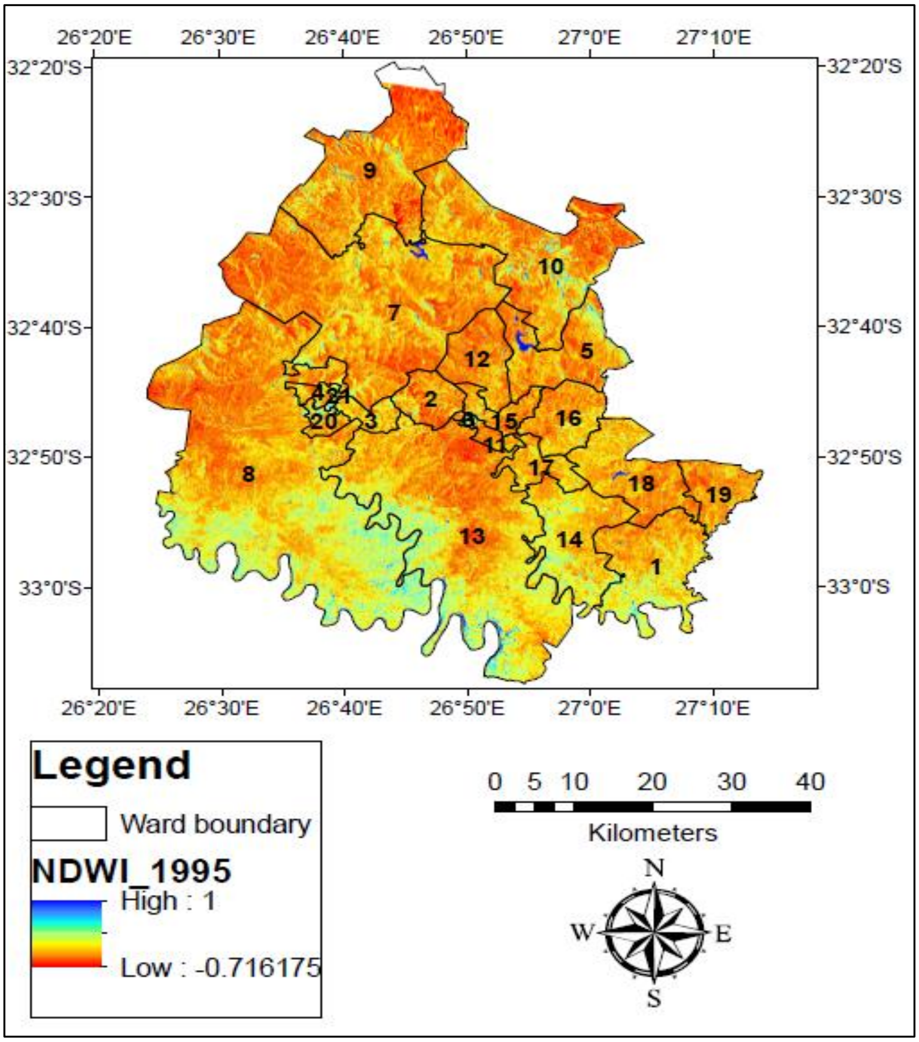


Figure 34: NDWI 1995

The vegetation water content was low (below NDWI value of 0.5) in almost all parts of the municipality. Although the NDVI for 1995 portrayed healthy vegetation in these areas, this was due to the presence of healthy thicket vegetation which has low water content in order to sustain the adverse aridity in the municipality.

4.4.7 NDWI 2005

The vegetation water content in year 2005 was revealed to be very poor (Figure 35). The adverse effects of the 2004 drought (ADM, 2004) could have resulted in the low vegetation water content due to high rates of evaporation and scarce rainfall.

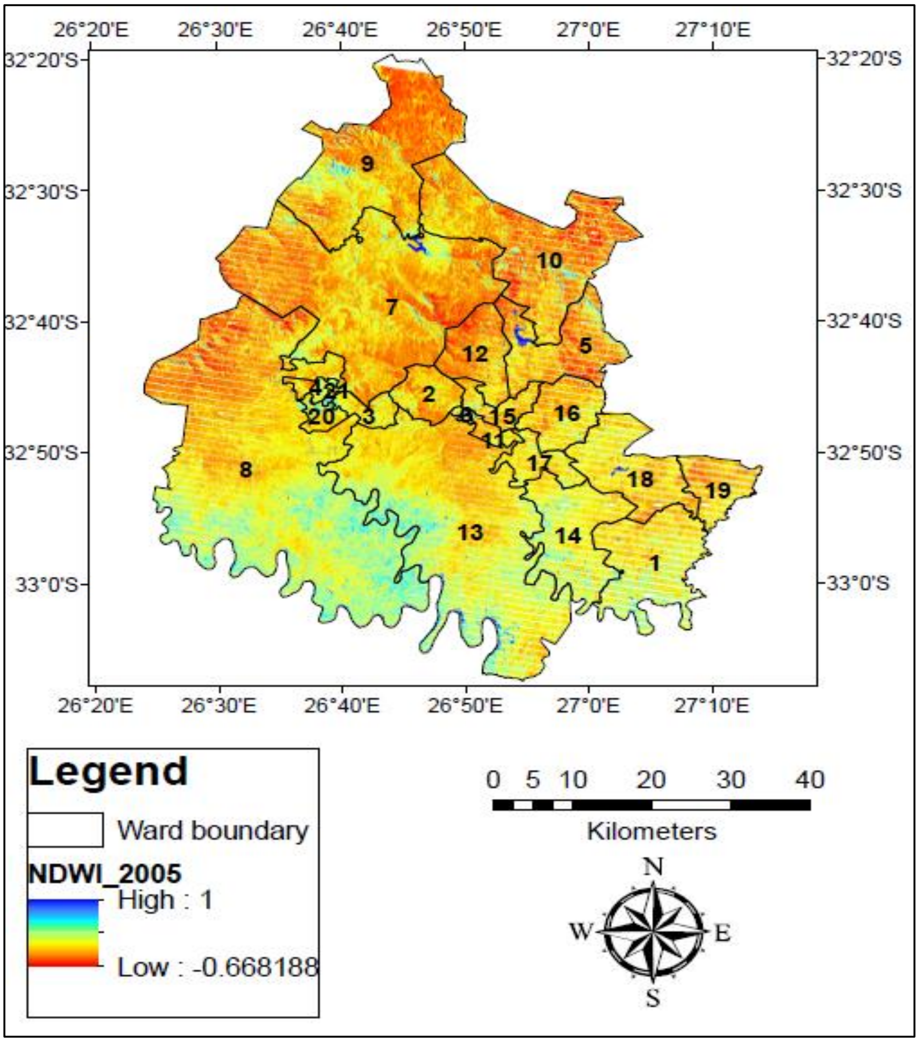


Figure 35: NDWI 2005

The upper parts of the municipality (wards 2, 5, 7, 9, 10 and 12) had the lowest vegetation water content. The highest NDWI value of 1 was mainly due to the occurrence of the Binfield and Katrivier dams located in wards 5 and 7 respectively, which serve as major water suppliers for the municipality.

4.4.8 NDWI 2014

In 2014, the regions in the lower half of the municipality (wards 1, 2, 8, 11, 17, 18, 19 and 20) had the least vegetation water content (figure 36), as compared to years 1985, 1995 and 2005 where regions in the upper half had the least vegetation water content.

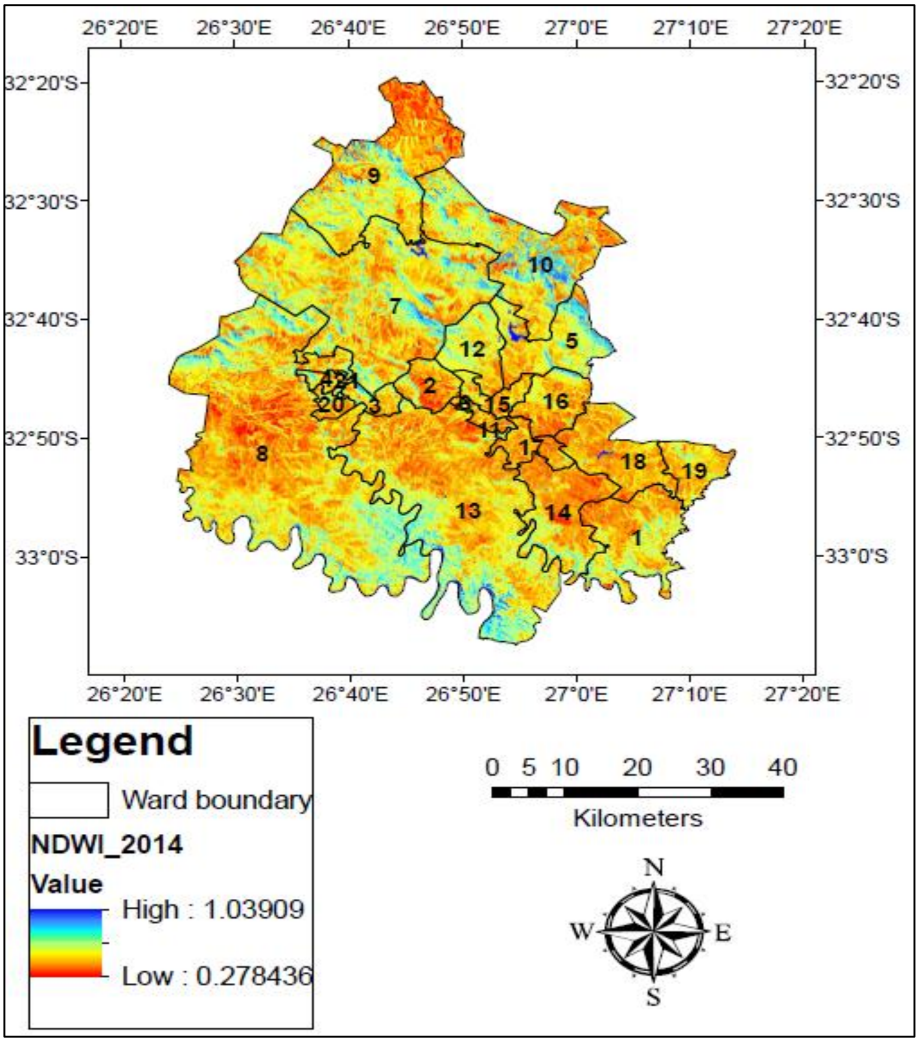


Figure 36: NDWI 2014

Generally the vegetation water content slowly increased as shown by lowest NDWI being 0.27 as compared to the -0.67 in year 2005. The increase in vegetation water content was probably due to the slight improvement in vegetation health (as shown in NDVI 2014).

5 DISCUSSION

5.1 Exposure discussion

The results of the CMIP5 climate projections from the exposure assessment illustrated that the whole municipality is still exposed to droughts owing to fluctuations in rainfall and temperature for the projected period 2015 - 2035. No accuracy assessment could be performed on the climate projections since they had been calculated from 10 statistically downscaled GCMs by the data providers.

5.2 Sensitivity of resource-poor households

The villages situated in the south-eastern part of the municipality (in wards 3, 11, 14, 16, 17, 18 and 19) were deemed most sensitive to droughts mainly owing to low quantities of groundwater occurrence and also very low ground water recharge. Keeping the natural environments in high groundwater recharge areas intact and healthy is critical to the functioning of groundwater dependent ecosystems, which can be in the immediate vicinity, or far removed from the recharge area, thus improving the vegetation health and water content. Severely water stressed villages revealed by sensitivity assessment need to be assisted by relevant authorities by sinking more boreholes and more irrigation schemes. Since the sensitivity assessment based mainly on shapefiles acquired from Department of Water Affairs, the data was assumed to be accurate and a representation of ground features.

5.3 Adaptive capacity discussion

Water access data acquired from three different service providers in the Nkonkobe Local Municipality was statistically checked for accuracy in order to determine the strength of the adaptive capacity assessment. A preliminary analysis on water access data from ECSECC, Quantec and StatsSA revealed violations of the independent-sample ANOVA assumptions[1] as shown in Table 10 and Figure 37.

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[1] (a) The p populations must be normally distributed; (b) The population variances must be homogeneous

Table 10: Mean and variance for water access from 3 different data providers

		ECSECC	Quantec	StatsSA
1	Regional/local water scheme	31571	33081	27453
2	Borehole/rain-water tank/well	697	317	3353
3	Dam/river/stream/spring	4972	823	2545
4	Water-carrier/tanker/Water vendor	216	517	1391
5	Other/Unspecified/Dummy	371	444	614
	Standard Deviation	13564.1305	14560.56471	11442.13019
	Variance (s^2)	183985636.3	212010044.8	130922343.2

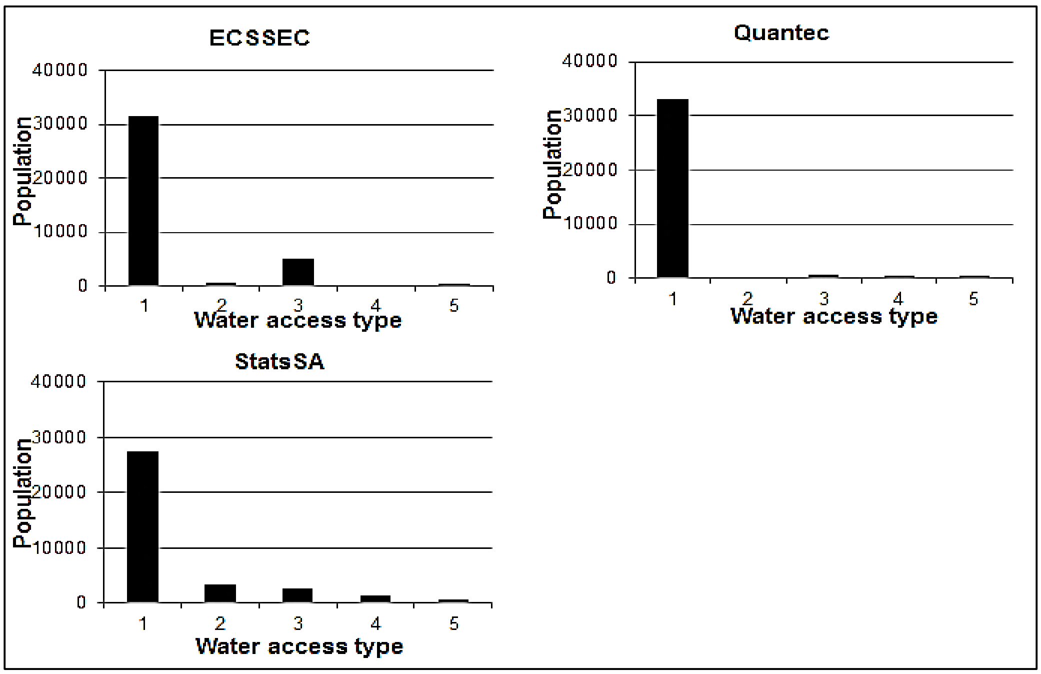

Figure 37: Population distributions from ECSECC, Quantec and StatsSA

Hence, the nonparametric Kruskal-Wallis *H* test was employed, after meeting the assumptions[2], using the following hypotheses:

H_o: The water access populations have identical distributions

H_1: The null is wrong

[2] (a) The samples from the k populations must be independent of each other; (b) Each of the samples must be obtained using independent random sampling and; (c) If $k = 3$ then all samples must have at least five observations

The three population groups were ranked as illustrated in Table 11 using the ranking procedures provided by Glenberg (1996).

Table 11: Kruskal-Wallis *H* test ranked population groups

	ECSSEC	**R_1**	**Quantec**	**R_2**	**StatsSA**	**R_3**
Regional/local water scheme	31571	14	33081	15	27453	13
Borehole/rain-water tank/well	697	7	317	2	3353	11
Dam/river/stream/spring	4972	12	823	8	2545	10
Water-carrier/tanker/Water vendor	216	1	517	5	1391	9
Other/Unspecified/Dummy	371	3	444	4	614	6
R total		37		34		49
Mean rank		7.4		6.8		9.8

Where ECSSEC = n_1, Quantec = n_2, StatsSA = n_3 and n is number of samples in a group; R_1, R_2, R_3 are assigned ranks for ECSSEC, Quantec and StatsSA respectively.

As a check on assignment of ranks[3], it was shown that $n\ (n+1)/2 = 15(16)/2 = 120$ which is equal to 37+34+49 = 120. The decision rule[4] set for the test was that at $\alpha = 0.05$ and $p = 3$, reject H_o if $H > 5.99$. Since there were no tied scores[5] amongst the ranked three population groups (Table 13), a Kruskal-Wallis test statistic (H) was computed based the following expression:

$$H = \left(\frac{12}{n(n+1)}\right)\left(\sum_{i=1}^{k}\frac{12}{n(n+1)}\right) - 3(n+1)$$

From the conditions: $n = 15$, $n_1 = 5$, $n_2 = 5$, $n_3 = 5$, $k = 3$, $R_1 = 37$, $R_2 = 34$, $R_3 = 49$, it was revealed that $H = 1.26$. Therefore, basing on the decision rule, H_o was not rejected. There was statistically significant evidence at $\alpha = 0.05$, showing that there is no difference in median water access sample data among the three different groups of data providers. It was concluded that the water access sample data have identical distributions hence the choice of sample data is not affected by choice of data provider. A significance level of 0.05 indicated a 5% risk of concluding that a

3 Sum of the ranks = n(n+1)/ 2

4 Reject H_o if $H \geq \chi^2_\alpha\ (k-1)$, where $\chi^2_\alpha\ (k-1)$ is the value of the χ^2 statistic with $k-1$ *df* that has α of the distribution above it; k is number of population groups

5 For tied scores in ranked populations, correct the test statistic using methods provided by Conover (1999)

difference exists when there is no actual difference. The p-value[6] was used to determine whether any of the differences between the medians are statistically significant and it was revealed p – value = 0.533 which implied that the differences between the medians are not statistically significant.

The whole municipality has no region which can be regarded as strategic water supply area of the country due to recharge values below 300. For a region to be regarded as a strategic water supply area, the groundwater recharge has to be greater than or equal to 300 according to the DWAF, 2005b report.

5.4 NDVI and NDWI relationship

Linear relationships between NDWI and NDVI were plotted as shown the following figure 38.

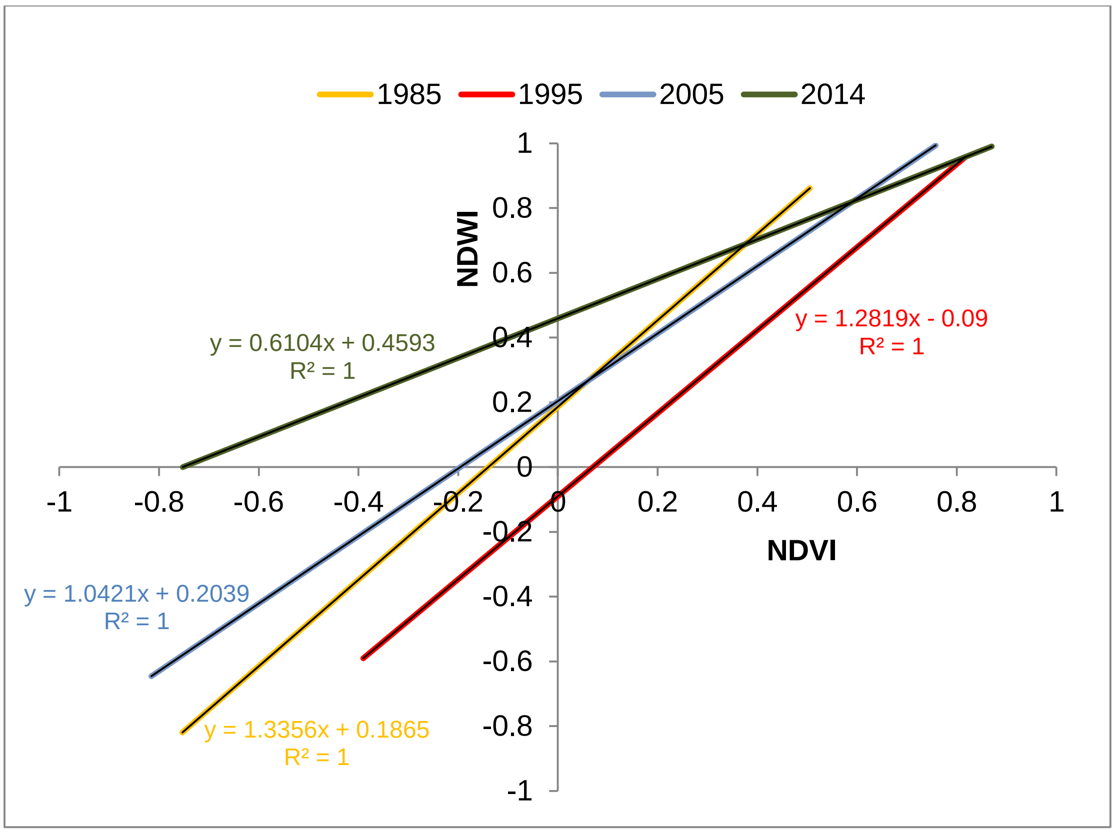

Figure 38: NDWI - NDVI simple linear regression analysis

Correlation coefficients (r-value) were: 1985 (r = 0.99609375), 1995 (r = 0.99609375), 2005 (r = 0.99609375), 2014 (r = 0.99609375). All the r – values showed a very strong positive correlation

[6] If p - value ≤ α, then the differences between the medians are statistically significant

coefficient between NDWI and NDVI in each of the years. There was a positive relationship between NDWI and NDVI as shown in Figure 38 by the positive gradients of the plotted lines for 1985, 1995, 2005 and 2014. All the plotted lines showed $R^2 = 1$ implying a very strong positive correlation between NDWI and NDVI. Thus any increase in rainfall will lead to increased surface water hence high NDWI and more vegetation greenness implying high NDVI values. The linkage between NDWI and NDVI is related to droughts because the lesser the land surface water, the lesser the vegetation cover or plant growth hence more drought conditions.

6 RECOMMENDATIONS AND CONCLUSION

6.1 Recommendations

Implementation of programmes to promote tertiary education is needed since most students are failing to complete secondary education. More income generating projects for the community such as irrigation-supported agriculture need to be implemented so as to create more employment, thus boosting the adaptive capacity of Nkonkobe Local Municipality.

More climate change adaptation measures need to be implemented since the municipality is expected to face more reductions in rainfall and increased temperatures according to the exposure assessment. The adaptation measures include introducing more irrigation schemes and construction of greenhouses which provide adequate humid conditions for agricultural productivity

Communities should be active participants in adaptation planning at the level of local authorities so as to promote a common understanding of suitable adaptation options to the climate variability-related droughts.

There is need to integrate science and policy of vulnerability assessments in order to assist in formulating suitable strategies for droughts. The policy maker's understanding of the scientific issues and technical constraints involved in addressing problems associated with drought is often limited. Likewise, scientists generally have a poor understanding of existing policy constraints for responding to the impacts of drought. Hence, communication and understanding between science and policy communities must be enhanced in order for the planning process to be successful. Integration of science and policy for vulnerability assessment during the planning process is useful in setting research priorities and synthesizing current level of understanding and capabilities.

6.2 Conclusion

The study provided a broader overview of the spatial distribution of copying capacity and sensitivity at a municipal scale which is a rapid decision-making tool for climate policy to identify villages moat vulnerable to droughts. It is therefore important that communities are active participants in adaptation planning at the level of local authorities.

The study showed that in the adaptive capacity assessment, the demographics results are independent on the choice of data from different data providers as proven by $H < \chi^2$ (2), at α = 0.05 in the Kruskal-Wallis H test with p - value = 0.533. There is a strong positive relationship between NDWI and NDVI as portrayed by the correlation coefficients and $R^2 = 1$ for years 1985, 1995, 2005 and 2014. This implies that 100% of NDWI is determined by NDVI meaning vegetation water content is absolutely determined by the vegetation health. The link between land surface water and vegetation cover is related to droughts.

The study has proven that GIS mapping and remote sensing can be used as a decision-making tool for climate policy to rapidly determine households with low adaptive capacity by narrowing a vulnerability assessment to a more localized and manageable scope, that is, from municipal level to village level which will in turn make it easier to determine targeted households. The selected villages with low adaptive capacity to climate change can then be deemed as the key places for performing a household surveys in order to assess the vulnerability to droughts at household level. Assessing vulnerability at household level will also be able to provide an insight of the gender dimensions of vulnerability.

GIS and remote sensing technologies are beneficial for vulnerability assessments to assist in the improvement of long-term policies of drought management. Utilization of up-to-date technologies, expansion of spatial decision support systems, impact assessment and early warning are some of the subjects that require to be addressed to reinforce agricultural drought management. It is imperative for decision-makers to comprehend village copying capacity to different types of climate threats so that this information can advise the choice of adaptation policies. Priority in adaptation planning should be given to villages that have identified themselves as being unable to cope with adverse impacts of climate change. Cautiousness of social adaptive capacity is vital to prevent the adverse impacts of poorly planned activities that could worsen impacts on those villages which are most vulnerable to climate change and variability. However, further consideration needs to be done during assessment design so as to attain an enhanced mobilization of copying capacity for suitable adaptation to droughts. Further responsiveness is essential to be given to assessment plan in order for an enhanced support of the mobilization of adaptive capacity for adaptation.

The study provided information which is potentially useful in guiding policy makers to formulate of informed climate change adaptation strategies within the Nkonkobe Local Municipality. The take-home message from this investigation is that strategies dealing with climate risk reduction should focus on enhancing capacities of communities with low resilience to mitigate droughts. Nkonkobe municipality is still vulnerable to droughts as revealed by the exposure, sensitivity, adaptive capacity and NDWI and NDVI analysis.

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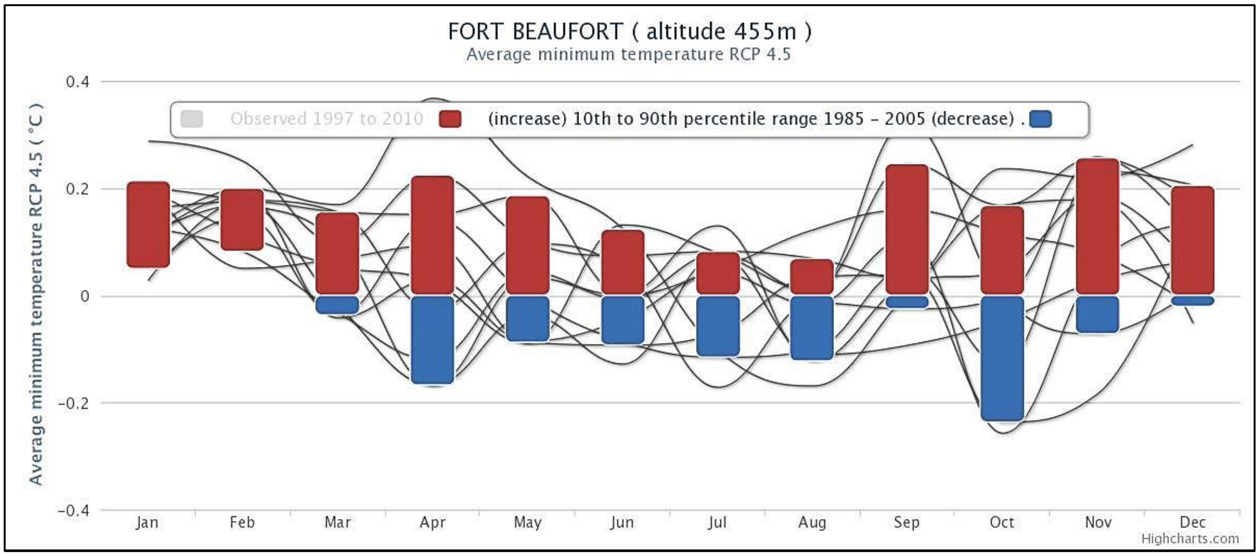
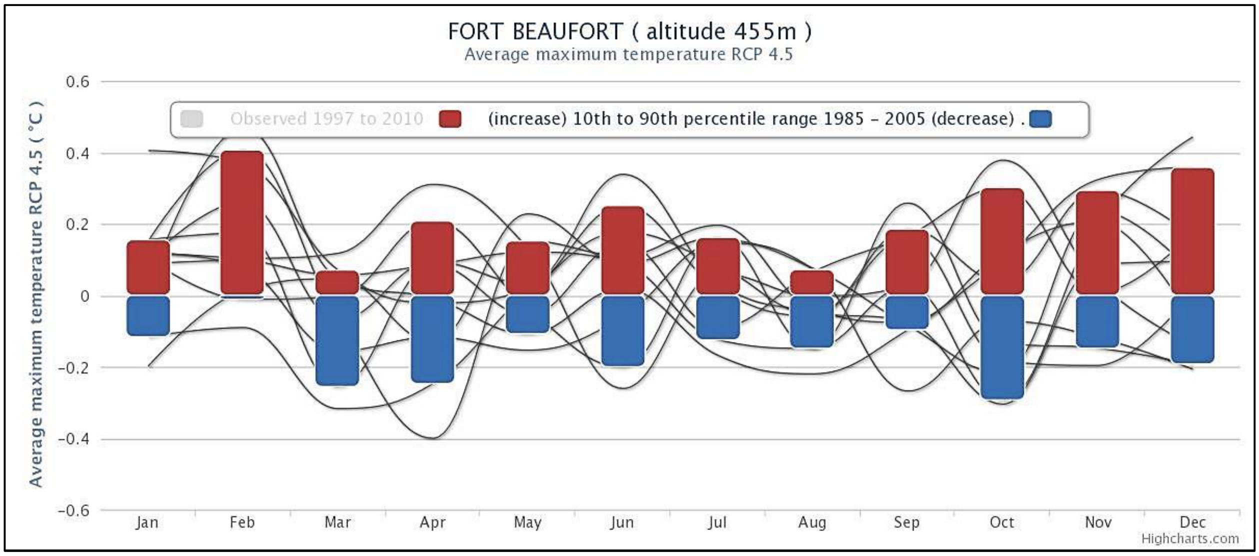
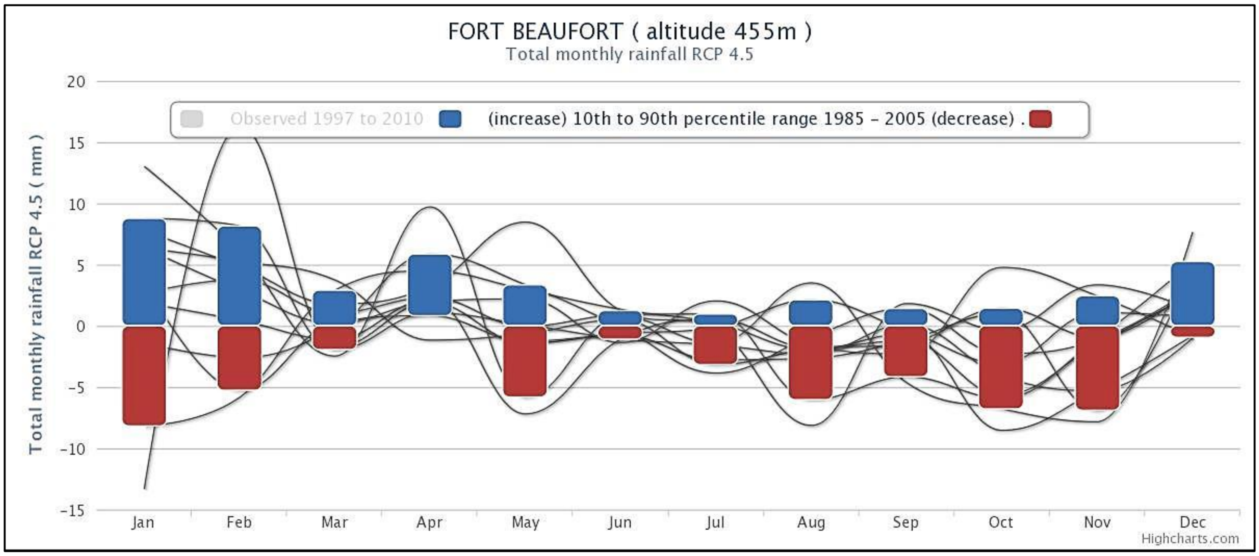
8 APPENDIX

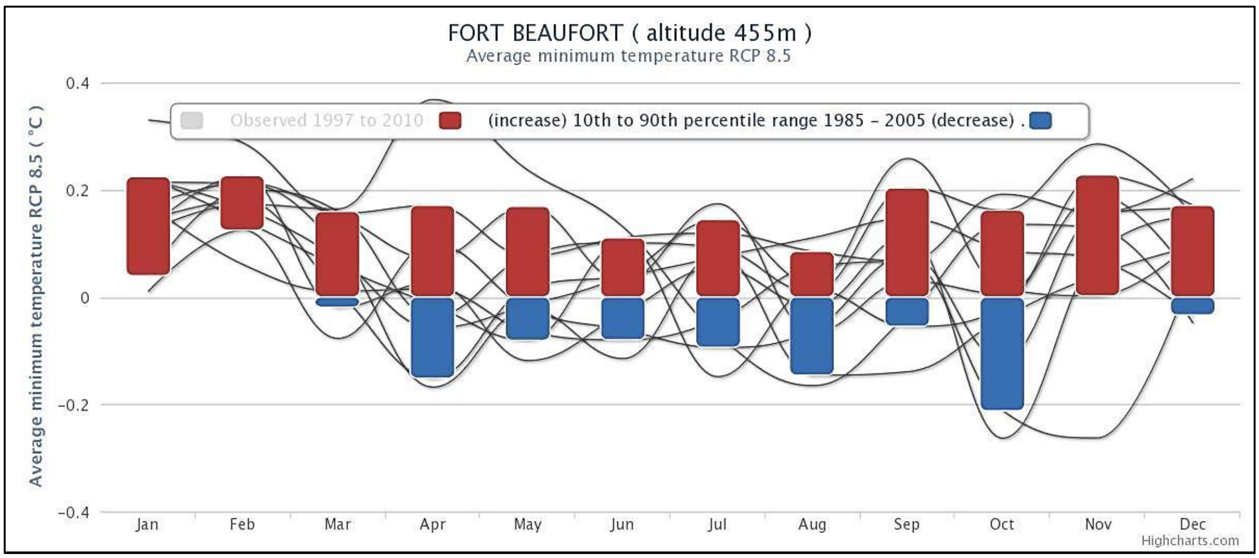
8.1 Annex 1: GCMs control periods for Fort Beaufort



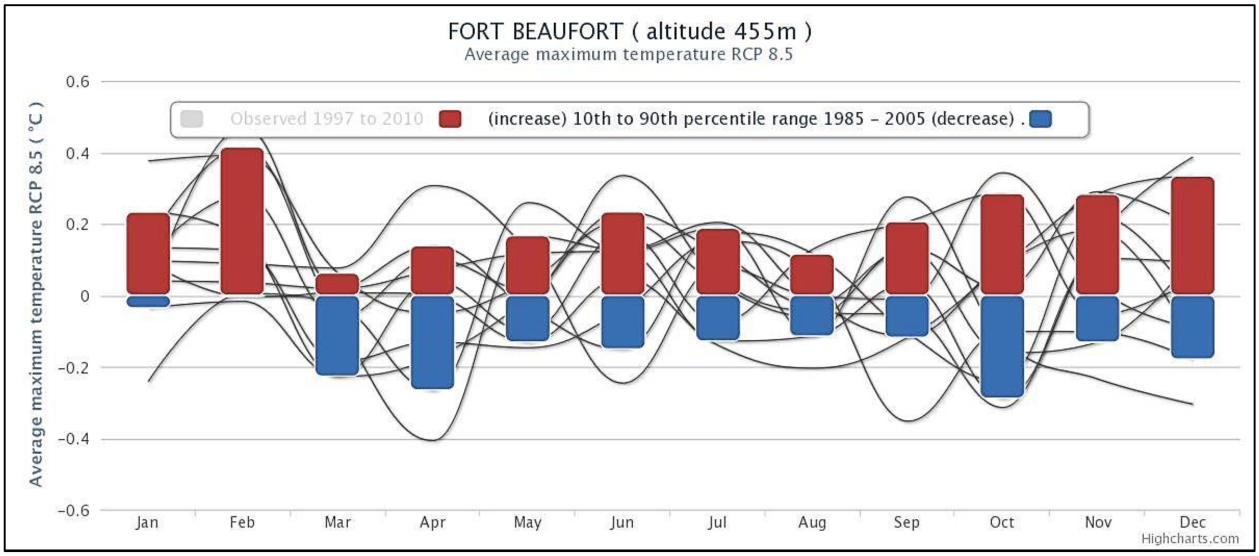


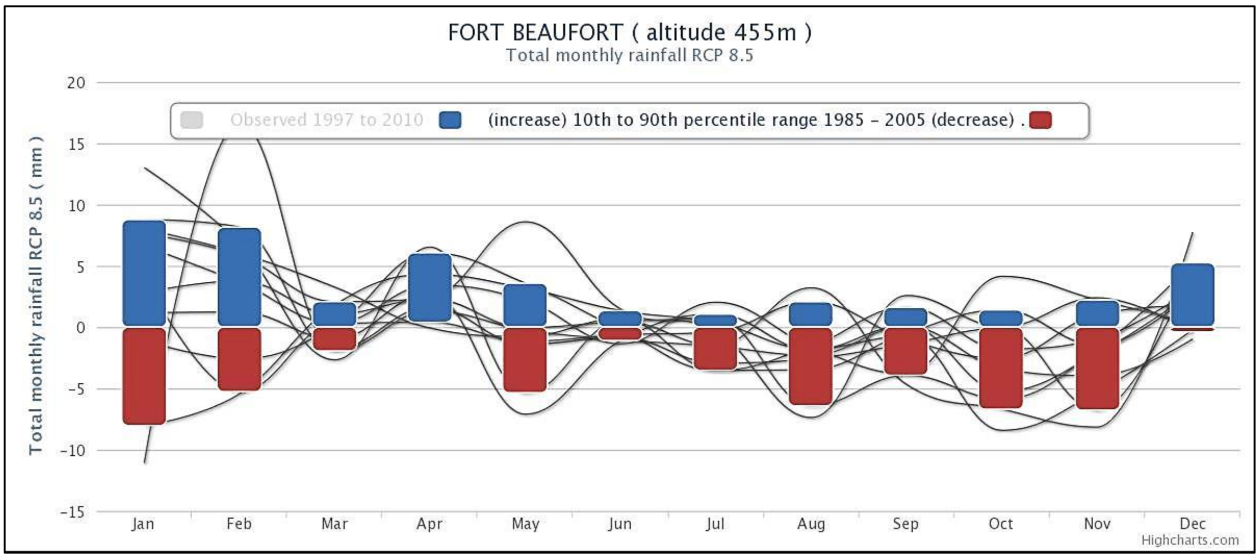
Source: http://cip.csag.uct.ac.za/webclient2/datasets/south-africa-cmip5/





Source: http://cip.csag.uct.ac.za/webclient2/datasets/south-africa-cmip5/





Source: http://cip.csag.uct.ac.za/webclient2/datasets/south-africa-cmip5/

8.2 **Annex 2:** Earth-Sun distances in astronomical units for Day of the Year (DOY)

Table 12: Earth-Sun distances in astronomical units for Day of the Year (DOY)

Earth-Sun distance (d) in astronomical units for Day of the Year (DOY)											
DOY	**d**	**DOY**	**d**	**DOY**	**d**	**DOY**	**d**	**DOY**	**d**	**DOY**	**d**
1	0.98331	**61**	0.99108	**121**	1.00756	**181**	1.01665	**241**	1.00992	**301**	0.99359
2	0.98330	**62**	0.99133	**122**	1.00781	**182**	1.01667	**242**	1.00969	**302**	0.99332
3	0.98330	**63**	0.99158	**123**	1.00806	**183**	1.01668	**243**	1.00946	**303**	0.99306
4	0.98330	**64**	0.99183	**124**	1.00831	**184**	1.01670	**244**	1.00922	**304**	0.99279
5	0.98330	**65**	0.99208	**125**	1.00856	**185**	1.01670	**245**	1.00898	**305**	0.99253
6	0.98332	**66**	0.99234	**126**	1.00880	**186**	1.01670	**246**	1.00874	**306**	0.99228
7	0.98333	**67**	0.99260	**127**	1.00904	**187**	1.01670	**247**	1.00850	**307**	0.99202
8	0.98335	**68**	0.99286	**128**	1.00928	**188**	1.01669	**248**	1.00825	**308**	0.99177
9	0.98338	**69**	0.99312	**129**	1.00952	**189**	1.01668	**249**	1.00800	**309**	0.99152
10	0.98341	**70**	0.99339	**130**	1.00975	**190**	1.01666	**250**	1.00775	**310**	0.99127
11	0.98345	**71**	0.99365	**131**	1.00998	**191**	1.01664	**251**	1.00750	**311**	0.99102
12	0.98349	**72**	0.99392	**132**	1.01020	**192**	1.01661	**252**	1.00724	**312**	0.99078
13	0.98354	**73**	0.99419	**133**	1.01043	**193**	1.01658	**253**	1.00698	**313**	0.99054
14	0.98359	**74**	0.99446	**134**	1.01065	**194**	1.01655	**254**	1.00672	**314**	0.99030
15	0.98365	**75**	0.99474	**135**	1.01087	**195**	1.01650	**255**	1.00646	**315**	0.99007
16	0.98371	**76**	0.99501	**136**	1.01108	**196**	1.01646	**256**	1.00620	**316**	0.98983
17	0.98378	**77**	0.99529	**137**	1.01129	**197**	1.01641	**257**	1.00593	**317**	0.98961
18	0.98385	**78**	0.99556	**138**	1.01150	**198**	1.01635	**258**	1.00566	**318**	0.98938
19	0.98393	**79**	0.99584	**139**	1.01170	**199**	1.01629	**259**	1.00539	**319**	0.98916
20	0.98401	**80**	0.99612	**140**	1.01191	**200**	1.01623	**260**	1.00512	**320**	0.98894
21	0.98410	**81**	0.99640	**141**	1.01210	**201**	1.01616	**261**	1.00485	**321**	0.98872
22	0.98419	**82**	0.99669	**142**	1.01230	**202**	1.01609	**262**	1.00457	**322**	0.98851
23	0.98428	**83**	0.99697	**143**	1.01249	**203**	1.01601	**263**	1.00430	**323**	0.98830
24	0.98439	**84**	0.99725	**144**	1.01267	**204**	1.01592	**264**	1.00402	**324**	0.98809
25	0.98449	**85**	0.99754	**145**	1.01286	**205**	1.01584	**265**	1.00374	**325**	0.98789
26	0.98460	**86**	0.99782	**146**	1.01304	**206**	1.01575	**266**	1.00346	**326**	0.98769
27	0.98472	**87**	0.99811	**147**	1.01321	**207**	1.01565	**267**	1.00318	**327**	0.98750
28	0.98484	**88**	0.99840	**148**	1.01338	**208**	1.01555	**268**	1.00290	**328**	0.98731
29	0.98496	**89**	0.99868	**149**	1.01355	**209**	1.01544	**269**	1.00262	**329**	0.98712
30	0.98509	**90**	0.99897	**150**	1.01371	**210**	1.01533	**270**	1.00234	**330**	0.98694
31	0.98523	**91**	0.99926	**151**	1.01387	**211**	1.01522	**271**	1.00205	**331**	0.98676
32	0.98536	**92**	0.99954	**152**	1.01403	**212**	1.01510	**272**	1.00177	**332**	0.98658
33	0.98551	**93**	0.99983	**153**	1.01418	**213**	1.01497	**273**	1.00148	**333**	0.98641
34	0.98565	**94**	1.00012	**154**	1.01433	**214**	1.01485	**274**	1.00119	**334**	0.98624
35	0.98580	**95**	1.00041	**155**	1.01447	**215**	1.01471	**275**	1.00091	**335**	0.98608
36	0.98596	**96**	1.00069	**156**	1.01461	**216**	1.01458	**276**	1.00062	**336**	0.98592
37	0.98612	**97**	1.00098	**157**	1.01475	**217**	1.01444	**277**	1.00033	**337**	0.98577
38	0.98628	**98**	1.00127	**158**	1.01488	**218**	1.01429	**278**	1.00005	**338**	0.98562

39	0.98645	**99**	1.00155	**159**	1.01500	**219**	1.01414	**279**	0.99976	**339**	0.98547
40	0.98662	**100**	1.00184	**160**	1.01513	**220**	1.01399	**280**	0.99947	**340**	0.98533
41	0.98680	**101**	1.00212	**161**	1.01524	**221**	1.01383	**281**	0.99918	**341**	0.98519
42	0.98698	**102**	1.00240	**162**	1.01536	**222**	1.01367	**282**	0.99890	**342**	0.98506
43	0.98717	**103**	1.00269	**163**	1.01547	**223**	1.01351	**283**	0.99861	**343**	0.98493
44	0.98735	**104**	1.00297	**164**	1.01557	**224**	1.01334	**284**	0.99832	**344**	0.98481
45	0.98755	**105**	1.00325	**165**	1.01567	**225**	1.01317	**285**	0.99804	**345**	0.98469
46	0.98774	**106**	1.00353	**166**	1.01577	**226**	1.01299	**286**	0.99775	**346**	0.98457
47	0.98794	**107**	1.00381	**167**	1.01586	**227**	1.01281	**287**	0.99747	**347**	0.98446
48	0.98814	**108**	1.00409	**168**	1.01595	**228**	1.01263	**288**	0.99718	**348**	0.98436
49	0.98835	**109**	1.00437	**169**	1.01603	**229**	1.01244	**289**	0.99690	**349**	0.98426
50	0.98856	**110**	1.00464	**170**	1.01610	**230**	1.01225	**290**	0.99662	**350**	0.98416
51	0.98877	**111**	1.00492	**171**	1.01618	**231**	1.01205	**291**	0.99634	**351**	0.98407
52	0.98899	**112**	1.00519	**172**	1.01625	**232**	1.01186	**292**	0.99605	**352**	0.98399
53	0.98921	**113**	1.00546	**173**	1.01631	**233**	1.01165	**293**	0.99577	**353**	0.98391
54	0.98944	**114**	1.00573	**174**	1.01637	**234**	1.01145	**294**	0.99550	**354**	0.98383
55	0.98966	**115**	1.00600	**175**	1.01642	**235**	1.01124	**295**	0.99522	**355**	0.98376
56	0.98989	**116**	1.00626	**176**	1.01647	**236**	1.01103	**296**	0.99494	**356**	0.98370
57	0.99012	**117**	1.00653	**177**	1.01652	**237**	1.01081	**297**	0.99467	**357**	0.98363
58	0.99036	**118**	1.00679	**178**	1.01656	**238**	1.01060	**298**	0.99440	**358**	0.98358
59	0.99060	**119**	1.00705	**179**	1.01659	**239**	1.01037	**299**	0.99412	**359**	0.98353
60	0.99084	**120**	1.00731	**180**	1.01662	**240**	1.01015	**300**	0.99385	**360**	0.98348
										361	0.98344
										362	0.98340
										363	0.98337
										364	0.98335
										365	0.98333
										366	0.98331

Source: Chander *et al.* 2009

8.3 **Annex 3:** Julian Day Calendar

Table 13: Julian Day Calendar

Leap years:

(2000, 2004, 2008, 2012, 2016, 2020...)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	1	32	61	92	122	153	183	214	245	275	306	336
2	2	33	62	93	123	154	184	215	246	276	307	337
3	3	34	63	94	124	155	185	216	247	277	308	338
4	4	35	64	95	125	156	186	217	248	278	309	339
5	5	36	65	96	126	157	187	218	249	279	310	340
6	6	37	66	97	127	158	188	219	250	280	311	341
7	7	38	67	98	128	159	189	220	251	281	312	342
8	8	39	68	99	129	160	190	221	252	282	313	343
9	9	40	69	100	130	161	191	222	253	283	314	344
10	10	41	70	101	131	162	192	223	254	284	315	345
11	11	42	71	102	132	163	193	224	255	285	316	346
12	12	43	72	103	133	164	194	225	256	286	317	347
13	13	44	73	104	134	165	195	226	257	287	318	348
14	14	45	74	105	135	166	196	227	258	288	319	349
15	15	46	75	106	136	167	197	228	259	289	320	350
16	16	47	76	107	137	168	198	229	260	290	321	351
17	17	48	77	108	138	169	199	230	261	291	322	352
18	18	49	78	109	139	170	200	231	262	292	323	353
19	19	50	79	110	140	171	201	232	263	293	324	354
20	20	51	80	111	141	172	202	233	264	294	325	355
21	21	52	81	112	142	173	203	234	265	295	326	356
22	22	53	82	113	143	174	204	235	266	296	327	357
23	23	54	83	114	144	175	205	236	267	297	328	358
24	24	55	84	115	145	176	206	237	268	298	329	359
25	25	56	85	116	146	177	207	238	269	299	330	360
26	26	57	86	117	147	178	208	239	270	300	331	361
27	27	58	87	118	148	179	209	240	271	301	332	362
28	28	59	88	119	149	180	210	241	272	302	333	363
29	29	60	89	120	150	181	211	242	273	303	334	364
30	30		90	121	151	182	212	243	274	304	335	365
31	31		91		152		213	244		305		366

Regular years:

(2001-2003, 2005-2007, 2009-2011, 2013-2015...)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	1	32	60	91	121	152	182	213	244	274	305	335
2	2	33	61	92	122	153	183	214	245	275	306	336
3	3	34	62	93	123	154	184	215	246	276	307	337
4	4	35	63	94	124	155	185	216	247	277	308	338
5	5	36	64	95	125	156	186	217	248	278	309	339
6	6	37	65	96	126	157	187	218	249	279	310	340
7	7	38	66	97	127	158	188	219	250	280	311	341
8	8	39	67	98	128	159	189	220	251	281	312	342
9	9	40	68	99	129	160	190	221	252	282	313	343
10	10	41	69	100	130	161	191	222	253	283	314	344
11	11	42	70	101	131	162	192	223	254	284	315	345
12	12	43	71	102	132	163	193	224	255	285	316	346
13	13	44	72	103	133	164	194	225	256	286	317	347
14	14	45	73	104	134	165	195	226	257	287	318	348
15	15	46	74	105	135	166	196	227	258	288	319	349
16	16	47	75	106	136	167	197	228	259	289	320	350
17	17	48	76	107	137	168	198	229	260	290	321	351
18	18	49	77	108	138	169	199	230	261	291	322	352
19	19	50	78	109	139	170	200	231	262	292	323	353
20	20	51	79	110	140	171	201	232	263	293	324	354
21	21	52	80	111	141	172	202	233	264	294	325	355
22	22	53	81	112	142	173	203	234	265	295	326	356
23	23	54	82	113	143	174	204	235	266	296	327	357
24	24	55	83	114	144	175	205	236	267	297	328	358
25	25	56	84	115	145	176	206	237	268	298	329	359
26	26	57	85	116	146	177	207	238	269	299	330	360
27	27	58	86	117	147	178	208	239	270	300	331	361
28	28	59	87	118	148	179	209	240	271	301	332	362
29	29		88	119	149	180	210	241	272	302	333	363
30	30		89	120	150	181	211	242	273	303	334	364
31	31		90		151		212	243		304		365

Source: http://landweb.nascom.nasa.gov/browse/calendar.html