Drought characterization in South Africa under a changing climate

By

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Declaration

I, Elelwani Phaduli , declare that the dissertation, which I hereby submit for the degree Master of Science in Meteorology at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

Signature: …………………………… Date: ………………………………

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Abstract

The outputs from the Global Climate Models (GCMs) and Regional Climate Models (RCMs) have been used worldwide to predict the evolution of extreme weather events such as floods and droughts. In this study the spatial and temporal characteristics of historical, current as well as future meteorological drought trends are computed using the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI). Statistical and trend analysis done using SPI time series derived from rainfall observations have shown that most parts of South Africa experienced moderate to severe droughts between 1981 and 2015. Gridded monthly precipitation data from the Tropical Rainfall Measuring Mission (TRMM) satellite was used to compute the SPI at each grid point of the domain. The computed SPI was used to obtain drought monitoring indicators such as drought intensity (DI), drought severity (DS), drought duration (DD) and drought frequency (DF) for the period 1998-2015. Results have shown decreasing (negative) trends in drought intensity and duration over most parts of South Africa mainly in provinces such as Gauteng, Limpopo, Free State and North West province. Furthermore results shows that SPI/SPEI computed using data from in-situ observations as well as the SPI computed using data from TRMM reproduced most of the major drought episodes that occurred in South Africa during 1981-2015. Additionally, the ensemble mean of climate simulations obtained when the

Rossby Centre for regional climate model (RCA4) is forced by nine GCM models was used to compute the Standardized Precipitation Evapotranspiration Index (SPEI) during the reference period (1971-2000) and future projections (2011-2040 and 2041-2070) under Representative Concentration Pathways (RCP 8.5). Statistical and trend analysis were done using drought intensity, severity, duration and frequency. Moreover, results show an overall increase in drought intensity, duration, severity and frequency during the two future periods 2011-2040 and 2041-2070 under RCP 8.5. Future studies will focus on the impact based assessment in order to complete the drought preparedness and mitigation plan.

Preface

South Africa is one of the drought prone countries in the African continent; therefore a proper drought preparedness and mitigation plan is required. Drought preparedness and mitigation plan is divided into four sections, namely prediction, monitoring, impact based assessment and response. Studies on the prediction and monitoring of droughts are increasing in Southern Africa. This study will contribute to monitoring and prediction of current and future droughts using observed rainfall and temperature observations.

Chapter 1: Covers the introductory notes and the background information on the drought phenomenon, including the definitions of the drought. In this chapter, a problem statement together with the aims and objectives of the current study are presented.

Chapter 2: A thorough review of the literature on droughts is described in this chapter. This also covers past studies on drought characterization in different parts of the world. Different drought indices and drought monitoring tools used across the globe as well as their advantages and shortcomings are explained.

Chapter 3: Provides a thorough description of the data and methodology used to carry out the analysis. Data preprocessing and data extraction methods are fully described in this chapter. Mathematical formulae used in all equations are also described in this chapter.

Chapter 4: and 5 Covers the analysis of results, with the emphasis on spatiotemporal analysis of droughts using the current and future datasets and the frequency analysis methods such as Probability Density Functions and trend analysis.

Chapter 6

This chapter summarizes the findings of the whole dissertation, including the recommendations, future work as well as the overall conclusions of the study.

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“For with God nothing is impossible” Luke 1:37(KJV)

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LIST OF ABBREVIATIONS

AWS	Automated Weather Stations
CDF	Cumulative Distribution Function
CMI	Crop Moisture Index
CORDEX	CO-ordinated Regional Downscaling Experiment
CRU	Climatic Research Unit
DEWS	Drought Early Warning Systems
DJF	December January February
DMI	Drought Monitoring Parameters
ENSO	El Niño Southern Oscillation
GCM	Global Circulation Models
GEV	Generalized Extreme Value
GPM	Global Precipitation Measuring Mission
IPCC	Intergovernmental Panel on Climate Change
JJA	June July August
MAM	March April May
MAP	Mean Annual Precipitation
NSMC	National Satellite Meteorological Center
NDVI	Normalized Difference Vegetation Index
PET	Potential Evapotranspiration

PDF	Probability Distribution Functions
PDSI	Palmer Drought Severity Index
PHDI	Palmer Hydrological Drought Index
RCM	Regional Climate Model
RMSE	Root Mean Squared Error
SAWS	South African Weather Service
SDM	Statistical Downscaling Model
SMI	Soil Moisture Index
SNHT	Standard Normal Homogeneity Testing
SOI	Southern Oscillation Index
SON	September October November
SPEI	Standardized Evapotranspiration Precipitation Index
SPI	Standardized Precipitation Index
SVI	Standardized Vegetation Index
TCI	Temperature Condition Index
TFPW	Trend Free Pre Whitening
TRMM	Tropical Rainfall Measuring Mission
VCI	Vegetation Condition Index
VSWI	Vegetation Supply Water Index

CHAPTER 1: BACKGROUND INFORMATION

1.1 Introduction

Drought is probably one of the most harmful extreme weather phenomena around the world, but its detriment occurs slowly compared to other natural disasters (Maybank et al. 1995). By definition, drought is a shortage of precipitation over an extended period of time (Qureshi & Akhtar 2004). Drought can be confused with other phenomena such as water scarcity, aridity, and desertification. However, unlike aridity drought is a temporary feature of climate that can be intensified by high temperatures, high winds, and low relative humidity (Wilhite 2005).

Meteorological parameters such as precipitation, evaporation, snow, humidity, wind and temperature may aggregate the severity and effects of droughts. Aridity, on the other hand is a permanent deficiency of rainfall usually common in dry regions. Desertification is defined as the degradation of land that usually occurs in arid, semi-arid and dry sub-humid areas caused by climatic variations and human activities (Philander 2008).

All droughts whether at the scale of days, seasons or years have been linked to a predominance of anticyclone conditions, which are a predominant control of weather and climate of Southern African region (Tyson P.D, Preston-Whyte 2000). In South Africa, drought usually occur during a period of below-normal rainfall following an El Niño event (Kruger 1999). Most droughts episodes that occurred since late 1960 in South Africa were associated with El Niño events (Rouault & Richard 2003).

According to Intergovernmental Panel on Climate Change (IPCC), the frequency of extreme events such as heat waves, droughts and floods are more likely to increase with the changing climate (IPCC, 2007). In response to climate change, the global average surface temperatures are reported to have increased by about 0.74^{0}C over the past century as reported by the IPCC. According to the IPCC reports the global surface temperatures will continue to increase unless greenhouse gas emissions are significantly reduced.

Droughts are categorized into four major categories namely agricultural, meteorological, hydrological and socio-economic drought (Wilhite & Glantz 1985). The type of drought depends mainly on the characteristics of drought namely intensity, duration, frequency, and area coverage. All climatic regions in South Africa are affected by different types of droughts, but varies in intensity, duration and spatial extension (Rouault & Richard 2005).

Drought indices play a vital role in quantifying the characteristics of different types of droughts. Those indices also plays a major role in drought mitigation, which is important for water resources planning and management. These indices requires quality long term time series of historical observations to analyze the frequency, duration and intensity of droughts. Most drought indices utilize precipitation data as input into their algorithms, and in most regions this data is not easily attainable.

There are numerous drought indices available in literature ranging from precipitation based drought indices to remote sensing based drought indices. Remote sensing based drought indices use data from geostationary or polar orbiting satellites as input into the equations, because in most countries particularly African countries long-term historical observations from ground instruments are either unavailable or lack good quality and has very low spatial resolution.

The construction of drought indices relies on the availability of long-term meteorological variables that were observed at meteorological stations. Drought indices examples includes Percentage of normal, Rainfall deciles (Gibbs and Maher, 1967), Standardized Precipitation Index (SPI) by (Mckee *et al*. 1993), Palmer Drought Severity Index (PDSI; Palmer,1965, Alley, 1984) and Effective Drought Index (EDI; Byun & Kim 2010). Some of these drought indices are reviewed in (Morid *et al.* 2006, Hayes *et al*. 2007).

For calculation of drought indices long-term time series of observations from ground instruments as well as from orbiting satellites is required. However, those observing systems can only give information on current drought episodes. Nevertheless information on drought duration, intensity and severity is also required for the future to predict the future prospects of droughts.

Recent studies are using statistically and dynamically downscaled General Circulation Models (GCMs) as well as Regional Climate Models (RCM) for the assessment of climate change impacts on drought (Berkeley *et al*. 2011, Törnros & Menzel 2014, Stagge *et al*. 2015, Kim *et al*. 2016) . Meteorological parameters such as temperatures, rainfall and soil moisture content obtained from those models can be used as input into the drought indices in order to predict future prospects of drought conditions. In South Africa studies of this nature are still limited.

The South African Weather Service (SAWS) like other National Meteorological "Services" is mandated with monitoring and issuing warnings regarding severe weather events in South Africa, this includes meteorological drought. Currently, SAWS is using SPI for real-time monitoring of meteorological drought.

1.2 Problem Statement

The African continent is more likely to face extreme and wide spread droughts in the future (Masih *et al*. 2014). Numerous studies on the analysis of historical droughts have been carried out in Southern Africa (Richard *et al*. 2001, Rouault & Richard 2003, Edossa *et al*. 2014). However, unavailability of reliable longterm dataset for drought monitoring still pose a challenge throughout the African continent (Naumann *et al*. 2014).

Satellite derived precipitation such as Tropical Rainfall Measuring Mission (TRMM) dataset have been used and recommended for drought monitoring in other parts of the world (Tao *et al*. 2016, De Jesús *et al*. 2016) including Africa (Naumann *et al*. 2012, Naumann *et al*. 2014). Studies that use satelltite based precipitation like TRMM are lacking in South Africa. The current study will attempt to use monthly rainfall data derived from TRMM satellite to calculate SPI over the South Africa domain. The characteristics of current and historical droughts will be analyzed using drought characteristics such as drought intensity, drought severity, drought duration and drought frequency.

Drought monitoring and disaster management centers throughout the world will require future information on the prediction of future droughts in order to plan properly and issue early warnings to the public. Several studies on the prediction of future droughts using Representative Concentration Pathways (RCP) scenarios has been conducted in countries such as Europe (Stagge et al. 2015), South Korea (Lee *et al*. 2016), Poland (Meresa *et al*. 2016) and China (Wang & Chen 2014). Projections of future rainfall and temperatures in South Africa has been studied (Engelbrecht *et al*. 2015, Jury 2013). Projected temperature and precipitation can be used to examine drought intensity, severity, frequency and duration in South Africa. In South Africa studies that apply projection of future temperature and precipitation for future drought projections are still lacking.

1.3 Aims and Objectives

The main aim of this study is to use SPI and SPEI drought indices to establish a statistical relationship between the present and future climate in order to characterize the future drought conditions in South Africa using downscaled regional climate models. To accomplish the given aim the following objectives will be applied.

1. Characterize historical and current drought conditions using in situ observations and satellite data from Tropical Rainfall Measuring Mission satellite.
2. Use temperature and rainfall from dynamically downscaled Regional Climate Models (RCM) to make future droughts projections.
3. Determine the present and future trend of drought intensity, severity, frequency and duration in South Africa using present and future climate conditions.

1.4 Summary

South Africa is one of the drought prone countries in the African continent, therefore a proper drought preparedness and mitigation plan is required. Drought preparedness and mitigation plan is divided into four sections, namely prediction, monitoring, impact based assessment and response. Studies on the prediction and monitoring of droughts are increasing in Southern Africa. This study will contribute to monitoring and prediction of current and future droughts using observed rainfall and temperature observations.

CHAPTER 2: LITERATURE REVIEW

This chapter gives summary of various aspects of drought monitoring and prediction across the globe and particullarly in South Africa. Economic, environmental and social impacts of droughts in South Africa and the rest of the Africa continent were reviewed. Different drought indices used in different parts of the world were reviewed and compared with those used in South Africa. This chapter also describes different methods used for characterizing spatial and temporal patterns of droughts and their relation to teleconnections and oceanic and atmospheric conditions.

2.1 Definitions of drought

The absence of a consensus definition of drought makes it difficult to formulate a common drought index. Droughts are defined using both conceptual and operational definitions (Wilhite & Glantz 1985). The conceptual definition of drought is more general and cannot assist in the mathematical formulation of the drought indices. An operational definition of drought tries to identify the onset, offset, severity and duration of the drought episode. Operational definitions of droughts divide droughts into four major categories namely meteorological, agricultural, hydrological and socio-economic (Wilhite & Glantz 1985).

Definitions of drought are also region specific because the climatic and meteorological conditions that cause drought are not identical throughout the world. In order to understand and asses the drought phenomenon, scientists use the definitions of droughts to formulate different drought indices. A drought index is a mathematical formula that incorporates different meteorological or hydrological parameters such as rainfall, streamflow, temperatures in order to create a single value or index that can be used for decision-making processes. By using a drought index meteorologists and climatologists are able to identify the intensity, severity, duration as well as the spatial extent of a particular drought phenomenon.

All droughts types originate from precipitation deficiency, high temperatures, and winds, low relative humidity. Precipitation deficiency is regarded as a major cause of meteorological drought. However, if the is no enough rainfall the evaporation and transpiration will increase leading to soil water deficiency. When there is not enough soil moisture, plants experience water stress and at this stage, the drought has escalated to agricultural drought.

If the precipitation deficiency persists over a long period stream flows, lakes and ponds will start to dry up, and this will start to affect the aquatic animals and all species that depend on water for survival. At this stage, the drought has escalated to the hydrological drought level. Both drought types explained above will have economic, social as well as environmental impacts. Figure 1, below is a schematic representation displaying how the three types of drought cascades.

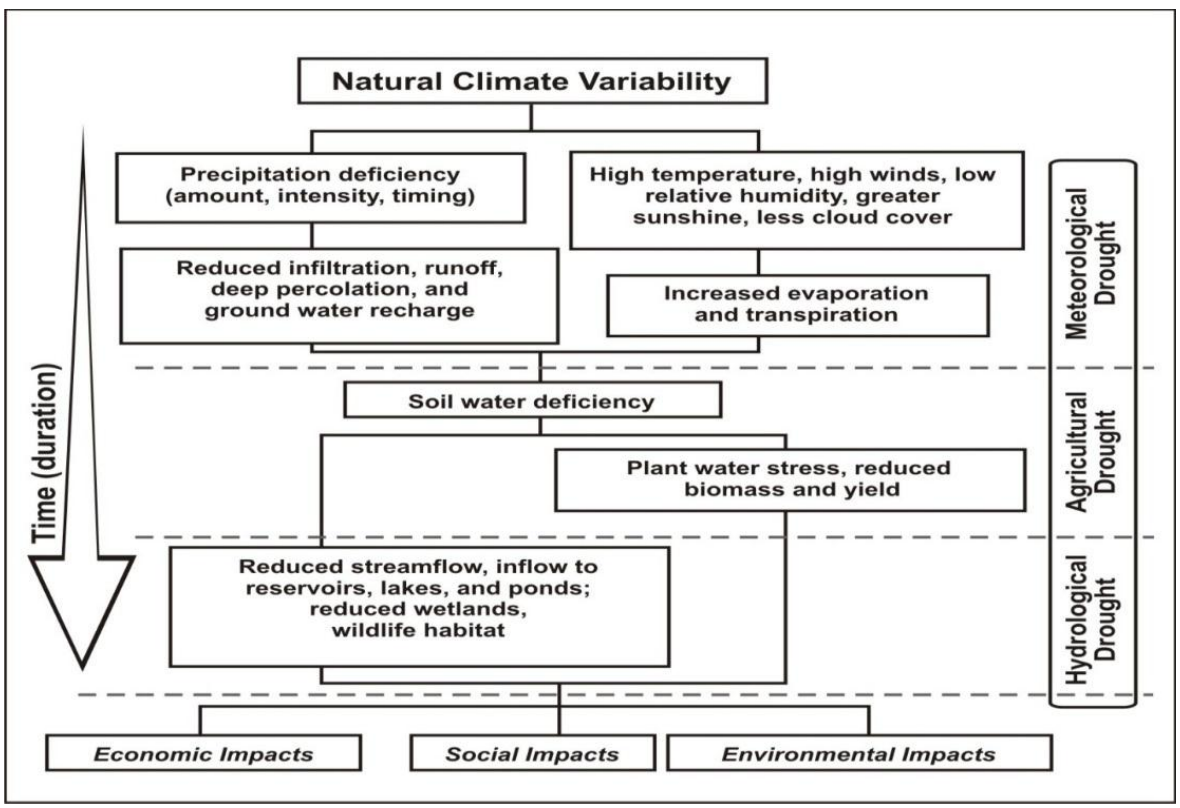

Figure 1: Describes the sequence of occurrence of drought and its impact for three types of droughts. Source (NDMC 2000).

2.2 Types of droughts

There are several drought indices that have been used in hydrology, meteorology and climate studies. Drought indices usually assimilate input data such as rainfall, snowpack, streamflow, and other water resource indicators depending on the operational use for which it is designed. Even though none of the drought indices are essentially superior to the others in all circumstances, some indices are better suited for certain tasks than others. (Heim 2002, Hayes *et al*. 2007, Mishra & Singh 2010, Zargar *et al*. 2011) reviewed strength and weaknesses of the major drought indices used in climatology and meteorology. Some of the widely used indices are described in Table 1.

Table 1: Drought indices (P: Precipitation, ET: Evapotranspiration, M: Meteorological, H: Hydrological, A: Agricultural, SM: Soil Moisture, SF: Streamflow), ReS: Reservoir storage, SP: Snowpack. (Zargar *et al*. 2011).

Drought index	Drought type	Inputs	Notes
Z-index Palmer (1965)	M	P, T, SF, SM, ET	Used for monitoring Short term droughts. Z- Index is useful to identify rapidly developing drought conditions.
Palmer Drought Severity Index (PDSI) Palmer (1965)	M	P, T, SF, SM, ET	PDSI uses readily available temperature and precipitation data to estimate relative dryness.
Palmer Modified Drought Index (PMDI) Palmer (1965)	M	P, T, SF, SM, ET	PMDI
Palmer Hydrological Drought Index (PHDI) Palmer (1965)	H	P, T, SF, SM, ET	PHDI is a modified version of the PDSI to take into account longer-term dryness that will affect water storage, streamflow and groundwater. PHDI has the ability to calculate the offset of the drought based on precipitation needed by using a ratio of moisture received to moisture required to end a drought.
Surface Water Supply Index SWSI (Shafer 1982)	H	P, SF ,ReS, SP	SWSI is calculated to provide an indication of how much surface water will be available for use in any given season.
Crop Specific Drought Index (CSDI)*(Meyer et al*. 2002)	A	P, T, ET	In addition to climatological data CSDI requires soil and crop information to estimates soil water availability for different zones and soil layers by daily intervals. CSDI includes Corn Drought Index and Soybeans Drought Index for Corn and Soybeans respectively.
Reclamation Drought Index RDI (Weghost 1996)	A	P, T, SF	RDI was developed by the Bureau of Reclamation with the aim to determine when a drought episode is severe enough for an area to receive emergency drought relief finds
Soil Moisture Deficit Index (SMDI) (ETDI) (Narasimhan & Srinivasan 2005)	A	M	SMDI and ETDI use a high resolution hydrological model that incorporates a crop growth model. The difference between SMDI and ETDI is that SMDI considers soil moisture in its calculations while ETDI considers the water stress ratio.
Standardized Precipitation Index (SPI) (Mckee *et al*. 1993)	M	P	SPI is simple drought indicator that requires only precipitation as input. It is effective for analysing both wet and dry periods.
Standardized Precipitation Evapotranspiration Index SPEI(Vicente-Serrano *et al*. 2010)	M	P, T, ET	Modified version of the SPI, however incorporates temperature data and considers water balance and evapotranspiration

2.2.1. Meteorological Drought

Meteorological drought is region specific and defined by means of the degree dryness and the duration of the dry period (Palmer, 1965). This measure is mostly used in regions characterized by all year round precipitation. In South Africa, this criterion of defining meteorological drought cannot be used because South Africa is not an all year round precipitation region. In South Africa, most of the areas experience rainfall in summer with few areas like the South Western Cape experiencing rainfall in winter.

Percentage of Normal (PN) is the simplest and one of the oldest methods to identify droughts (Hayes *et al*., 2007). This method compares the observed precipitation with normal precipitation for a particular location and time period. The observed precipitation is then divided by the normal precipitation and multiplied by 100 to get the percentage of normal. Percent of normal is easy to compute and works on a specific location, but it can also be misunderstood because the mean and the median are often different and the data is not normalized.

The deciles or Decile Index (DI) is an index developed by (Gibbs and Maher, 1967) to correct some of the weaknesses of the Percentage of Normal and it is widely used in Australia. This method was applied by the Australian Drought Watch System to characterize and monitor drought, and it requires simple alculations. The DI works by organizing monthly precipitation into deciles, thereby avoiding the problem of fitting a function to the data distribution.

The cumulative frequency distributions are then divided into deciles. The first decile is the group of precipitation values not exceeded by ten percent of all precipitation values. Other decile groups are described by (Monacelli *et al*. 2005; Morid *et al*. 2006). The disadvantage of the DI is that the long-term climatological records needed to calculate deciles might not be available in some data scarce regions(Gibbs and Maher, 1967).

The Palmer Drought Severity Index (PDSI) is one of the oldest and widely used drought index in the United States developed by Palmer (Palmer 1965; Byun & Wilhite 1999; Dai 2011). The PDSI uses precipitation, temperature and soil moisture data as input its mathematical equations. The PDSI received many criticisms which lead to many improvements of the index, some of the limitations and assumptions of the PDSI are documented by (Alley 1984). The self-calibrated PDSI (SC PDSI) tried to improve some of the shortfalls of the PDSI (Alley 1984; Wells *et al*. 2004).

Some indices derived from the PDSI include the Palmer Hydrological Drought Index (PHDI, Mishra & Singh 2012), Palmer Modified Drought Index (PMDI, Dai 2011) and the Palmer Z-index (Karl 1986). Both those indices and others were described in the Review of Twentieth-Century Drought Indices used in the United States of America (Heim 2002). Algorithms to calculate the PDSI and its derivatives can be obtained from (Jacobi *et al*. 2013). The complexity and limitations of the PDSI are due to the fact that it requires extra data other than precipitation time series which prevents many meteorological institutions from using this index.

The World Meteorological Organization (WMO) recommends the Standardized Precipitation Index (SPI) to be used by Meteorological and Hydrological Services as the common meteorological drought index globally (Ren *et al*. 2008). Unlike other indices, the SPI requires only a long-term time series (at least 30 years) of precipitation data (Smakhtin & Hughes 2004; Ren *et al.* 2008). The data is then fitted to a normal distribution, then SPI can be computed for different accumulation periods i.e. 1, 2, 3, 6 12 and 24 months.

The SPI accumulations are only reliable up to 24 months, larger time scales such as 48 months are not reliable unless the rainfall time series contains more than 50 years of data (Guttman 1999). The original computation of SPI by (Mckee *et al*. 1993) fitted the gamma distribution to the precipitation dataset. There has been an attempt by others to fit other probability density functions to the precipitation datasets. Blain (2011) recommended the use of Pearson type III distribution within the calculation algorithm of the SPI for the State of Sao Paulo in Brazil.

For near real-time monitoring of droughts in South Africa, the South African Weather Service (SAWS) is currently using Standardized Precipitation Index (SPI) developed by (Mckee *et al*. 1993). Figure 2, depicts the SPI produced by SAWS at four accumulation periods, computed using monthly rainfall data from South African Weather Service observation network. It can be valuable to calculate the SPI using other probability density functions because the climate of South Africa is unique as compared to the regions where the original SPI was computed.

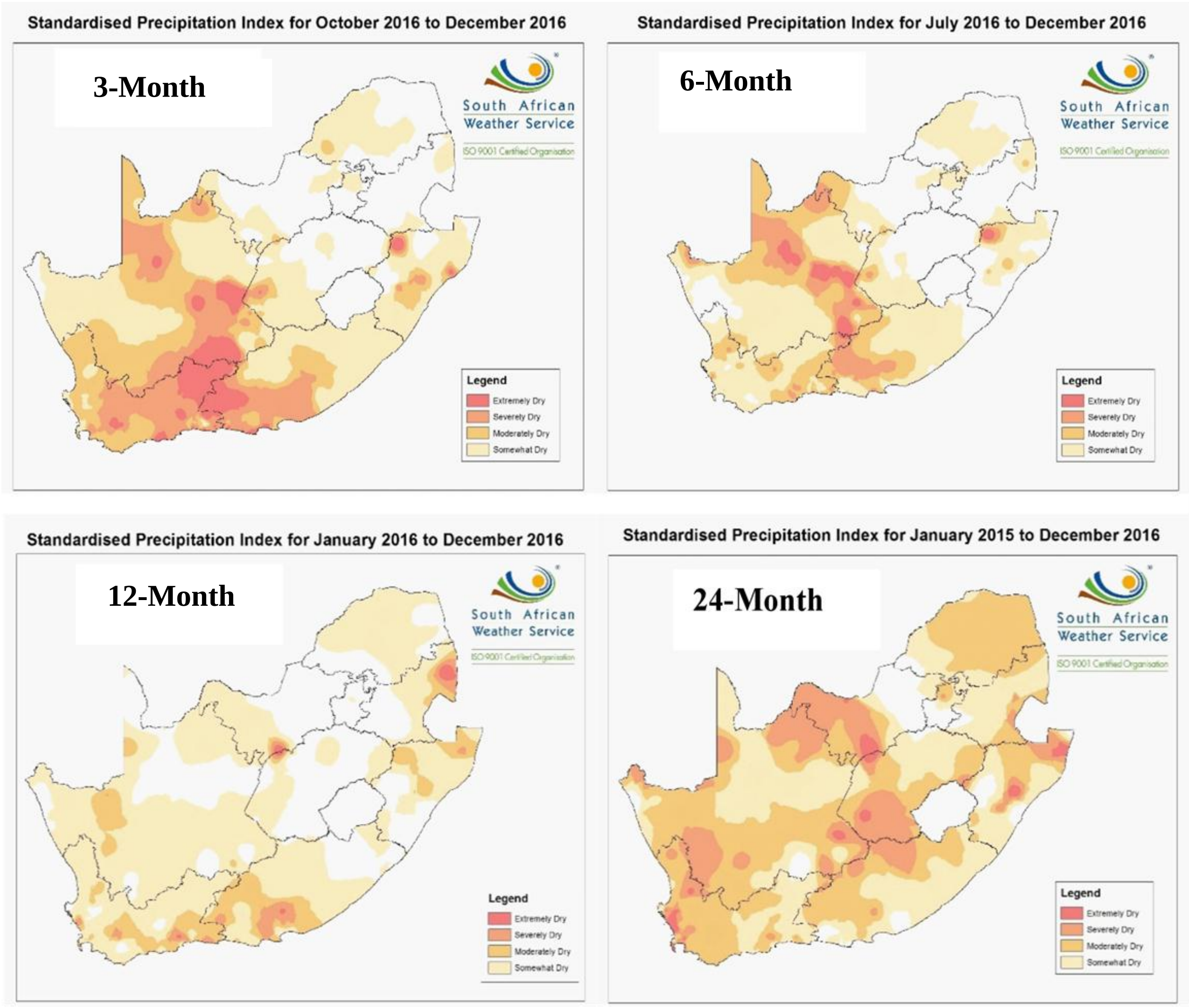

Figure 2: The 3, 6, 12 and 24 months SPI for December 2016 (Obtained from the South African Weather Service).

2.2.2 Agricultural drought

Agriculture is one of the major contributors to the South African economy. Agricultural drought is usually manifested by a deficiency in soil moisture which affects a particular crop at a particular time (Panu & Sharma 2002). The soil moisture availability to plants drops to a level that it is insufficient for normal crop growth and development which in turn affects the crop yield (Mannocchi & Francesca 2004). The possibility using remote sensing data for monitoring agricultural drought have been explored by (Bhuiyan *et al*. 2006).

Crop Specific Drought Index (CSDI) is a PDSI derivative which is used as a crop specific agricultural drought indicator (Meyer *et al.* 1993). CSDI takes into account the water needed during the specific periods of crop growth using the water balance model at the spatial scale of a crop reporting district. The CSDI integrates crop and soil specificity, and the ratio of water consumed by the crop to potential consumption as well as the crop sensitivity during growth stage in which water stress occurs (Meyer *et al*. 1993). The CSDI was developed for corn, but others modified it to include other crops such as soybeans (Wu *et al*. 2004).

Crop Moisture Index (CMI) is an index developed to monitor weekly or short-term crop water conditions across major crop producing regions (Palmer 1968). CMI is defined using the concept of abnormal evapotranspiration deficit, calculated as the difference in actual and computed evapotranspiration. CMI is effective for the detection of short-term agricultural drought by detecting soil moisture in both top and subsoil. One disadvantage of CMI is that it is limited to use only during the growing season, hence it cannot determine the long-term drought.

Soil Moisture Drought Index (SMDI) and the Evapotranspiration Deficit Index (ETDI) are newly developed agricultural drought indices (Narasimhan & Srinivasan 2005). The SMDI is computed using weekly soil moisture deficit normalized by long-term statistics, whereas ETDI is computed in a similar way to SMDI but it also considers the water stress ratio of potential to actual evapotranspiration instead of soil moisture.

2.2.3 Hydrological drought

Hydrological drought may result from long-term meteorological drought which occurs over longer timescales of 24 to 48 months, its severity can be expressed by using drought indices such as Palmer Hydrological Drought Index, Effective Drought Index, and Surface Water Supply Index (Van Loon 2015). The Palmer Hydrological Drought Index (PHDl) is a derivative of PDSI and is based on the daily inflow and soil moisture storage, but does not account for snow accumulation (Mishra & Singh 2012). PHDI may change more slowly than PDSI.

Hydrological drought is caused by the reduction of both surface water and ground water caused by meteorological drought (Sheffield *et al*. 2004). There are many factors that lead to the depletion of those natural water sources, factors such as deforestation. Surface Water Supply Index (SWSI) is used for frequency analysis to normalize long-term data such as precipitation, snowpack, and streamflow and reservoir level (Shafer 1982).

The SWSI is very useful for indicating snowpack conditions in the mountain areas to measure the water supplied for a community, but changing a data collection station or water management policies requires a new algorithm to be calculated. Reclamation Drought Index (RDI) is similar to SWSI but combines the functions of supply, demand, and duration (Weghost 1996) .

Aggregate Drought Index (ADI) is multivariate drought index that considers the bulk quantity of water across meteorological, agricultural and hydrological regimes of drought (Keyantash & Dracup 2004). The ADI is based on six hydrological variables namely precipitation, evapotranspiration, streamflow, reservoir storage, soil moisture content, and snow water content.

Normalized Difference Vegetation Index (NDVI) is the most commonly used vegetation based index that can be used for drought monitoring (Tucker 1979). The NDVI which is based on the difference between maximum absorption of radiation in Red as a result of chlorophyll pigment and the maximum reflectance in Near Infra-Red (NIR) spectral region as result of leaf cellular structure (Tucker *et al.* 2001). The Anomaly of the Normalized Difference Vegetation Index was also developed called Normalized Difference Vegetation Index Anomaly.

Peters *et al* (2002) developed another NDVI derivative called the Standardized Vegetation Index (SVI). This index is based on the fact that vegetation conditions are linked to weather and climate conditions. The SVI describes the probability of variation from normal NDVI over multiple years of data on a weekly time step.

Vegetation Condition Index (VCI) is an NDVI derivative which compares the present NDVI to the range of values observed in the same period in previous years. The VCI is expressed in percentage and gives an idea where the observed value is situated between the extreme values in the previous years. Lower and higher values of VCI indicates bad and good vegetation state conditions, respectively (Liu & Kogan 1996).

2.2.4 Socio Economic drought

Droughts can severely affect the social, environmental and economic well being of a country. After the occurrence of meteorological, hydrological and agricultural drought a Socio-Economic drought may follow. During the abovementioned drought types, the demand and supply of some economic goods such as water, hydro-electricity and some main grain crops such as maize and rice may be reduced. Socio-Economic droughts may cause the demand for economic goods to exceed their supply; this might be caused by weather-related shortage in water supply.

The social impacts of droughts include a shortage of water resources, poverty, unemployment, reduced income, and famine. For instance, the 1992 drought that occurred in South Africa lead to about 50, 000 job losses in the agricultural sector (Ngaka *et al.* 2012). Droughts also affect the environment in many ways such as loss of crops and biodiversity, increase in air pollution, fire hazards and water-borne diseases. A table containing social, economic and environmental impacts of droughts in South Africa can be found in (Vogel *et al.* 1999). Impacts of droughts can be reduced by the availability of proper drought preparedness plans. The number countries who are implementing drought plans are increasing (Wilhite *et al*. 2007)

2.3. Spatial-temporal Analysis of drought

Spatial and temporal patterns of droughts are often hard to describe using simple methods. Recently many studies started to utilize complicated spectral analysis methods such as Fast Fourier Transform (Jehangir & Deg-Hyo 2016), Empirical Mode Decomposition (Zheng *et al*. 2010) and Principal Component Analysis (Sigdel & Ikeda 2010) to analyze time series of different drought indices.

In most studies drought occurrences were analyzed using indices such as the SPI (Jain *et al*. 2014; Vicente-Serrano *et al*. 2010), SPEI (Beguería *et al*. 2014) and the PDSI (Wells *et al*. 2004). Links between drought episodes, oceanic as well as atmospheric indices such as Southern Oscillation Index (SOI), the North Atlantic Oscillation (NAO) Index and other indices have been observed. It has been proved that there is a significant correlation between SOI and summer rainfall in South Africa (Rouault & Richard 2003). SOI is an indication of the development and intensity of El Niño and La Niña in the Pacific Ocean. The SOI is computed using monthly mean sea level pressure anomalies at Tahiti and Darwin Australia (Tularam 2010).

Self-Organizing Maps (SOM's) or neural network method is an important method for recognizing spatially homogeneous clusters in the dataset (Kohonen 1995). One of the disadvantages of SOM's is that they sometimes fail to obtain the right data. However, one of the benefits of SOM's is that they are able to recognize the most significant characteristics of the vector space (Villmann 1999). SOM's are also vital for analysing extreme events such as droughts (Liu 2017) and floods (Kussul & Skakun 2011; Akande *et al.* 2017).

2.4 Drought indices and drought monitoring

Droughts are characterized mainly by using different drought indices. Various countries have developed their own indices, depending on their specifications. In this section, the status of drought monitoring will be discussed for selected drought-prone continents around the world. Drought preparedness, plans and mitigation strategies for Europe, United States of America, Asia, Africa, and South Africa will be presented.

A technical report from Netherlands on drought which also includes other European countries shows that Netherland uses the following indices such as the SPI, SPEI, Standardized Runoff Index (SRI), and the Soil Moisture Anomalies for drought monitoring (Broek 2014). In the report, it was established that drought indices calculated from different variables shows the same major drought events around Netherlands, whereas the indices calculated based on precipitation and evapotranspiration are more variable in time while the indices calculated from discharge and ground water have a smoothed signal.

Tigkas (2008) attempted to develop the drought monitoring system in Greece for four drought-prone areas of Greece namely Thessaly, Athens, Cyclades and Eastern Crete using the Reconnaissance Drought Index (RDI). The SPI was used as an indicator for drought monitoring and early warning in Pinios river basin (Vasiliades & Loukas 2013). The application of the early warning drought system showed reliable and accurate predictions of drought characteristics such as severity, duration, frequency and duration. The SPI was estimated for medium-term prediction intervals at larger timescales of SPI-9, SPI-12, and SPI-24 as well as for short-term prediction intervals at smaller timescales of SPI-3, SPI-6 (Vasiliades & Loukas 2013).

In Portugal, there are two Drought Monitoring Systems managed by the Drought Observatory and the National Information System for Water. The occurrence of meteorological droughts is based on calculations of SPI and PDSI averaged for main river basins and for mainland Portugal, and agricultural droughts based on soil percentage of water content (Santos *et al*. 2010).

In Italy, the Drought Early Warning System for the Po River also known as the DEWS-Po was developed to monitor the drought in the Po river basin. The DEWS-Po is a numerical modelling system providing advanced tools to simulate natural hydrology and water use that affect river flows, allowing managing events through real-time evaluations. The model data from the European Centre for Medium-Range Weather Forecasts (ECMWF) was used as input to the DEWS-Po model. The Drought monitoring system in Italy is based on a set of hydrological or meteorological indices that are calculated at real time and for prediction purposes. Drought indices such as the SPI, SRI, length of the dry period, return period of the dry period, return period of the hydrological drought are used.

Following the 2003 drought that affected most of the European countries, the German Weather Service developed the operational drought monitoring tool based on the Soil Moisture Index (SMI). The SMI is divided into five drought categories ranging from dry to exceptionally dry conditions (Zink *et al.* 2016).

The decile method was selected as the meteorological measurement of drought within the Australian Drought Watch System because it is relatively simple to calculate and requires fewer data and fewer assumptions as compared to other indices like the PDSI (Smith *et al*. 1993). This system has assisted Australian authorities in determining appropriate drought responses. The uniformity in drought classifications, unlike a system based on the percent of normal precipitation. The disadvantage of the decile system is that a long climatological record is needed to calculate the deciles accurately (Gibbs & Maher 1967).

Sectors that are responsible for drought monitoring in the United States of America (USA) are North American Drought Monitor (NADM), National Drought Mitigation Centre (NDMC) and National Integrated Drought Information System (NIDIS). Across all the sectors mentioned above the use of PDSI dominates across the USA, because the PDSI was formulated for their topography (Alley 1984). Across the US the use of US Drought monitor across different drought relief organizations is growing (Svoboda *et al*. 2002).

The US Drought monitor is a decision-making tool produced by the National Oceanic and Atmospheric Administration (NOAA) together with the U.S. Department of Agriculture as well as the National Disaster Management Centre (NDMC). This drought monitoring system was established in 1999, and combine different drought indices to produce one single map every week.

Drought indices based on remote sensing data has been used in the USA and when compared with other standard drought indices they demonstrated greater skill in detecting drought in the Little River Experimental Watershed Georgia United States (Choi *et al*. 2013). This study demonstrated that the Evaporative Stress Index (ESI), Vegetation Health Index (VHI) and the PDSI have greater skill in the area. The inclusion of SPI and SPEI may perhaps result in different results because comparison been SPEI and other indices have proved that it is a better index (Beguería *et al*. 2014).

Asia is the biggest continent in the world as a result, it consists of a wide range of climatic conditions. Monsoon is responsible for 80% of rainfall that falls within the continent. In Asia, countries like India, Afghanistan, Iran, and Pakistan more likely to be affected by droughts. The worst drought in a century that occurred in India has affected about 130 million people, approximately 15 percent of its entire population. The situation is more critical in Afghanistan and Pakistan, where millions of people are at risk but fewer resources to monitor and mitigate droughts are available (Miyan 2015).

There are numerous drought indices that are used over East Asia, such as Precipitation Anomaly (PA), PDSI, SPI, Composite Drought Index (CDI) and Effective Drought Index (EDI; Byun & Kim 2010). The National Climate Center of the China Meteorological Administration uses the SPI for operational monitoring of drought. The China Z- Index (CZI) is also extensively used by the National Climate Center of China for monitoring drought conditions in China. Recently the CZI was compared to other indices such as EDI and SPI (Jain *et al*. 2014). They concluded that the EDI demonstrated the drought condition of the Ken River basin more realistically than other drought Indices.

The South of Asia is comprised countries like, India, Afghanistan, Malaysia, Nepal, Bhutan, Bangladesh, Maldives, Pakistan and Sri Lanka. Of all the mentioned countries only Pakistan and India have reliable Drought Early Warning Systems (DEWS). Most countries that have the DEWS use the SPI for drought monitoring. The use of remote sensing data for drought monitoring is also increasing in Asia (Kogan 1990).

The NDVI and its derivatives such as the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI) were compared in other Asian countries such as India, Afghanistan and Pakistan (Bhuiyan *et al.* 2006). In India SPI, Standardized Soil Moisture Index (SSI), Standardized Runoff Index (SRI) are used to monitor meteorological, agricultural and hydrological droughts respectively (Shah & Mishra, 2015). A report compiled by the Pakistan Meteorological Department shows that the country uses SPI, Cumulative Precipitation Anomaly, soil moisture analysis and the water level of reservoirs for monitoring different types of droughts in the area. (Anon., 2015).

In Africa, various regions have formed specialized centers to help with the mitigation of droughts in the region. The AGRrometeorology HYdrology METeorology (AGRYMET) regional centre was formed in 1974 after the severe drought that affected the Sahel region, to help in monitoring agrometeorological and hydrological systems and act against drought in the Sahel region. The Sahel region is composed of countries such as Bernini, Burkina Faso, Cape Verde, Chad, Ivory Coast, Gambia, Guinea, Guinea Bissau, Mali, Mauritania, Niger, Senegal and Togo.

In 1989 the Intergovernmental Authority on Development (IGAD) Climate Prediction and Application Center (ICPAC) was formed in the Greater Horn of Africa (GHA) region by the contributing countries to provide early climatic warnings regarding weather and climate related disasters. The Greater Horn of Africa (GHA) is one part of Africa that is susceptible to extreme weather conditions such as droughts and floods. The GHA region consists of countries such as Burundi, Djibouti, Eritrea, Ethiopia, Kenya, Rwanda, Somalia, Tanzania and Uganda, Sudan and South Sudan.

Some studies on droughts have been done around the African continent, many of those studies make use of the Standardized Precipitation Index for characterization of droughts. Recently the studies that use the Standardized Evapotranspiration Index (SPEI) are increasing (Stagge & Tallaksen 2014; Edossa et al. 2014; Botai *et al*. 2016).

Masih *et al*. (2014), used geospatial methods to review some of the major droughts over the African continent. Other studies on the characterization of droughts on the African continent include East Africa (Mwangi *et al*. 2014), Northern Africa (Touchan *et al*. 2011), Western Africa (Mishra & Singh 2010) and Southern Africa (Vogel 1994; Vogel *et al.* 2010).

There are also numerous studies that are based on the comparison of different drought indices. Ntale & Gan (2003) modified three drought indices namely PDSI, SPI and the Bhalme–Mooley Index (BMI) to give good description of drought in East Africa. The description and fornulation of the BMI can be found in (Bhalme & Mooley 1980). They concluded that the original PDSI was designed for USA climate conditions, but the modified SPI produced more realistic results than the original index. This modified SPI uses the Pearson III distribution function instead of the original Gamma distribution index.

The SPEI was used to examine the link between the drought and the El Niño events in South Africa (Edossa *et al.* 2014). They concluded that the drought events in the central region of South Africa lag behind the El Niño events by a lag time of approximately eight months. Scientists in the field of meteorology and disaster management officials can utilize this information to develop a drought monitoring desk that can help in planning and prevention.

Most African countries, including South Africa lacks reliable up to date precipitation data, due to sparse distrubution of rain gauges (Naumann *et al*. 2014). Researchers are also looking at the possibility of using other data sources such as reanalysis datasets and satellite derived data for drought monitoring purposes. The feasibility of using the Tropical Rainfall Measuring Mission (TRMM, Huffman et al. 2007), Global Precipitation Climatology Center (GPCC, Becker *et al.* 2013) and European Center for Medium Range Weather Forecasting Center (ECMWF ERA40, Berrisford *et al.* 2009) reanalysis datasets to assess the droughts in four river basins in the Greater Horn of Africa was studied by (Naumann *et al*. 2014). They concluded that it is feasible to use the TRMM dataset for drought monitoring over parts of Africa because of its high resolution.

Institutions in South Africa, such as the University of Cape Town (UCT, Richard *et al*. 2001, Ujeneza 2015, Meque 2015) Central University of Technology (CUT, Edossa et al. 2014), Water Research Commission (WRC, Jordaan 2014) and the South African National Space Agency (SANSA) have been involved in drought monitoring research. SANSA used the remotely sensed data to develop a drought observatory using vegetation change visualization.

2.5 Climate change and droughts

According to the IPCC report, it was projected that the globe will continue to warm during the 21st century (IPCC, 2013). Like many other countries around the globe, climate change is a major concern in South Africa. Climate change will impact numerous sectors in all provinces of South Africa. The main sectors to be impacted by climate change are water, biodiversity, economic, agriculture, energy, air quality, tourism and health. The impacts of climate change in the sectors mentioned above will include, decrease runoff or stream flow, decreased water resources, increased fire danger, decreased water quality and crop production.

Research has shown that South Africa is warming faster than the global average trends (Engelbrecht *et al*. 2015). For instance the mean annual temperatures are projected to increase by 1.5 more as compared to the global average of 0.65^{0}C over the past five decades (Jury 2013; Ziervogel *et al*. 2014). Due to this the frequency of extreme events such as floods, heat waves and droughts are expected to increase (IPCC 2014; Spinoni *et al*. 2015; IPCC 2017) .

As a result of global warming and climate change droughts are also projected to increase in frequency, duration and severity in many areas around the globe (Burke *et al*. 2006; Loukas *et al*. 2008; Dai 2011; Duffy *et al*. 2015). The increase in frequency, duration and severity of droughts were also found to be significant in the African continent (Spinoni 2014).

Recent droughts in South Africa has resulted in serious economic, environmental and socio-economic consequences (Meissner & Jacobs-Mata 2016) The 1992/93 was one of the most severe droughts in South Africa (Ngaka *et al*. 2012 ;Austin 2008). The drought also resulted in crop failure and loss of jobs in the agricultural sector. Staple foods like maize had to be imported from other countries (Ngaka *et al*. 2012).

As the frequency of droughts is expected to increase in South Africa a reliable drought preparedness plan to prepare for future droughts will be required. Following the 2015/2016 drought it was recommended that South Africa need to be more proactive in its preparedness for droughts (Meissner & Jacobs-Mata 2016). A proficient drought preparedness plan will require Drought- Early Warning System, drought preparedness plan, Mitigation and Management (Wilhite *et al*. 2007; Meissner & Jacobs-Mata 2016).

The ability to predict changes in the agro-hydrological system remains uncertain due to its complexity (Duffy *et al.* 2015). Global Climate Models are essential tools for projecting future climate at gridded scale, however GCM's typically have course resolution and cointains bias (Meresa *et al.* 2016). Numerous studies have applied bias correction methods to RCM/GCM before using them for agro-hydrological analysis (Lafon *et al*. 2013; Teng *et al*. 2014)

The CO-ordinated Regional Downscaling Experiment (CORDEX) was designed to generate high resolution regional climate change projections, explanations of the CORDEX experiments are documented by (Gutowski *et al.* 2016).The CORDEX experiments were performed for different regions including Africa (Nikulin *et al*. 2012) and Europe (EURO CORDEX, Jacob *et a*l. 2014).

The output from the CORDEX experiments are datasets containing different atmospheric variables with defined domains and model resolutions (Gutowski *et al*. 2016). Stagge *et al* (2015) used the EURO CORDEX data to project meteorological droughts in Europe. Over the Asian continent, numerous studies on the projection of future drought were done (Lee *et al*. 2016; Kim *et al*. 2016). Studies on using future projections for drought predictions in Africa including South Africa are inadequate.

One of the objectives of this study is to use temperature and precipitation from Africa CORDEX experiments to analyse future trends of drought intensity, severity, frequency and duration in South Africa. This information will be very useful for future droughts preparedness in South Africa, especially in arid and semi-arid drought prone regions.

CHAPTER 3: DATA AND METHODS

This chapter gives an overview of the data analysis and the methodology followed to carry out the analysis. It also contains the description of the study area which includes the climatic conditions as well as socio-economic, biophysical and ecological aspects of the study are. Different datasets used in this study were also described. Methods used to analyse the models and observations were also explained. This also includes the mathematical formulae and software's used to carry out the analysis.

3.1 Study Area

South Africa is located in the sub tropics about (22^0-35^0)S and (17^0-33^0)E covering about 1 219 603km^2 (Edward 2016). The country receives about 495mm per year average annual rainfall compared the global average of 860mm per year (Tadross & Johnston 2012). The climate varies from tropical and sub-tropical in the North/central regions, to semi-arid and arid climates in the South (Tadross & Johnston 2012). All climate regions in South Africa contribute to both crop and animal farming. Therefore droughts will pose threat to water supply, which will affect agriculture and productivity in South Africa.

The climate of South Africa is highly variable and composed of Arid (desert), semi-arid (steppe), tropical wet and tropical wet-and-dry as shown in Figure 3 . The Semi-arid areas in South Africa are characterised by high rainfall variability, frequent droughts, low soil moisture and extreme events such as flash floods (Vogel 1994; Vetter 2009). Most people living in semi-arid areas in Southern Africa are generally poor and dependent on rain-fed agriculture for survival (Dian *et al.* 2015).

Vegetation change is one of the major challenges in the arid and semi-arid area of South Africa (Vetter 2009). In South Africa rangelands are often degraded and grazing becomes inadequate during dry period due to overgrazing and droughts (Archer *et al*. 2008)**.** Productivity in the rangelands will be affected by climate change (Archer *et al*. 2008).

Most parts of the Western and Eastern Cape provinces are characterized by Mediterranean climate. This region receives between 300 to 900 mm average rainfall per year mostly during winter (Dian *et al*. 2015). Agriculture consumes most of the water in this area; therefore decrease in water supply due to agricultural droughts will impact on fruit exports. This will also have big impact on seasonal employment especially in the fruit industry. On the other hand the economic growth for the province and the country will be highly affected.

3.2 Data

3.2.1 Ground network of Automatic Weather Stations (AWS)

For characterization of historical drought conditions in South Africa the historical/observational data of precipitation and temperature from 10 meteorological stations in South Africa will be used in this study. A map showing geographical location of the stations used in this study is shown in Figure 3. The map of the study area in Figure 3, was further divided according to different climatic regions.

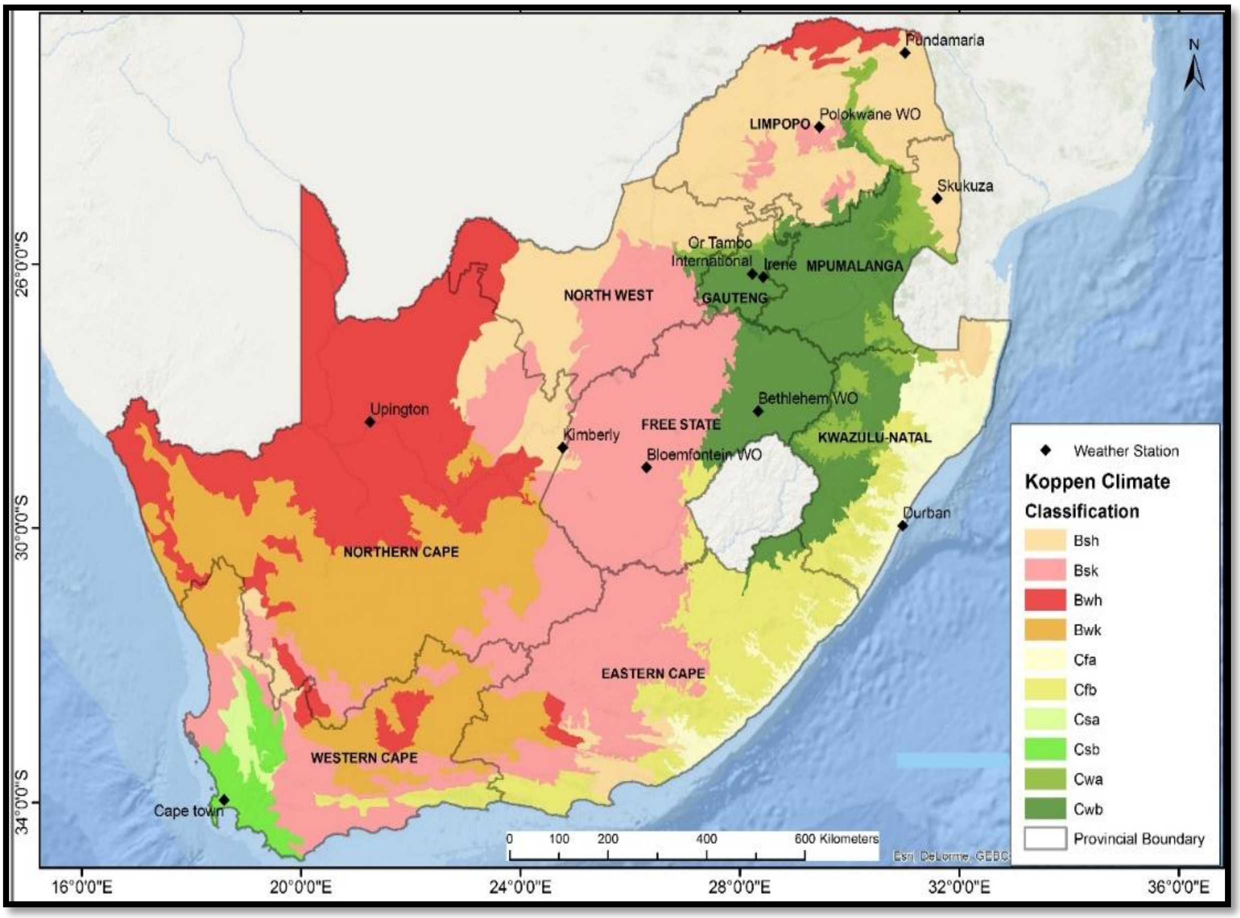

Figure 3 : Map showing geographical location of 10 Automated Weather Stations used in the study. Different climatic regions shown in the map are BW (Desert/Arid), BS (Steppe/Semi Arid), Csa (Winter rain with hot summers), Csb (Winter rain with coolsummers), Cfa (All year Rain with hot summers), Cfb (All year rain with cool summer Cwa (All year rain with hot summers), Cwb (All year rain with cool summers).

Table 2: List of Automated Weather Stations (AWS) used in this study.

Station Name	Latitude	Longitude	%Data gaps	Elevation(m)
Bloemfontein WO	-29.1	26.3	0.00133	1353
Durban	-29.97	30.97	0.0489	14
Cape town	-33.97	18.60	0.0511	42
Irene	-26.2	28.43	0.00904	1524
Or Tambo International	-26.15	28.23	0.00697	1695
Kimberly	-28.8	24.77	0.000995	1196
Bethlehem WO	-28.2497	28.3336	0.0379	1687
Upington	-28.41	21.26	0.0612	835
Polokwane WO	-23.86	29.45	0.0151	1226
Skukuza	-24.98	31.6	0.00922	276
Pundamaria	-22.6920	31.058	0.0170	457

3.2.2 Tropical Rainfall Measuring Mission data

In most African countries there is still a challenge regarding the availability and spatial distribution of rainfall gauges or Automated Weather Stations. Reanalysis datasets and other precipitation estimation tools play an important role in supplementing observational datasets. In this study gridded rainfall data from Tropical Rainfall Measuring Mission (TRMM) satellite was used. TRMM is a Multi satellite Precipitation Analysis estimation dataset available from 1998 to 2015. This dataset combines the estimates from TRMM, 3B-42 satellite, the Climate Anomaly Monitoring System gridded rain gauge data and the Global Precipitation Climate Center (GPCC) global rain gauge dataset at $0.25^0 \times 0.25^0$ resolution (Huffman *et al*. 2007).

3.2.3 Regional Climate Model data

In order to compare the current drought conditions with the predicted future droughts, the Rossby Center Regional Climate Model (RCA4) was used. The RCA4 is the Swedish Meteorological and Hydrological Institute RCM that participated in downscaling Global Climate Models under the Coordinated Regional Downscaling Experiments (CORDEX, Kjellström *et al*. 2016). An ensemble of nine models GCM models from CORDEX Africa experiment downscaled using RCA4 model under Representative Concentration Pathway (RCP) 8.5 was used in this study.

The list of the GCM's used to create the ensemble average of precipitation and temperature data is shown in Table 3. RCP8.5 scenario forms part of a range of forcing levels that are associated with other emission scenarios published in the literature. High population with relatively slow income growth with a modest rate of technological change and energy intensity improvements are modeled into the models (Riahi *et al*. 2011). This leads to long-term to high energy demand and greenhouse gases emissions. Other emission scenarios such as RCP2.6 and RCP4.5 are also described in (Meinshausen *et al*. 2011).

Surface temperature and precipitation from an RCM driven by nine GCM's were used to calculate the SPEI time series. The historical base period of 1971-2000 and for two future periods 2011-2040 and 2041-2070. All GCM's have differerent horizontal resolutions as shown in Table 3, therefore reggridding was done to harmonise all models to the common grid of 0.25^0 (about 25km).

Table 3: List of 9 CMIP5 GCMs that have been used to provide boundary conditions for the RCA4 runs.

	Center Name	Model Name	Resolution	References
1.	Canadian Centre for Climate Modelling and Analysis	CanESM2	165x126	(Chylek *et al*. 2011)
2.	Centre National de Recherches Météorologiques	CNRM-CM5	165x126	(Voldoire *et al*. 2013)
3.	EC-EARTH consortium	EC-EARTH	165x126	(Hazeleger *et al*. 2012)
4.	NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2M	165x126	(Dunne *et al*. 2012)
5.	Met Office Hadley Centre	HadGEM2-ES	165x126	(Jones *et al*. 2011)
6.	Institut Pierre-Simon Laplace	IPSL-CM5A-MR	165x126	(Dufresne *et al*. 2013)
7.	National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	MIROC5	165x126	(Watanabe *et al*. 2010)
8.	Max Planck Institute for Meteorology	MPI-ESM-LR	165x126	(Giorgetta *et al*. 2013)
9.	Norwegian Climate Centre	NorESM1-M	165x126	(Bentsen *et al*. 2012)

3.3 Method of analysis

3.3.1 Data homogenization

The quality of meteorological data such as precipitation and temperatures depends on a number of factors, such as a location of the measuring instruments, the method of recording and collection. Many statistical methods have been proposed for quality control and testing homogeneity in a meteorological or hydrological time series (Kanji 2006). These methods can be classified into absolute and relative methods. Absolute methods are mainly applied to isolated stations without considering neighbors, whereas relative methods use records from neighboring stations which are presumed to be homogeneous (Wijngaard *et al*. 2003).

Various statistical methods have been used in the literature to test the homogeneity of a time series, these include, Von Neumann Ratio Test (VNR, Von Neumann 1961; Kang & Yusof 2012) , Buishand range test (Buishand 1982) and Standard Normal Homogeneity Test (SNHT, Alexandersson & Moberg 1997; Toreti *et al*. 2011). In this study, two methods were used to test the homogeneity of the rainfall time series before the drought indices are calculated. The VNR is a test that uses the ratio of mean square successive (year to year) difference of variance. The Formula is as follows.

$$N = \frac{\sum_{i=1}^{n-1}(Y_i - Y_{i+1})^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \qquad (1)$$

Yi = is asssumed to be successive observations on stationary Gaussian time series

$\bar{Y}$ = Average of Yi’

n = Total number of observations

The Standard Normal Homogeneity Test (SNHT) is one of the commonly used methods of testing the homogeneity of the time series (Alexandersson & Moberg 1997). The SNHT is based on the assumption that the precipitation amount at the station being tested is proportional to the average of the surrounding stations (Alexandersson 1986). The null hypothesis is that the whole series is homogeneous, which implies that entire series is normally distributed with the mean of zero and the standard deviation of 1.

The alternative hypothesis suggests that the series have some breaks and the mean value changes abruptly (Alexandersson & Moberg 1997). Unlike other homogeneity testing methods, SNHT is able to detect the breaks near the beginning and the end of the series.The test statistic *T*(*y*) is used to compare the mean of the first *y* years with the last of (*n*-*y*) years. *T*(*y*) can be calculated using the following equation.

$$T_y = y \times \overline{z}_1 - (n-y)_i \, \overline{z}_2 \qquad y = 1, 2, ...n \qquad (2)$$

The first step is to calculate the standardized series of ratios z_i given by:

$$z_i = \frac{(q_i - \overline{q})}{s_q} \qquad (3)$$

where $\overline{q}$ = is the arithmetic mean of the ratios and s_q is the sample standard deviation of the ratios

The standardized series of ratios are given in equation 4.

$$\overline{z}_1 = \frac{1}{y}\sum_{i=1}^{n}\frac{y_i - \overline{y}}{s} \quad \text{and} \quad \overline{z}_2 = \frac{1}{n-y}\sum_{i=y+1}^{n}\frac{y_i - \overline{y}}{s} \qquad (4)$$

The year *y* consisted of break if value of *T* is maximum. To reject null hypothesis, the test statistic, T_0 must be exceeds a certain critical value at a certain confidence level, depending on the sample size. However the 90% confidence level is preferable since the real inhomogeneous series can be easily detected

Where $$T_0 = \max_{1 \le y \le n} Ty \qquad (5)$$

3.3.2 Drought Indices (DI)

Standardized Precipitation Index (SPI)

In this study, the Standardized Precipitation Index (SPI) developed by (Mckee *et al* ., 1993,1995) is used to characterize the past and future drought conditions since it requires only precipitation data as input. The first step in calculating the SPI index is to determine a Probability Density Function (PDF) that describes precipitation time series of observations under analysis (Guttman 1999).

The two parameter Gamma distribution function and the Pearson type III distribution is tested in this study to describe the precipitation observations for all time scales at a site or nearby station. Once the PDF is determined, the cumulative probability of an observed precipitation will be determined (Blain 2013).The inverse normal function is then applied to the cumulative probability resulting in SPI.

The Gamma distribution function is defined by:

$$g(P) = \frac{1}{\Gamma(\alpha)} P^{\alpha-1} e^{-P/\beta} \quad \text{for } P>0 \tag{6}$$

Where α >0 α is a shape parameter

β >0 β is a scale parameter

P >0 P is the precipitation amount

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \tag{7}$$

In equation 7 $\Gamma(\alpha)$ is the Gamma Function. Where Alpha (α) and beta (β) are estimated by the following equations:

$$\alpha = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right. \tag{8}$$

$$\beta = \frac{P}{\alpha} \tag{9}$$

$$A = \ln(\overline{P}) - \frac{\sum \ln P}{n} \tag{10}$$

n = is the number of observations

The Gamma function is undefined for P=0, therefore, the cumulative probability function becomes:

$$H(P) = q + (1 - q)G(P) \quad (11)$$

Where H (P) = Cumulative probability

q = Probability of a zero

G (P) = Cumulative probability of the incomplete Gamma function

The cumulative probability function $H(P)$ is converged into the standard normal cumulative distribution function so that both of them have the same probability. The normal cumulative distribution function is then transformed to the standard normal random variable z with the mean equal to one, which is the value of the SPI. Accumulated SPI are values used to analyze drought severity. Drought begins when the SPI value falls below zero and ends when SPI becomes positive (Mckee *et al*. 1993). Drought intensities are categorized by McKee *et al*. 1993 using the categories described in Table 4.

Table 4: SPI values and their measure of severity.

SPI values	Drought category
2.0+	Extremely wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.00 to -1.49	Moderately Dry
1.50 to -1.99	Severely dry
<=-2.00	Extremely dry

One advantage of the SPI is that it can be calculated for various accumulation periods. SPI-3 measures rainfall accumulation thee months period. SPI-3 is often used for meteorological or basic drought monitoring. The six month accumulation period (SPI-6) is used for agricultural drought monitoring, whereas the twelve month accumulation period SPI-12 is used for hydrological drought monitoring.

Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI), developed by (Vicente-Serrano *et al*. 2010) was also used in this study. The SPEI is the modified version of the SPI. The inclusion of the evapotranspiration in the calculation of SPEI makes it possible for it to explore the effects of global warming (Beguería *et al*. 2014). SPEI also considers the monthly climatic balance which is precipitation less the Potential Evapotranspiration (P-PET) in its calculations. Different methods are available for calculating PET, but the Thornthwaite method will be used in this study because it requires only temperature measurements (Thornthwaite 1948).

$$PET = 16K\left(\frac{10T}{I}\right)^{m} \tag{12}$$

Where T is the average monthly temperature, I is the heat index, K is the correction coefficient

I is given by $$I = \left(\frac{T}{5}\right)^{1.514} \tag{13}$$

K is given by $$K = \left(\frac{N}{12}\right)\left(\frac{NDM}{30}\right) \tag{14}$$

Where N= Maximum number of sun hours

NDM = Number of days in a month

Unlike with the SPI, the three parameter Pearson III distribution is needed to calculate the SPEI, whereas the SPI requires two parameter distribution such as the Gamma distribution.

3.3.3. Time series Analysis

Trends

Parametric and Non-parametric methods have been developed to detect trends in hydrometeorological time series. Methods such as linear regression, Man-Kendall Test (MK) Sen slope estimator and Bayesian procedure have been used for trend detection in the time series (Gocic & Trajkovic 2013). One of the widely used methods for trend detection is the nonparametric Mann-Kendall statistical test (Drapela & Drapelova 2011).

The main aim of the MK Test is to evaluate if there exists a statistical monotonic upward or downward trend of the variable over time. One of the disadvantages of the MK test is that it does not take into account the presence of a positive serial correlation in a time series (Yue *et al*. 2003). Serial correlation in a time series may increase the probability of the significant trend to be detected by the MK test.

In order to resolve the serial correlation problem, proposed a pre-whitening procedure for reducing the influence of auto regression component on the application of the MK test was proposed by (VonStorch, 1995). Pre-Whitening can be done using two methods, namely the Zhang method (Zhang *et al*. 2000) as well as the Yue and Pilon method (Yue et al. 2002). The two methods differ in their pre-whitening approach. The Yue and Pilon method will be used in the current analysis. In this method, the first step is to calculate the slope using the Theil-Sen Approach (TSA, Theil 1950; Sen 1968).

3.3.4 Drought monitoring indicators

According to (Dracup & Lee 1980), a drought event can be characterized using its onset and offset intensity, duration, frequency, and magnitude. Indicators such as drought intensity, drought severity, and drought frequency can be calculated using mathematical formulae based on the drought index and further presented using spatial maps. The knowledge of drought monitoring characteristics can help the drought monitoring centers as well as the disaster management centers to assess the impact caused by drought.

Drought Frequency

Drought frequency is usually defined by its return period or by the average lag time between two drought events. Drought frequency (F_S) is an indicator used to measure the drought liability during a study period. F_S is given by the equation below:

$$F_s = \frac{n_s}{N_s} \times 100\% \qquad (15)$$

where n_s = is the number of droughts events

N_s = is the total number of years for the study period

s = Station

Drought Magnitude or Severity

Drought magnitude or severity (S_e) is defined as the absolute value of the sum of the drought index (i.e. SPI/SPEI) values during the drought event. S_e is given by the equation below:

$$S_e = \left| \sum_{j=1}^{m} index \right|_e \qquad (16)$$

M=number of months

Drought Intensity

Drought Intensity (DI_e) is calculated by using the drought severity (S_e) divided by the drought duration (*m*). DI_e is given by the equation below:

$$DI_e = \frac{S_e}{m} \qquad (17)$$

The larger the DI_e value the more severe the drought.

CHAPTER 4: CHARACTERIZATION OF DROUGHTS IN SOUTH AFRICA USING IN-SITU OBSERVATIONS

4.1 Introduction

Spatio-temporal variation of historical droughts in South Africa was done using point observations as well as gridded TRMM satellite datasets. Several statistical parameters were calculated for all stations in the study area. Other frequency analysis methods such as probability density functions and trend analysis were used to determine the probability and trends in mild, moderate, severe, and extreme drought events.

4.2 Temporal variability of droughts derived from SAWS station network

In order to characterize temporal evolution of historical droughts in South Africa time series of SPI-3 and SPEI-3 were analyzed using data from 10 stations. In particular, SPI-3/SPEI-3 time series shown in Figure 4 and Figure 5 have been analyzed in order to illustrate the inherent temporal patterns of historical droughts at the selected stations. The red color or negative values of SPI-3/SPEI-3 depicts dry condition whereas the blue color (positive values) denotes wet conditions. It is evident from the figures that there exists some seasonal, inter-annual and decadal variability in both wet and dry conditions in South Africa. SPI-3 and SPEI-3 show similar wet and dry spells temporal patterns with slight differences in the intensity.

Both indices managed to detect the severity and duration of drought episodes experienced between 1980 and 2015. The magnitude of the drought episodes differs in different stations and in different climatic regions. The onset and end period of the drought episodes also differs according to stations. Drought duration in South Africa ranges from 1 up to 36 months. The longest drought duration was experienced in Upington in the Northern Cape province which lasted for 36 months during 1990/91/92. Stations such as Pundamaria, Skukuza and Upington experinced extreme drought during 1982/83.

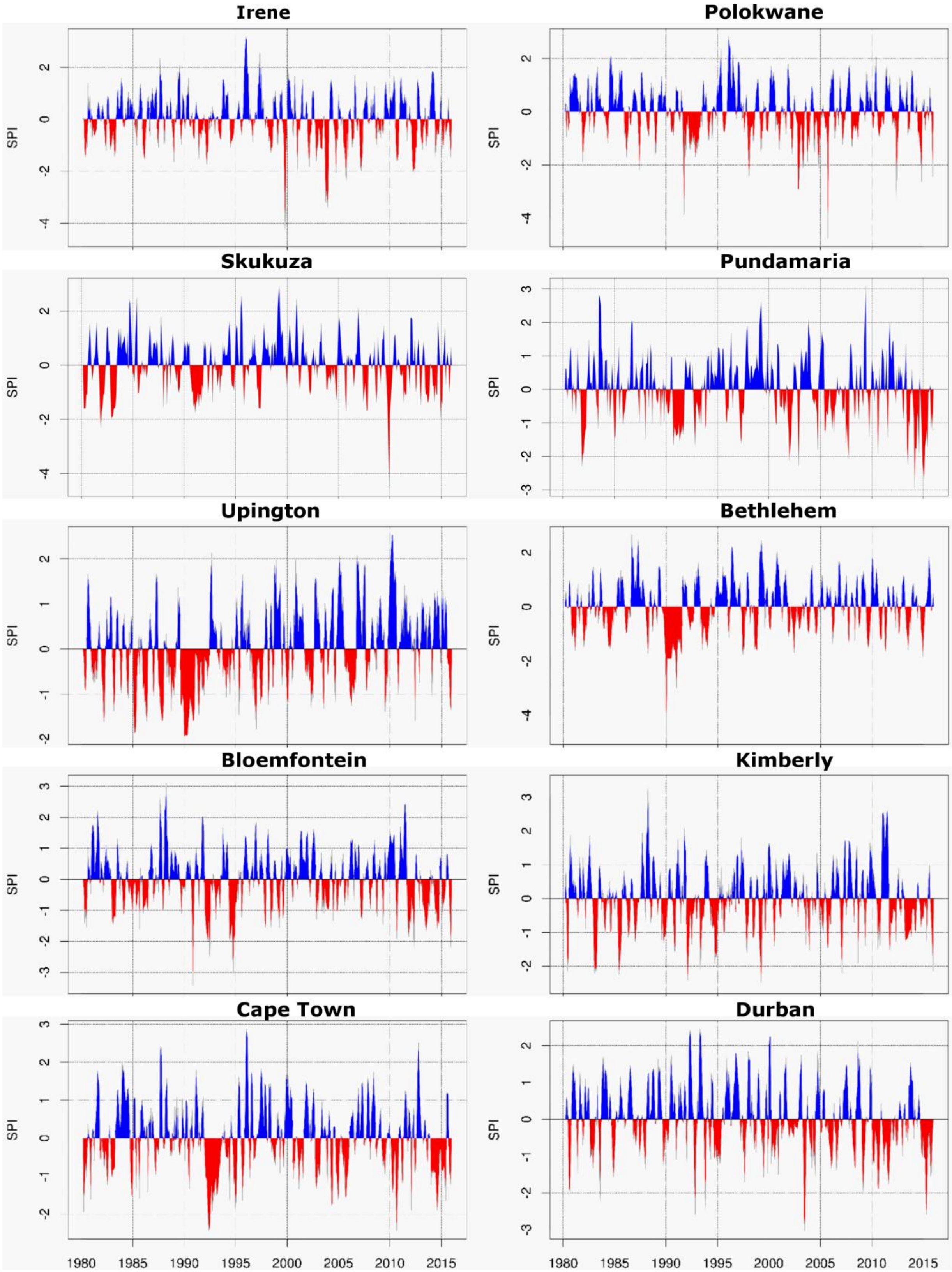

Figure 4: Temporal variation of droughts based on SPI-3 time series for the period 1980-2015 for 10 station selected.The blue and red color indicates wet and dry conditions respectively.

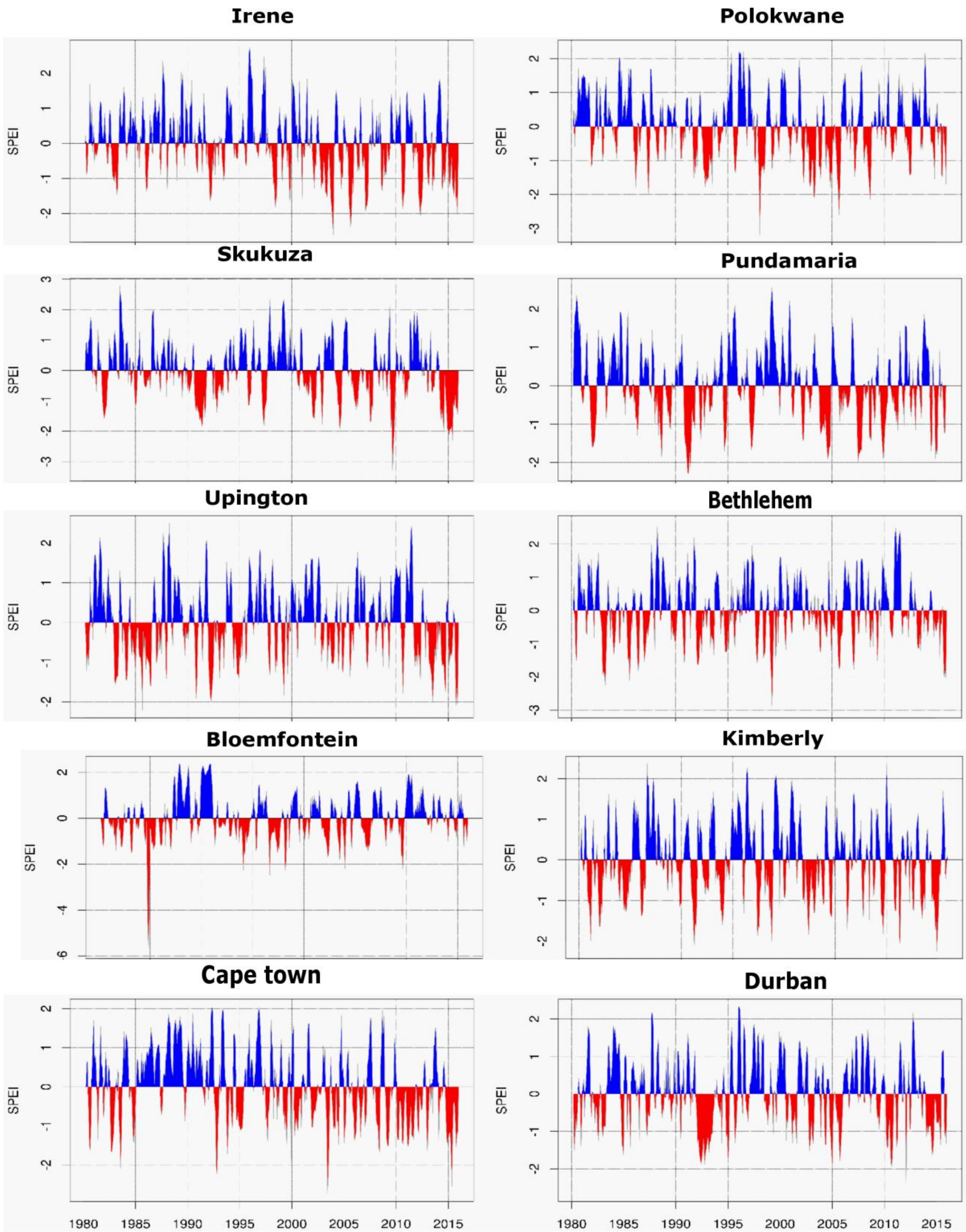

Figure 5 : Temporal variation of droughts based on SPEI-3 time series for the period 1980-2015 for 10 stations selected. The blue and red color indicates wet and dry conditions respectively.

The overall percentage of dry and wet spells varies at each station as shown in Figure 6. Overall Polokwane exhibits fewer dry spells compared to all other stations, whereas Kimberly has the highest total number dry spells events. The lowest number of dry spells in Polokwane might be attributed to the fact that the area is classified as having subtropical climate and Kimberly is classified as having an arid climate.

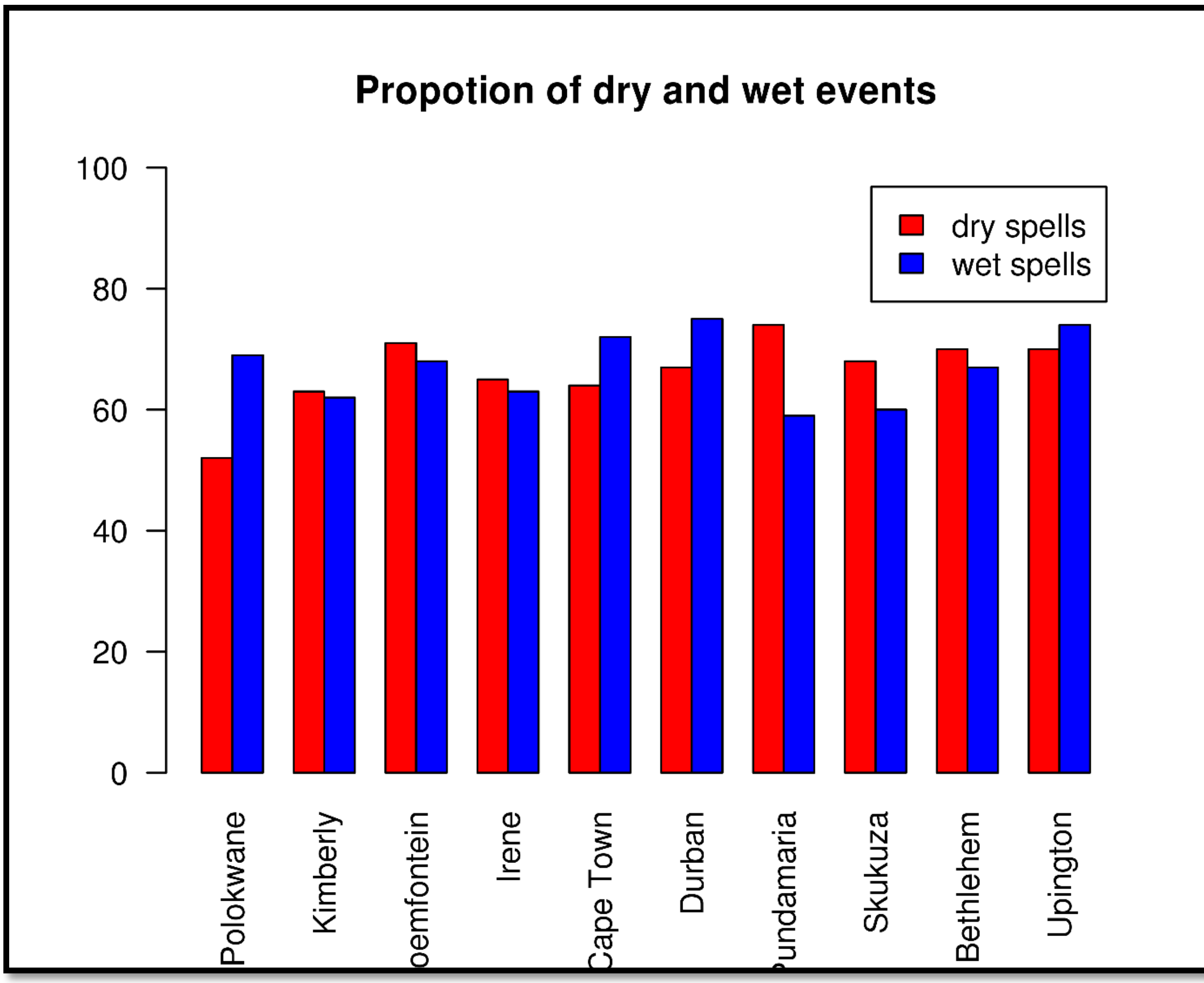

Figure 6: Overall proportion of dry and wet spells across different stations within the study area, calculated using SPEI-3.

4.2.1 Statistical Analysis

Statistical analysis of the SPI-3 and SPEI-3 confirms the variability of droughts in different stations as shown by the results in Table 5. The SPI-3 and SPEI -3 statistical parameters seem to be very comparable for all the ten stations analyzed. Bloemfontein has the highest mean value (i.e -0.83, -0.82) for both SPI-3 and SPEI-3 time series whilst Cape Town has the lowest mean value (i.e -0.72) of SPI-3 time series.

All ten stations have negative skewness with Polokwane having the lowest value (-2.22) of skewness, whist Durban has the highest value (-0.70) of SPI-3 skewness. The negative value of skewness indicates that the dry spells are skewed to the left of the normal distribution. The kurtosis on the other hand is positive for most of the stations representing the heavy tailed distribution, except for Durban which has negative kurtosis for both SPI-3 and SPEI-3 time series.

The highest value of SPEI-3 kurtosis(19.6) was observed at Upington, whilst the lowest value of kurtosis(-0.47) for the SPI-3 time series was observed at Bloemfontein WO. The SPEI-3 time series seems to have lower skewness values as compared to the SPI-3. Two stations, Bloemfontein and Irene have negative kurtosis, which implies that the data from the two stations have light tails and lack outliers.

Table 5: Summary of statistical parameters calculated for both SPI-3 (<0) and SPEI-3(<0) time series

	SPI					SPEI				
Station	mean	sd	median	skew	kurtosis	mean	sd	median	skew	kurtosis
Polokwane WO	-0.79	0.68	-0.63	-2.22	7.4	-0.82	0.56	-0.70	-0.82	0.70
Bloemfontein WO	-0.83	0.59	-0.78	-1.13	2.15	-0.82	0.49	-0.81	-0.38	-0.42
Irene WO	-0.79	0.67	-0.63	-1.89	5.83	-0.78	0.57	-0.67	-0.65	-0.32
Kimberly WO	-0.76	0.58	-0.62	-0.88	0.15	-0.78	0.54	-0.67	-0.8	0.46
Durban	-0.77	0.54	-0.67	-0.70	-0.15	-0.82	0.52	-0.75	-0.45	-0.41
Cape Town WO	-0.72	0.58	-0.60	-1.25	1.81	-0.81	0.53	-0.78	-0.63	0.27
Pundamaria	-0.80	0.61	-0.75	-1.50	8.88	-0.79	0.56	-0.67	-0.58	2.36
Skukuza	-0.79	0.60	-0.67	-0.91	3.45	-0.79	0.59	-0.67	-0.93	3.91
Upington	-0.76	0.49	-0.68	-0.46	3.40	-0.73	0.70	-0.54	-3.10	19.16
Bethlehem WO	-0.80	0.62	-0.71	-1.66	2.48	-0.79	0.51	-0.72	-0.53	2.48

4.2.2 Trend Analysis

The significance of the trends in the SPEI-3 time series was tested using the TFPW test and the results are shown in Table 6. Two statistics namely the probability value (p-value) and the Kendall tau statistic were used to test for trends in the dataset. The Kendall tau statistic tests whether there exists a positive (increasing) or negative (decreasing) trends in the time series. However, the p-value is used to deduce if the trend is statistically significant at 95% confidence interval (i.e. $p<0.05$). The SPEI-3 time series was divided into three decades as shown in Table 6, the (p-value) as well as the Kendall tau statistics were calculated for the three decades. Statistically significant time series are highlighted by a grey color.

Negative or decreasing trends were observed in Polokwane, Pundamaria, Skukuza, Bethlehem, Durban and Cape Town during the decade 1986-1995 however, the decreasing trend was not statistically significant since the calculated p-value was greater than the critical value (i.e 0.05). During the same decade positive/increasing trends were observed in Irene, Bloemfontein and Kimberly but the trends were not statistically significant.

During 1996-2005 decade, a decreasing trend was observed in all stations except for Cape Town however, only Irene and Durban exhibits statistically significant trends with a p-value less than the critical value. During the 2006-2015 decade negative/decreasing trends were observed in all stations except for Upington, but the decrease was only significant in Irene, Kimberly and Cape Town. Four stations, namely Bethlehem, Skukuza, Polokwane and Durban have shown a decreasing trend in all the three decades.

Table 6: The results of the TFPW performed on the SPEI-3 time series.

Station	1986-1995		1996-2005		2006-2015	
	p-value	tau	p-value	tau	p-value	tau
Polokwane	0.77	-0.0259	0.75	-0.0313	0.471	0.0449
Irene	0.86	0.0159	0.0218	-0.206	0.00580	0.1750
Bloemfontein	0.23	0.119	0.205	-0.103	0.569	0.0354
Kimberly	0.23	0.104	0.55	-0.0536	0.0262	0.1380
Durban	0.25	-0.0974	0.020	-0.214	0.0262	0.0137
Cape Town	0.27	-1.045	0.76	0.0269	0.013	0.229
Pundamaria	0.53	-0.0062	0.31	-0.020	0.51	0.0031
Skukuza	0.17	-0.0077	0.53	-0.0019	0.159	0.0072
Upington	0.59	0.0024	0.90	0.00027	0.27	0.0073
Bethlehem	0.93	-0.373	0.98	-0.0027	0.11	0.0095

In general, the boxplots in figures Figure 7, Figure 8 and Figure 9 ,shows that the observed SPI-3 and SPEI-3 does not vary significantly. For Polokwane and Irene, the box plots show higher probability in the occurrence of moderate and severe droughts. Cape Town and Durban there is a higher probability of severe droughts as depicted by both the 3-month SPI and 3-month SPEI.

The probability of occurrence of moderate and severe dry events is higher in all six stations, with a low probability of occurrence of mild and extremely dry events. Both SPI-3 and SPEI-3 time series showed similar results except for Bloemfontein where SPEI-3 show a higher probability of occurrence of extremely dry events. Cape Town and Durban show the same probability of occurrence percentage.

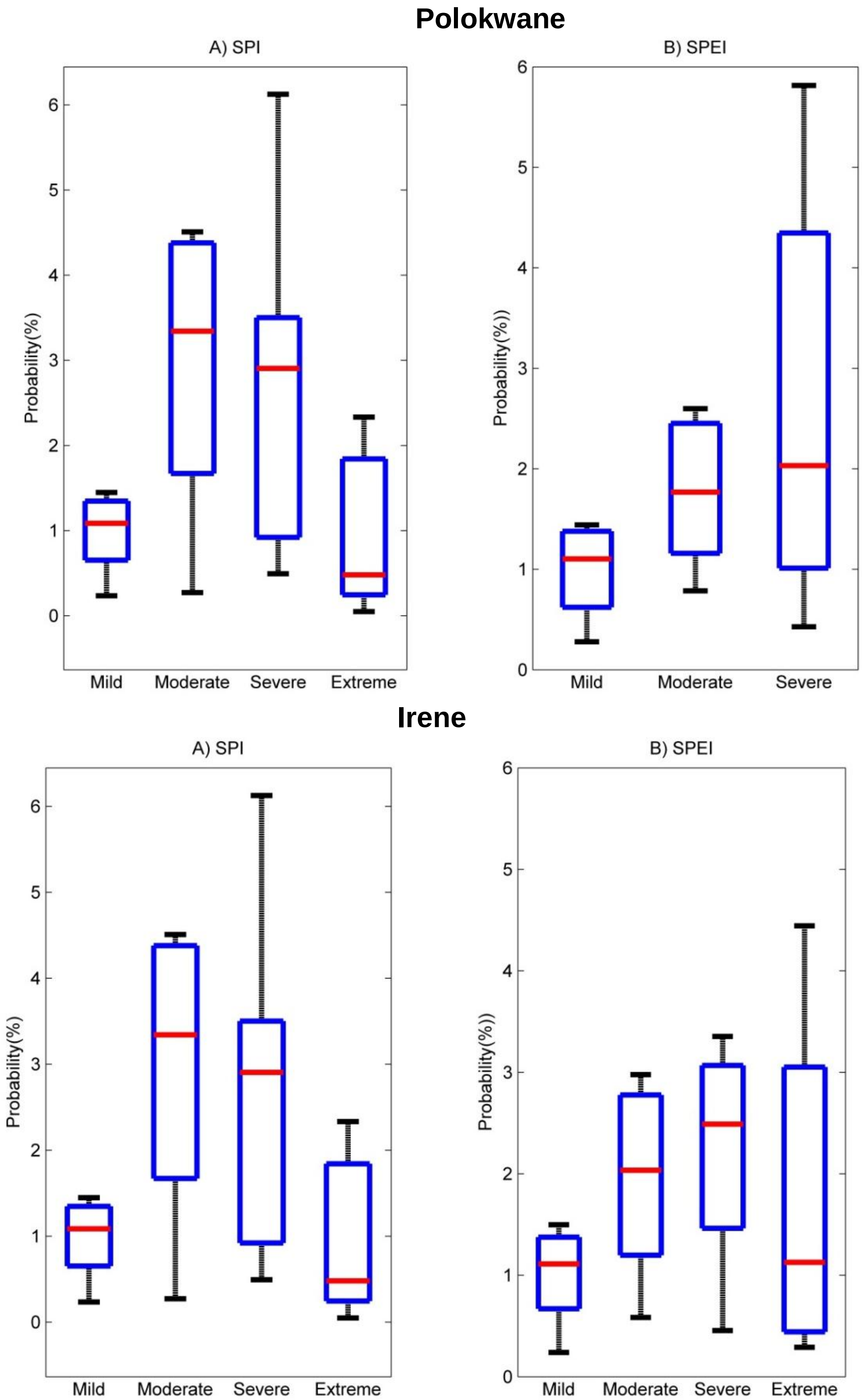

Figure 7: Boxplots of the probability of occurrence of mild, Moderate and severe drought conditions
using SPI-3(A) and SPEI-3 (B).

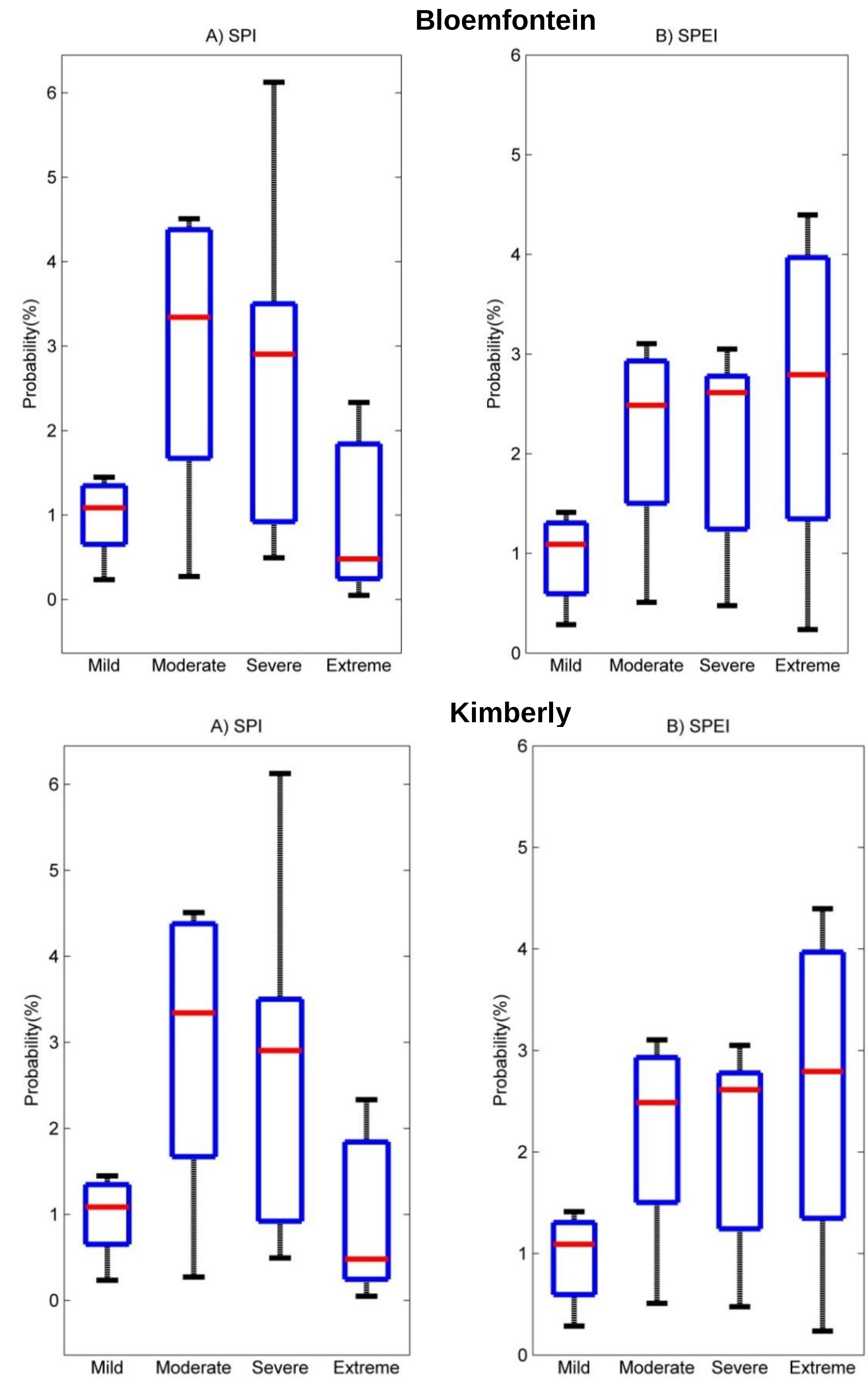

Figure 8: Boxplots of the probability of occurrence of mild, Moderate and severe drought conditions using SPI-3 (A) and SPEI-3 (B).

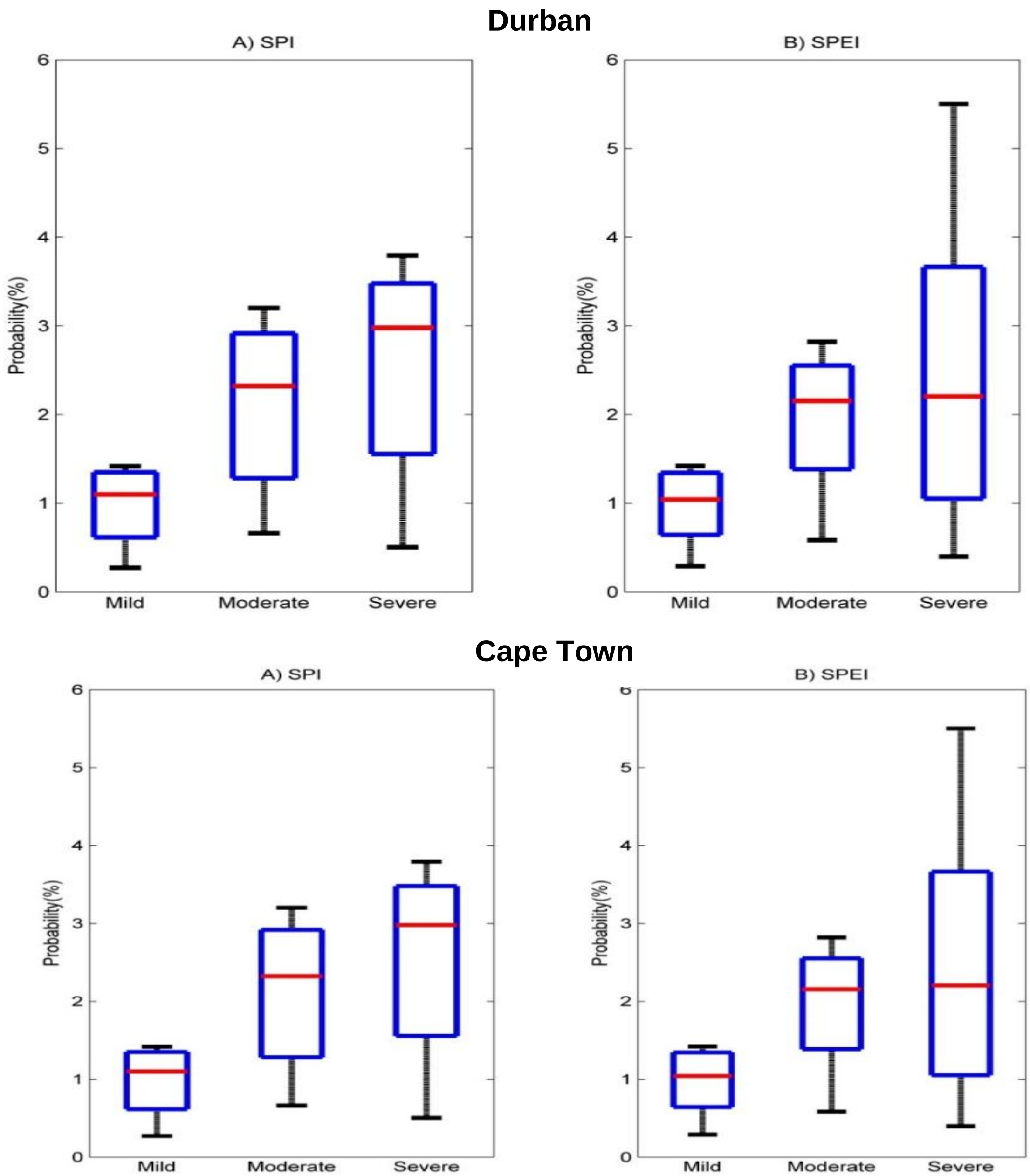

Figure 9: Boxplots of the probability of occurrence of mild, Moderate severedrought conditions using SPI-3 (A) and SPEI-3 (B).

4.3 Characteristics of droughts based on TRMM data

Droughts can be classified using duration, magnitude, intensity and severity (Mckee et al. 1993). In this section, the intensity, duration, frequency and severity of historical droughts episodes in South Africa was determined using gridded dataset obtained from Tropical Rainfall Measuring Mission (TRMM). The TRMM dataset has been used and recommended for drought monitoring in Southern Africa (Naumann *et al*. 2012 ; Naumann *et al*. 2014), in Mexico (De Jesus *et al*. 2016) and China (Li *et al*. 2013, Tao *et al*. 2016), due to its high spatial resolution.

The TRMM dataset is no longer available and had been replaced by the Global Precipitation Measurements (GPM) dataset (Hou et al. 2014). When compared with other datasets such as ECMWF reanalysis, the TRMM data is regarded as the best data for drought monitoring over the African continent (Naumann *et al*. 2014). Spatial distribution of dry and wet conditions across South Africa as described during the summer months ()(DJF) was done using SPI-3 as plotted in Figure 10 and Figure 11. Using the SPI-3 calculated using rainfall obtained from the TRMM datasets, several dry and wet periods were identified between 1996 and 2015.

In February 2000 almost the whole of South Africa received a substantial amount of rainfall; this is evident in Figure 10. The same year in December severe drought was experienced over the South Western/Eastern parts of South Africa. However on average, the 1999/2000 DJF season was very wet in most parts of South Africa, this might be caused by the moderate to weak La Niña event that was observed during that season (Shabbar & Yu 2009). The wet season during 1999/2000 was followed by a dry season in DJF (2000/01). During January 2001 the spatial extent as well as the intensity of the drought increased, the drought also extends to the North Eastern and the North Western parts of the Limpopo province in February 2001.

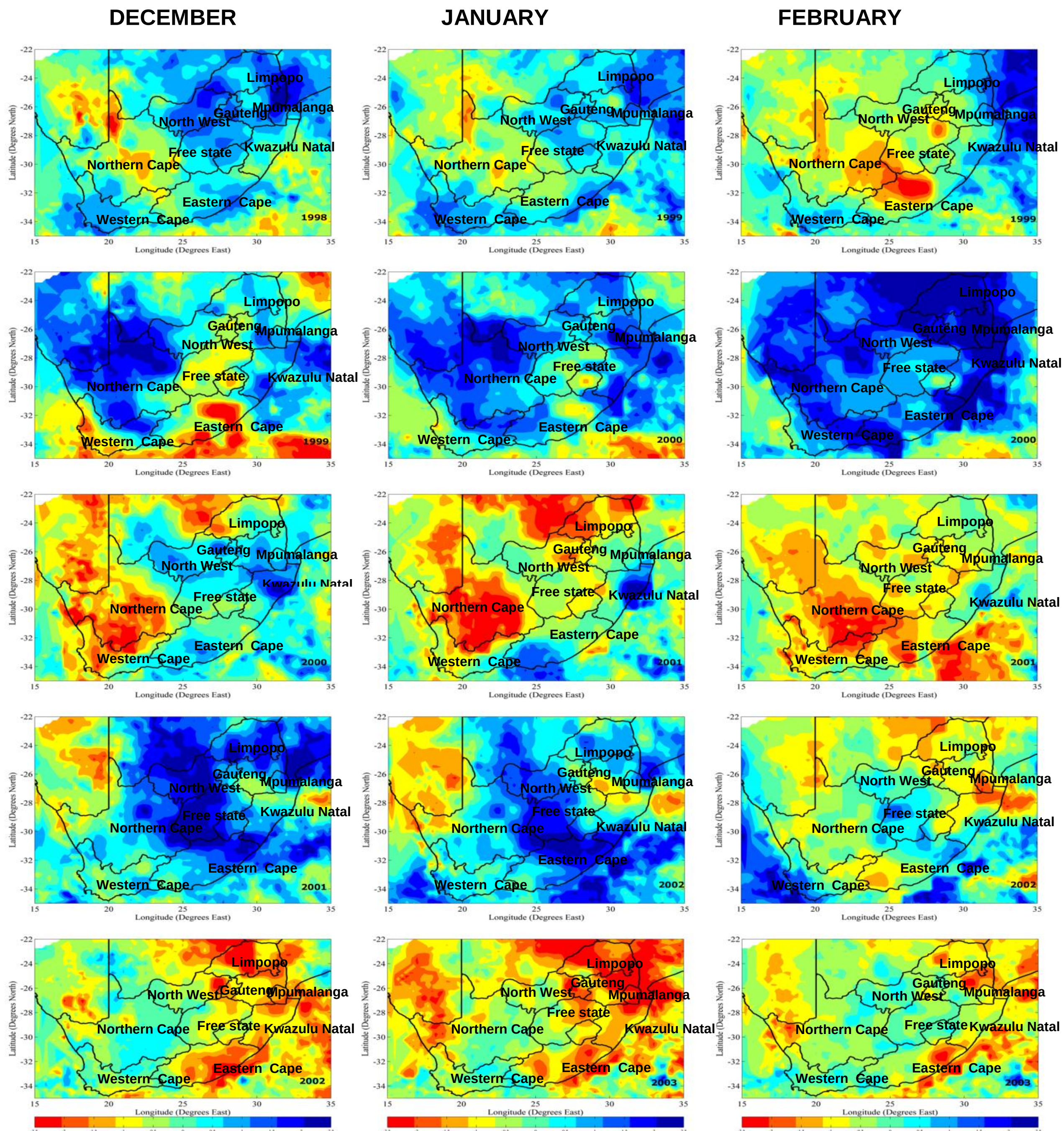

Figure 10: Spatial distribution of SPI-3 across South Africa for the DJF season between 1998 and 2003.

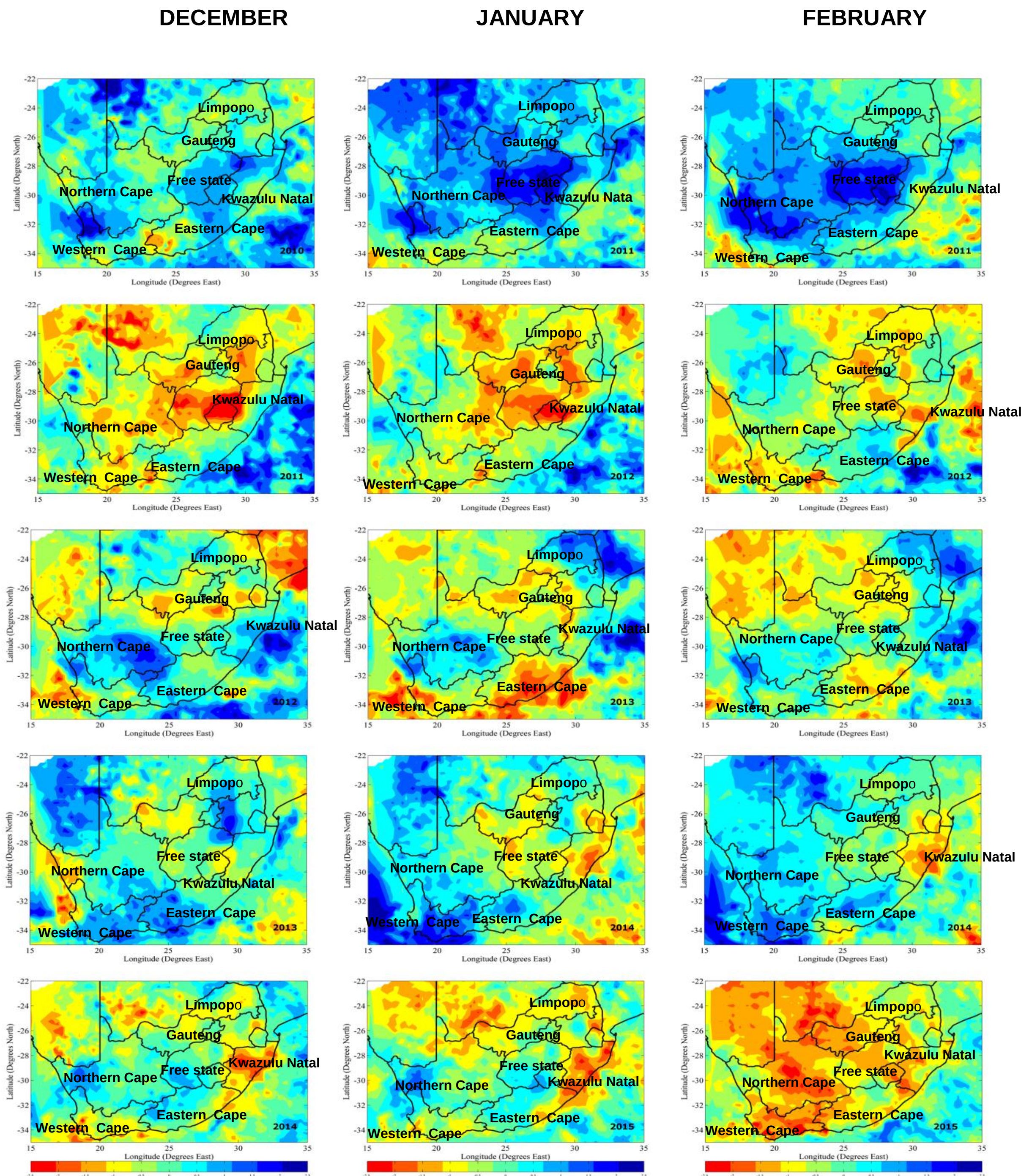

Figure 11: Spatial distribution of SPI-3 across South Africa for the DJF season between 2010 and 2015.

Boxplots in Figure 12, shows the average SPI values for all nine provinces in South Africa. The highest average SPI values were observed in Limpopo and Mpumalanga province, whilst the lowest average values were observed in the Western Cape and Northern Cape provinces.

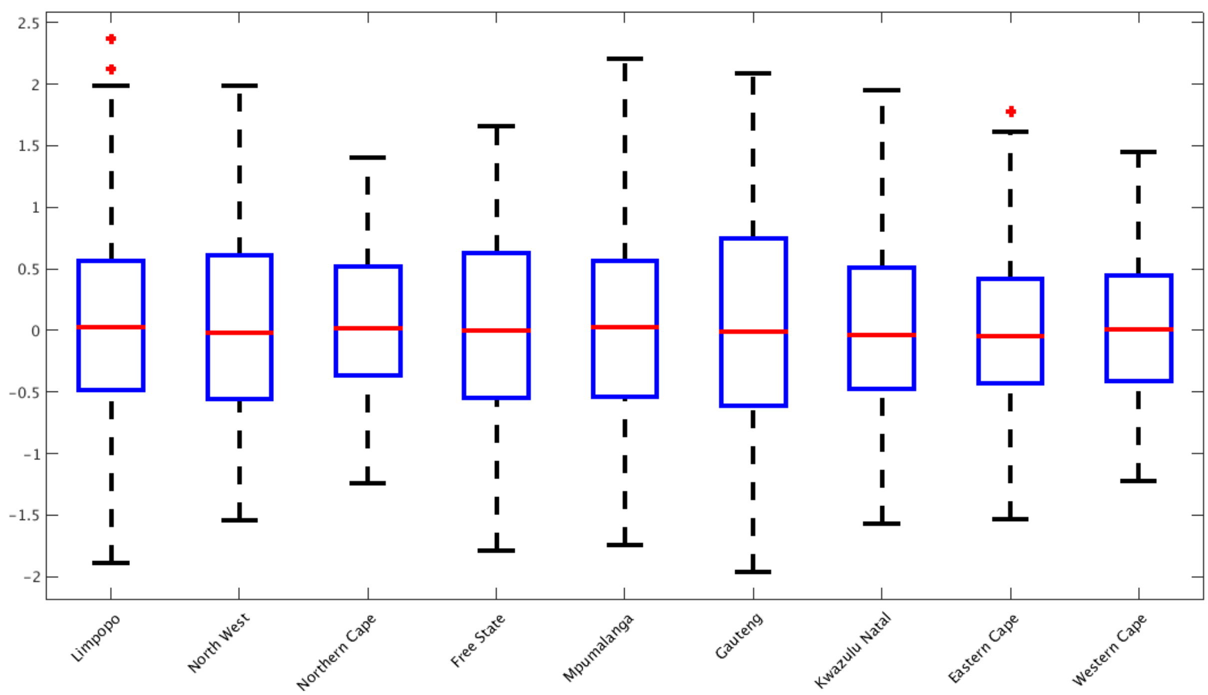

Figure 12: Boxplots showing average SPI-3 for all nine provinces in SA obtained using TRMM data.

4.3.1 Drought monitoring indicators

To identify the regions that are vulnerable to drought in South Africa, spatial maps of drought monitoring parameters such as drought intensity, drought frequency and duration were analyzed as shown in Figure 13. The North Eastern parts of South Africa seem to have experienced more severe droughts between 1998 and 2015. This region covers most parts of the country with semi-arid climatic conditions. The Western parts of South Africa which is mainly composed of the arid climate seem to have experienced more intense droughts with shorter duration between 1998 and 2015. During the same period the South Western parts of South Africa experienced less frequent droughts with shorter durations. The climatic condition of this region is mainly Mediterranean.

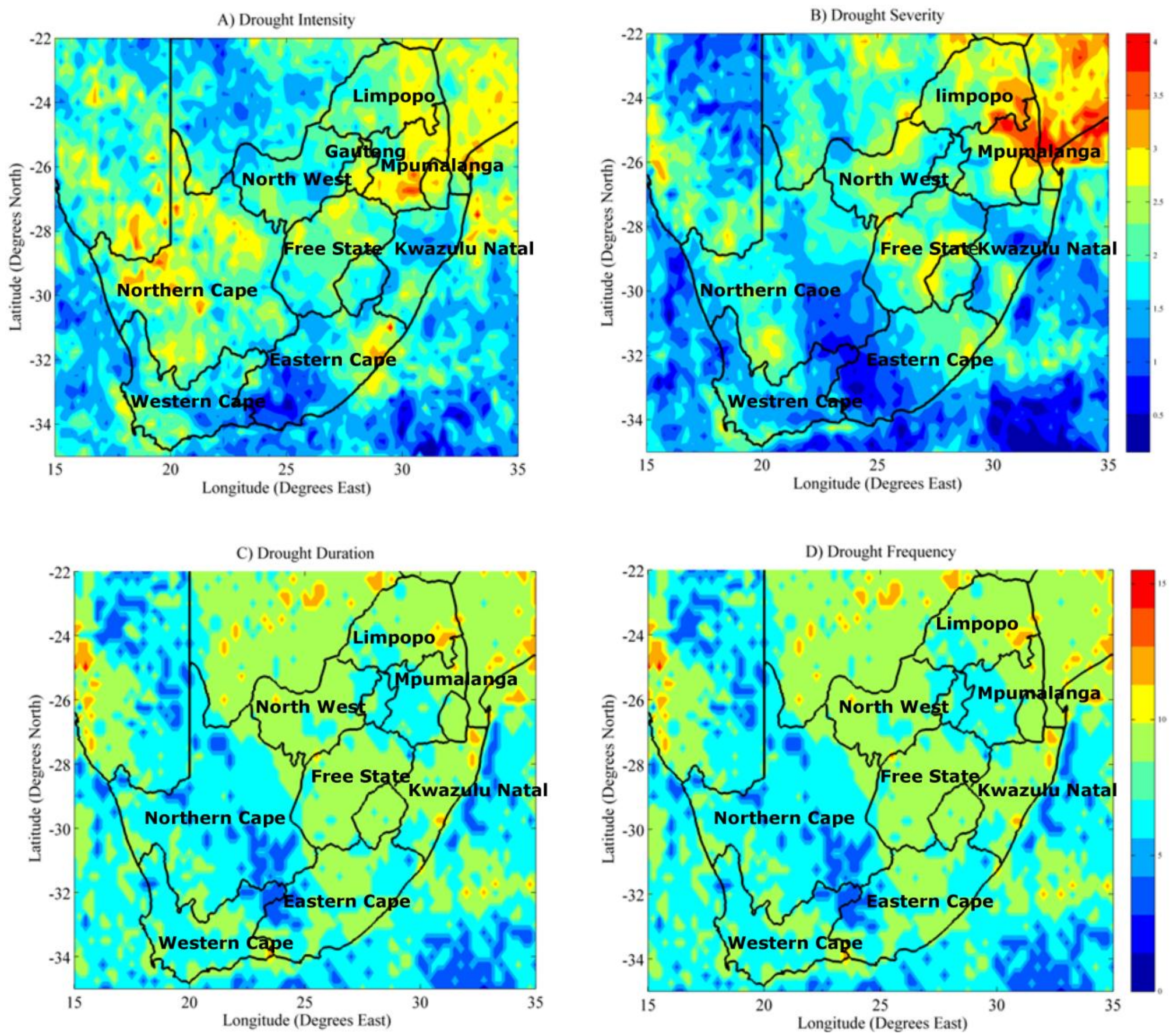

Figure 13: Spatial representation of drought intensity, severity, duration and frequency calculated from TRMM satellite datasets. Drought intensity and frequency are unitless, drought duration is measured in months whereas drought frequency is measured in months/year.

4.3.2 Trend Analysis

To analyze the trend and significance of a trend the Yue and Pilon method (also known as Trend Free Pre-Whitening (TFPW) procedure proposed by (Yue *et al.* 2002) was used in this section. A detailed description of the Yue and Pilon method is given in the data and methodology section.

Figure 14, shows the spatial representation of the Trends and significance trends in mild and moderate drought respectively. Most parts of South Africa with the exception of some parts of the Northern Cape Province experienced mild droughts with positive trends. Negative Sen Slope over most parts of South Africa with the p-value>0.05 in most parts of the country indicates the increasing in mild and moderate droughts but the increase is not significant. Most parts of South Africa seem to exhibit positive or increasing trends in both drought intensity and drought duration, but the decrease was not significant

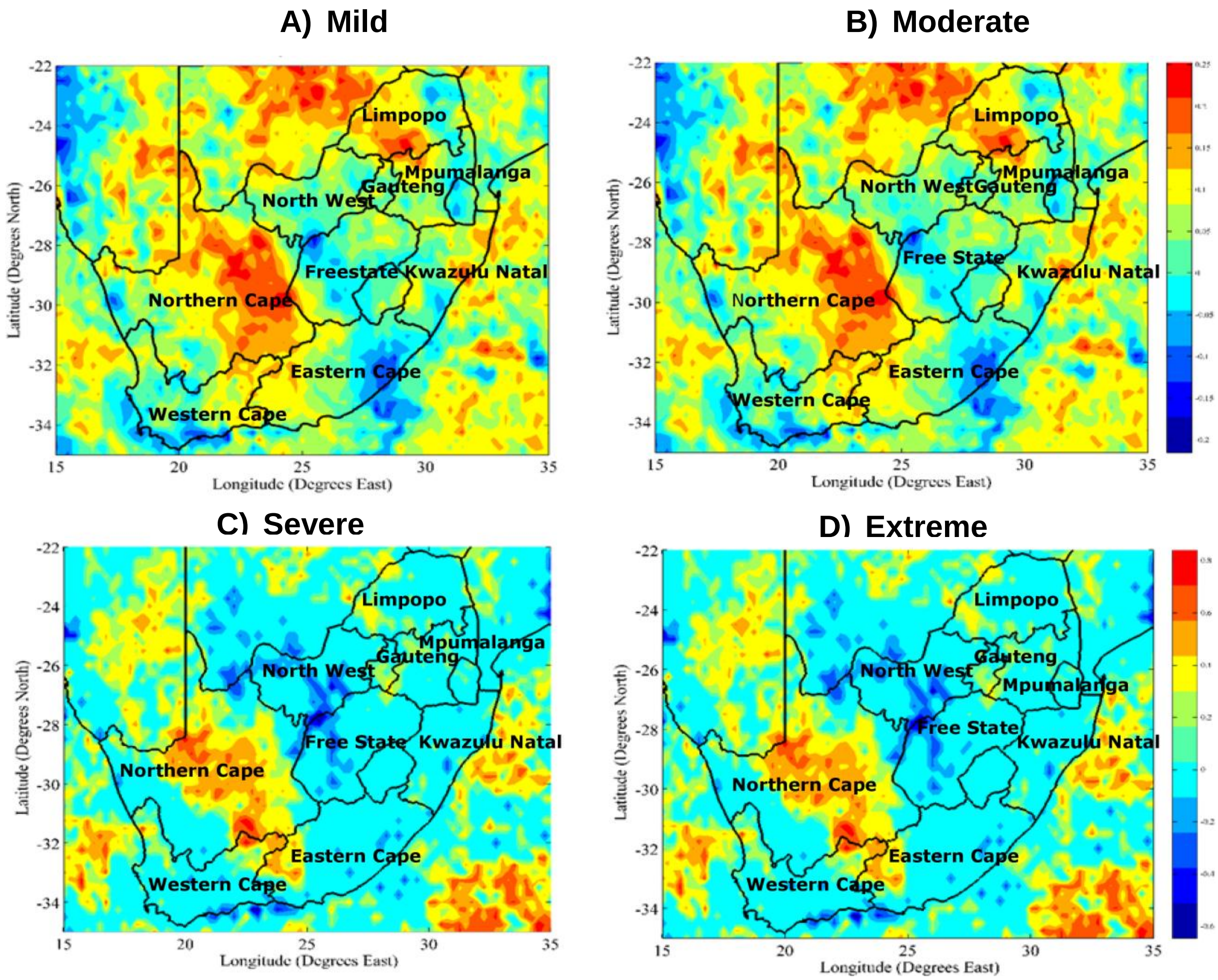

Figure 14: Trends in mild. Moderate, severe and extreme droughts calculated using TRMM dataset.

Table 7 shows the p-values and the Kendall tau test statistic for all the nine provinces in South Africa. In all the nine provinces the increases as well as a decrease in trends were observed. Both the Zhang and the Yuepilon methods show some negative or decreasing trends in provinces such as Gauteng, Limpopo, Free State and North West. Two provinces namely Kwazulu Natal and Northern Cape result in increasing positive trends. In all the nine provinces the increase or decrease in trends was not statistically significant (i.e. p-value>0.05).

Table 7: The results of the TFPW performed on SPI3 data for in all nine provinces of South Africa calculated using TRMM data.

	Yuepilon		Zhang	
Province	tau	p-value	tau	p-value
Gauteng	-0.0463	0.329	-0.0465	0.328
Limpopo	-0.0509	0.283	-0.0513	0.279
Free State	-0.0554	0.243	-0.0554	0.243
Northern Cape	0.0655	0.167	0.0651	0.170
North West	-0.0790	0.0961	-0.0791	0.0956
Kwazulu Natal	0.020	0.674	0.0199	0.675
Western Cape	0.0302	0.515	0.0203	0.972
Eastern Cape	-0.00671	0.885	-0.0129	0.663
Mpumalanga	0.00738	0.874	-0.00166	0.782

The probability of occurrence of mild, moderate, severe and extremely dry conditions for the nine provinces selected from the study area are shown in Figure 15. All nine provinces have the highest probability of occurrence of moderate to severe drought conditions. The probability of extreme droughts occurrence is lowest in all the nine provinces. All nine provinces in South Africa are more likely to experience moderate and severe droughts episodes.

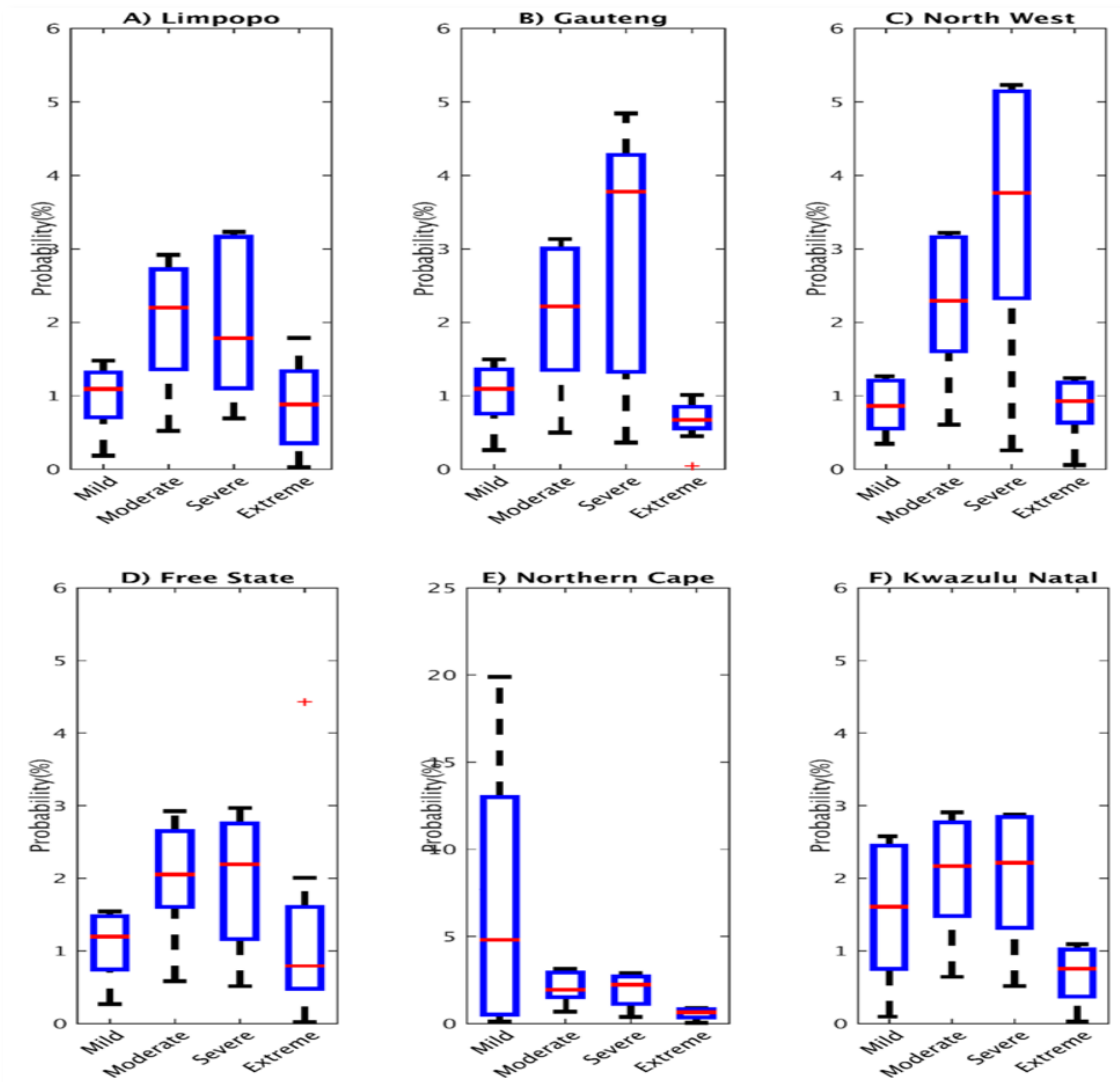

Figure 15: Boxplots of the probability of occurrence of mild, Moderate and severe drought conditions using SPI-3.

4.4 Discussion

Temporal patterns of droughts in South Africa were analysed using SPI-3 and SPEI-3 time series. Both indices managed to detect all historical droughts that occurred in South Africa during 1980-2015, some of those drought episodes are documented in (Masih *et al*. 2014) . Even though both indices managed to detect all the historical drought conditions in South Africa, the SPEI is often preferred over the SPI (Tan *et al*. 2015).

The severity and duration of droughts seem to vary according to the climatic regions, similar results were also obtained by (Rouault & Richard 2003; Edossa *et al.* 2014). Stations with arid and semi-arid climates seem to experience severe and extreme drought conditions with longer durations, whereas other stations experienced moderate to severe droughts. Similar results were also reported in (Vogel 1994; Vogel *et al*. 2010).

Spatial characteristics of historical droughts in South Africa were evaluated using gridded TRMM dataset. Even though the TRMM dataset consist of a shorter time series, it has been proven to be feasible for drought monitoring over the African continent (Naumann *et al*. 2014; Tao *et al*. 2016; De Jesus *et al*. 2016). Spatial characteristics of drought monitoring indicators such as intensity, severity, duration and frequency were assessed using the gridded TRMM dataset. In most cases the drought periods coincided with El Niño Southern Oscillation (ENSO) events as reported by (Richard *et al*. 2001; Rouault & Richard 2005; Edossa *et al*. 2014).

All nine provinces in South Africa were more likely to experience moderate and severe droughts between 1998 and 2015, but in most parts the increase in the severity if droughts were not significant. The North Eastern parts of South Africa seem to have experienced more severe droughts between 1998 and 2015. This region covers most parts of the country with semi-arid climatic conditions. The Western parts of South Africa which is mainly composed of the arid climate seem to have experienced more intense droughts with shorter duration between 1998 and 2015.

CHAPTER 5: ANALYSIS OF DROUGHTS USING RCA4 REGIONAL MODEL

5.1 Introduction

Spatial-temporal analysis of future droughts in South Africa was done using gridded downscaled CORDEX GCM models. The performance of all nine GCM models was evaluated against TRMM and CRU datasets. Future droughts were characterized spatially by their intensity, severity, duration and frequency. Statistical summary of historical, near-future and future droughts were done using boxplots. Historical and future trends of mild, moderate and severe droughts were also analysed.

5.2 Evaluation 9 GCM's used to downscale RCA4 regional model

Regional Climate Model (RCM) and Global Climate Model (GCM's) are indispenseble tools for asessing or predicting future extreme events that might be caused by climate change. However to obtain reliable future projection the quality of those models must be evaluated. To evaluate the quality of the nine downscaled GCM models used in this study, both subjective and objective evaluation methods were used. The spatial distribution of Mean Annual Precipitation (MAP) of all nine GCM models compared to the MAP of the TRMM and CRU datasets is shown in Figure 16.

Though the downscaled GCM models tend to over predict the amount of rainfall, there is an overall agreement between the different downscaled GCM models and the TRMM and CRU datasets with respect to the spatial distribution of Mean Annual Precipitation. TRMM dataset displays better spatial correlation to the model data than the CRU dataset as depicted in Figure 16.

This might be due to the fact that the TRMM data has a higher spatial resolution (i.e $0.25^o X 0.25^o$) and is based on the remote sensing estimation whereas the CRU data has a coarser resolution of about (i.e $0.5^o X 0.5^o$). The CRU data is based on reanalyses model data which introduce some bias to the data and in-situ measurements which are scarce in Southern Africa.The downscaled GCM's have well captured the areas of maximum/minimum precipitation over South Africa. The drier climatic conditions over the South Western parts of South Africa was also well predicted by the GCM models. Figure 16 shows that the Western parts of Namibia, the CRU has shown the lowest MAP, this was also evident in other GCM's such as CanESM, CSIRO, HadGEM, and IPSL.

Though the GCM's tends to capture the main features of the MAP distribution in both the summer and winter rainfall regions, they tend to overestimates the MAP whencompared with TRMM and CRU datasets, especially over the Eastern and the South Eastern parts of South Africa. Both datasets display highest MAP over the Eastern as well as the South Eastern parts of South Africa. GFDL and NorESM1 models have similar spatial distributions especially over the Eastern and the North Eastern parts of South Africa.

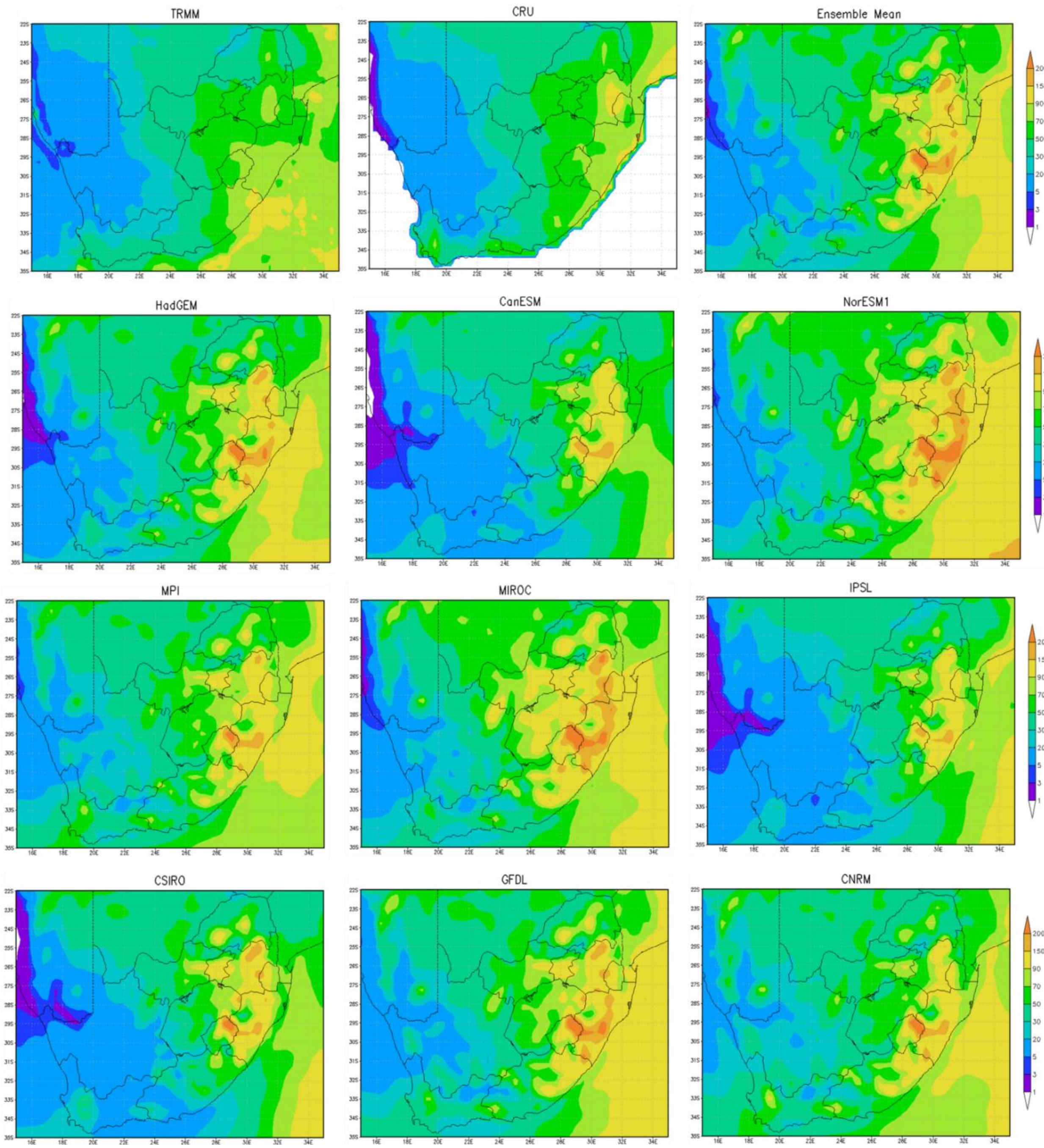

Figure 16: Mean Annual Precipitation (MAP) 9 GCM's used to drive RCA4 regional model compared to their ensemble mean. to MAP for TRMM and CRU observational datasets.

For an objective evaluation of rainfall obtained from nine GCM's a Taylor diagram was used as shown in Figure 17. A Taylor diagram has been used to summarize multiple aspects of model performance (Taylor 2001). The Taylor diagram in Figure 17 shows the correlation coefficient, Root Mean Squared Error and the standard deviation of rainfall obtained from different GCM's models against TRMM and CRU datasets.

The ensemble average of the nine models has shown high correlation and low standard deviation when compared to both TRMM and CRU datasets, however there is better correlation between the downscalled GCM's and the TRMM data. Good correlation between the ensemble average and the TRMM datasets is attributed to the fact that opposite signed biases across different GCM's tends to cancel each other.

The correlation between TRMM and the GCM's ranges between 0.4 and 0.6, whereas the correlation between CRU and the GCM's ranges between 0.1 and 0.3. MIROC5 has shown higher standard deviation when compared to both TRMM and CRU datasets. Given the good performance of the ensemble average of precipitation obtained from the nine GCM's, ensemble average of temperature and precipitation will be used as input to the SPEI equations for the prediction of future droughts prospects in South Africa. Using an ensemble average of nine GCM's will decrease model errors as well uncertainity of the ensemble (Giorgi & Mearns 2002, Grillakis, 2013).

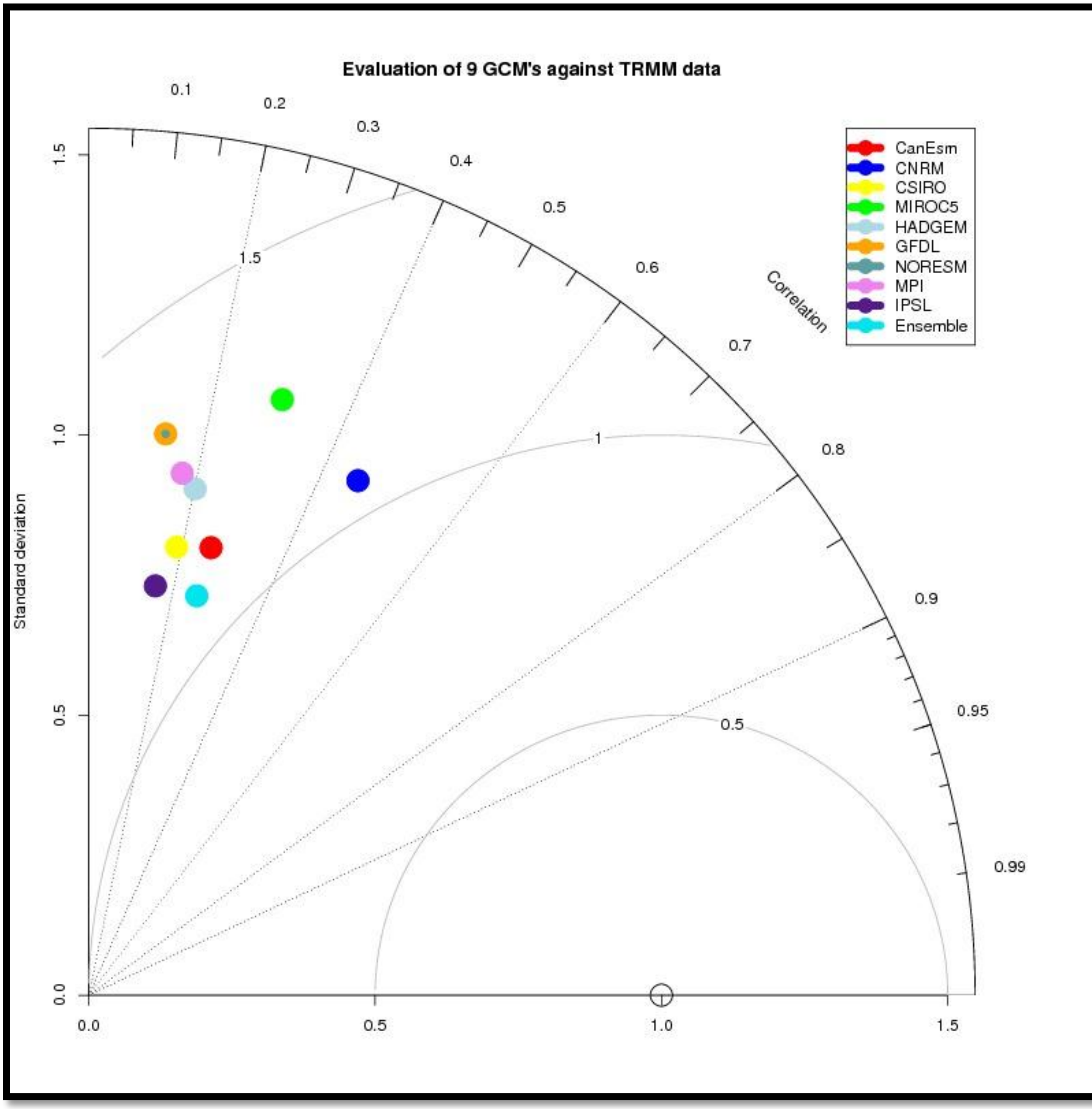

Figure 17: The Taylor diagram summarizing the performance of the 9 GCM models and their ensemble mean against TRMM dataset over the South African domain.

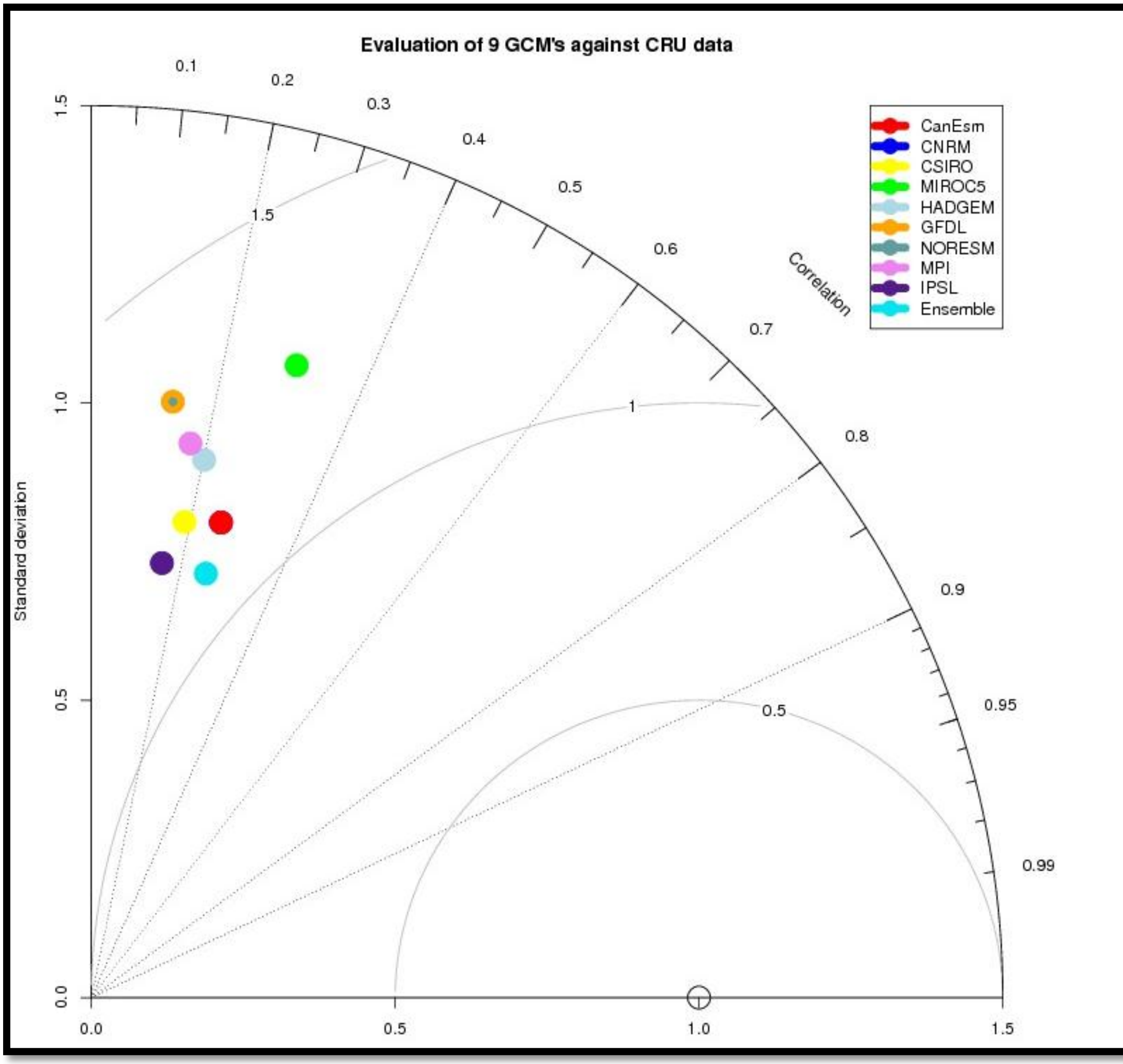

Figure 18: The Taylor diagram summarizing the performance of the 9 GCM models and their ensemble mean against CRU dataset over the South African domain.

The Ensemble mean of the GCM models predicted an increase from West to East and South to North of drought intensity, severity, duration, and frequency during the historical period. However, during the near future period an increase in drought intensity and severity was also evident in the previous chapter, where drought monitoring indicators were calculated using SPI-3 calculated using TRMM datasets. During the near future and the future period, increase in drought severity, intensity, duration, and frequency was predicted to be from East to West and North to South.

5.3 Characterization of future droughts

In chapter 4, drought was characterized by the present climate conditions using surface or in situ observations and TRMM data. In this chapter, the characteristics of droughts will be evaluated using SPEI-3 calculated from monthly mean rainfall and monthly average temperatures obtained from an ensemble mean of the 9 GCM models used to force the RCA4 regional model. The simulations were made for three periods namely 1971-2000, 2011-2040, 2041-2070. The period 1971-2000 is referred as the historical or reference period, the period 2011-2040 is referred to as the near future and 2041-2070 is the future period. Droughts were characterized using intensity, duration, severity, and frequency for the three periods as shown in Figure 19.

The four characteristics of droughts mentioned above are referred to a drought monitoring indicators. Drought monitoring indicators were calculated at each model grid point using SPEI-3 data calculated from the rainfall and temperature obtained from an ensemble mean of 9 dynamically downscaled GCM's. Spatial maps of drought severity, intensity, duration and frequency were plotted for the whole of South Africa as shown in Figure 19.

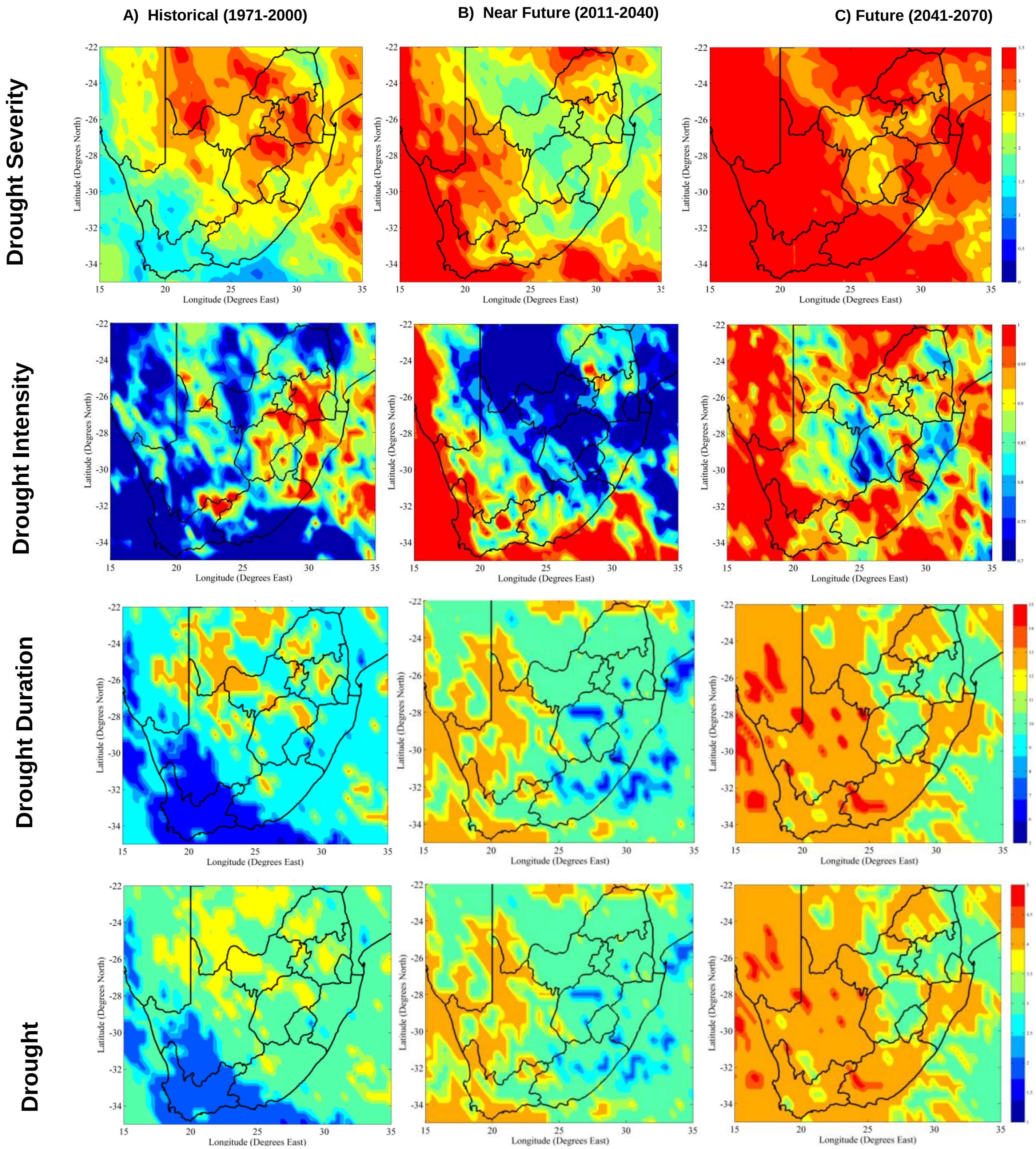

Figure 19: Spatial maps of Drought Monitoring Indicators for three periods namely Historical (1971-2000), Near Future (2011-2040),Future(2041-2070).

The variability of drought characteristics is evident in different climatic regions of South Africa as shown in Figure 20. Four drought monitoring indicators are presented spatially in different climatic regions of South Africa. The demarcation of the climatic regions was done according to Koppen classifications (Koppen, 1900). On average the models predicted an overall increase in drought intensity, severity, duration, and frequency during the near-future and the future periods.

Most severe droughts are predicted to occur in arid (BW) and semi-arid (BS) regions of South Africa. Droughts with longer duration are also predicted for the near-future (2011-2040) and future (2041-2070) periods as compared to the historical period (i.e. 1971-2000). The arid or desert regions of South Africa comprises most parts of the Northern Cape Province. Semi-arid or Steppe regions encompasses most parts of the Free State, Limpopo, Western Cape and the Eastern Cape Province (Koppen, 1900).

Frequent droughts with longer durations are predicted in the future period (2041-2070) especially for arid, semi-arid, Csa (winter rain with hot summers) and Csb (winter rain with cool summers) climatic regions. The winter rainfall regions (i.e. Csa and Csb) use to experience less intense droughts with shorter duration and frequency during the historical period. However, the GCM models predicted severe and more frequent droughts with longer duration in those climatic regions.

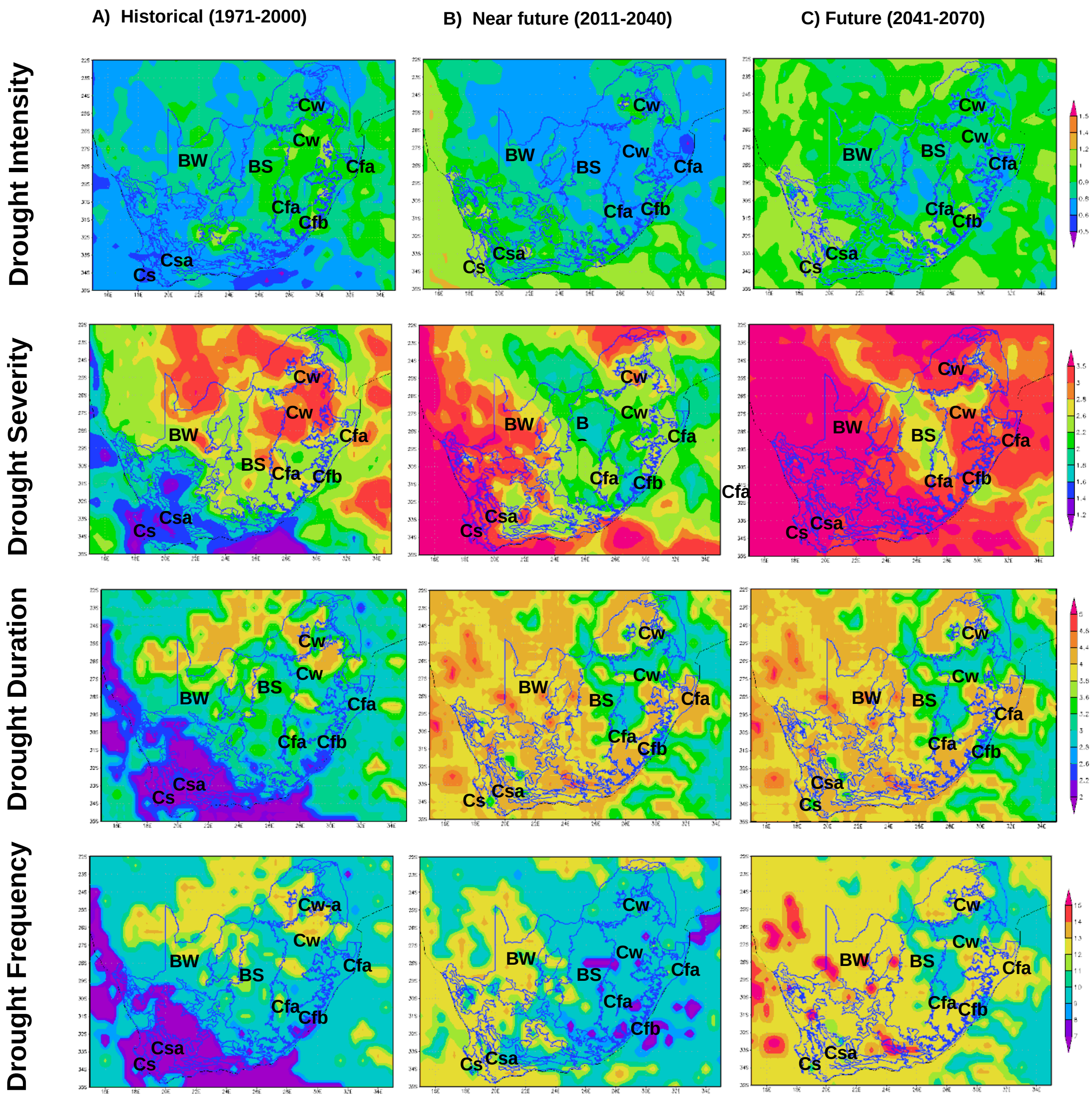

Figure 20: Spatial maps of Drought Monitoring Indicators A: Drought Severity, B: Drought Intensity, C: Drought Duration D: Drought Frequency for three periods namely Historical (1971-2000), Near Future (2011-2040), Future (2041-2070).

Figure 21, present the summary of historical, near future and future drought intensity in the nine provinces of South Africa. The lowest drought intensity was predicted in the Western Cape province during the historical period. The highest drought intensity was also predicted for the Western Cape province during the near future (2011-2040) and the future period (2041-2070). A notable increase in the median of drought intensity was also predicted in the two future periods as compared to the historical period. The increase in the median drought intensity was also predicted for provinces such as Limpopo, Northern Cape, Eastern Cape, North West and Western Cape province. Provinces such as Mpumalanga, Northern Cape and Free State are predicted to have lower drought intensity median.

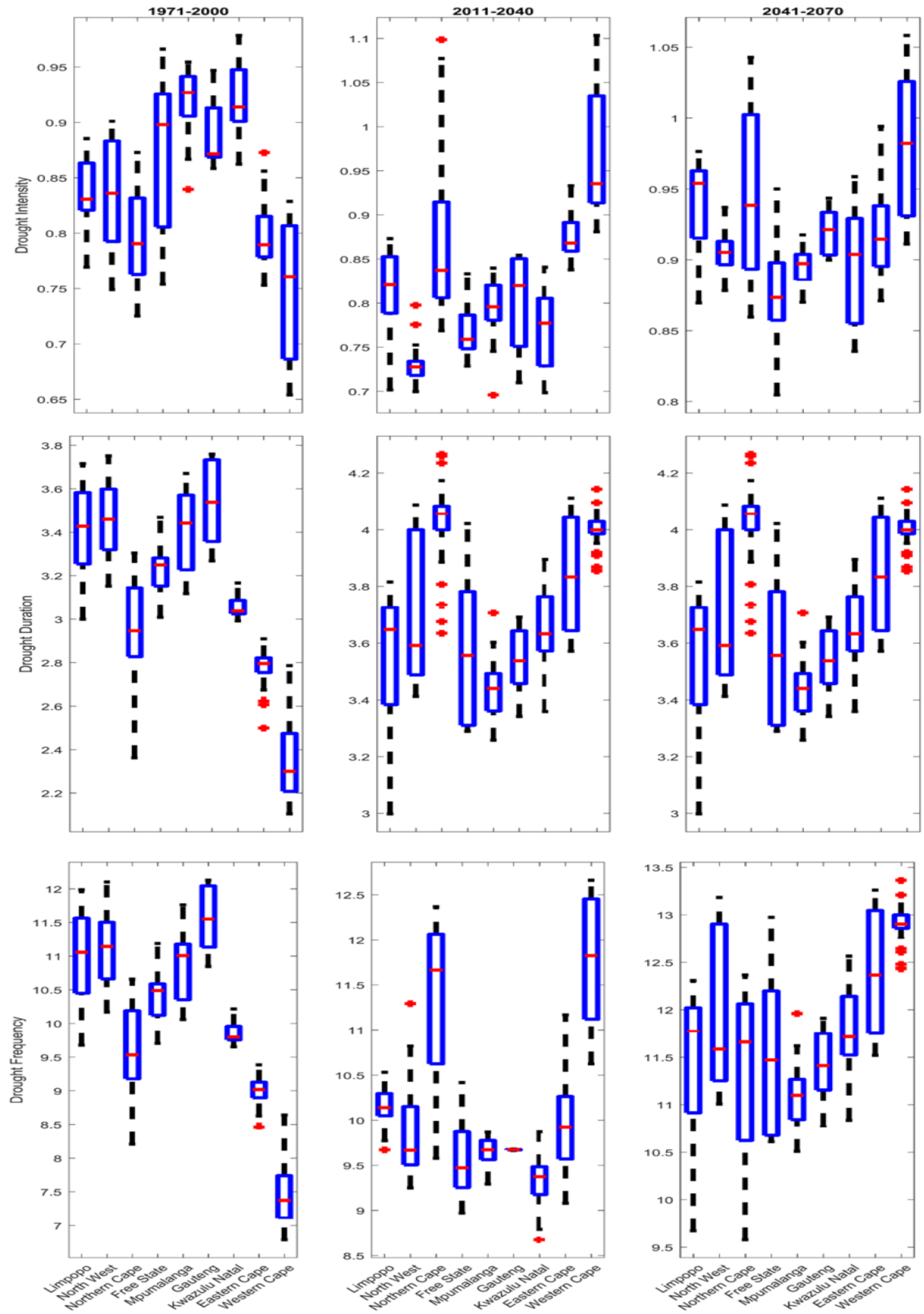

Figure 21: Boxplots showing statistical parameters of Drought intensity, duration and frequency for three periods (1971-2000, 2011-2040, 2041-2070).

5.4 Trends

Trend analysis of 3-month SPEI time series was done using the Mann-Kendall (MK) trend analysis method (Mann, Kendall). The MK tend analysis was used to determine whether the mild, moderate and severe droughts will increase or decrease during historical (1971-2000), near future (2011-2040) and future (2041-2070) as predicted by the ensemble mean of the RCA4 regional model driven by nine different GCM's.

Figure 22 presents the spatial maps comparing the trends in mild, moderate and severe droughts for the three periods of study. The GCM models show decreasing trends in mild droughts during the three periods. The Western parts of Northen Cape as well as the Western Cape province predicted an incresing trends in mild droughts. An increasing trends in moderate droughts in the Easten parts of the country during the near future period. During the near future and future periods moderate drought shows an increasing trends in most parts of the country including the Western Cape, Eastern Cape and the Western parts of the Northern Cape province.

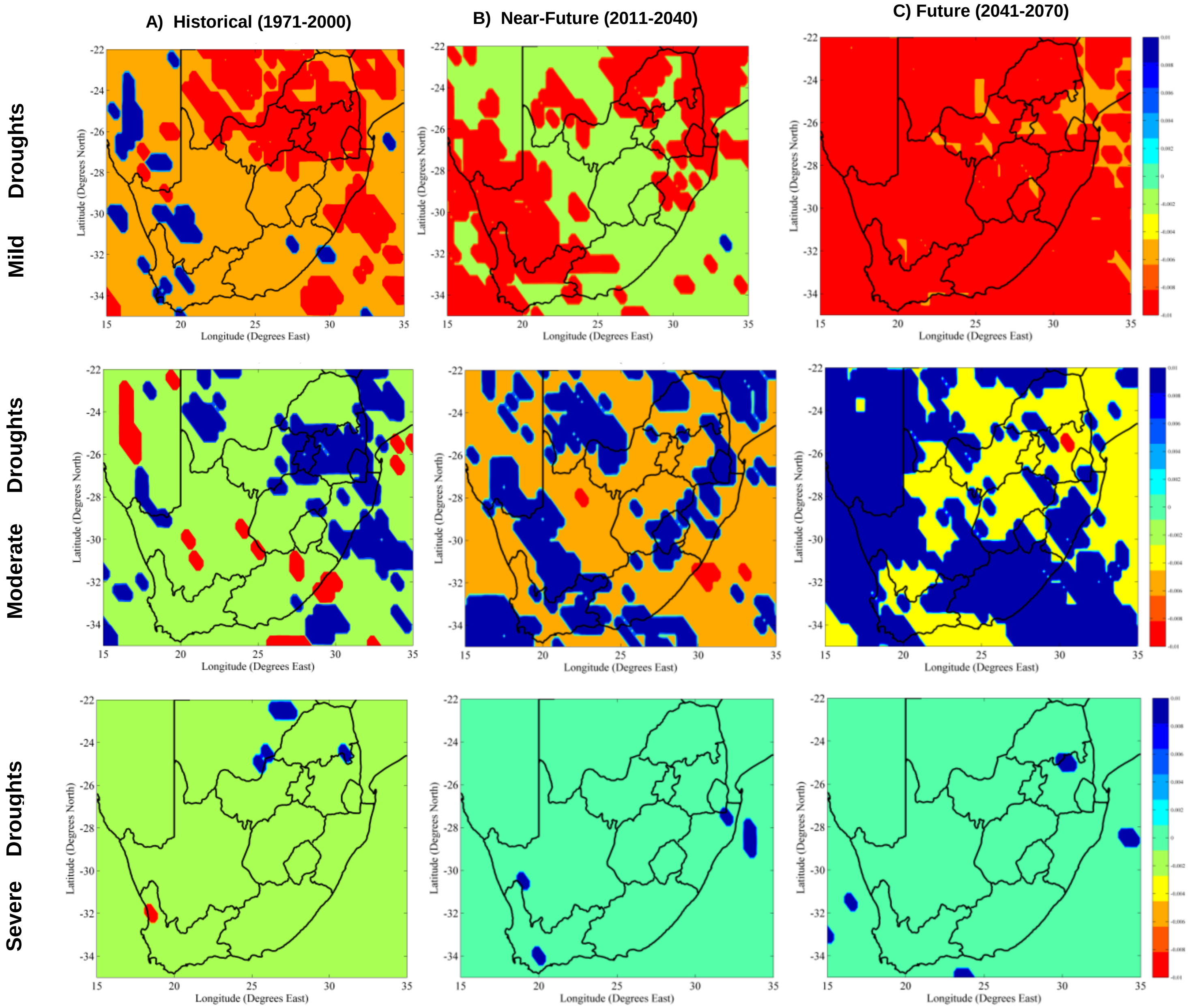

Figure 22: Trends in Mild, Moderate and Severe droughts for three periods i.e. historical (1971-2000), Near-future (2011-2040), future (2041-2070).

The Sen Slope estimator and p values calculated for average drought frequency and severity for all nine provinces of South Africa are presented in Table 8 and Table 9 . During the historical period, most of the provinces predicted an increase in drought frequency trends except for Northern Cape and Kwazulu Natal province. However, for all the nine provinces the increase/decrease in drought frequency trends was not significant. During the near future period provinces such as Mpumalanga, Gauteng, Northern Cape, Eastern Cape and Kwazulu

Natal were predicted to have increased drought frequency however, only the Western Cape province drought frequency trends are significant. With the exception of the North West and the Northern Cape province all other provinces will experience an increase in drought frequency trends, but the increase will be significant only in Mpumalanga and Kwazulu Natal Province.

Gauteng province will experienced a decrease in drought severity trends in all the three periods, but the decrease will only be significant during the near future period. Western Cape, Kwazulu Natal and Free State Provinces will experience an increase in drought severity trends in both the near future and the future periods, but the trends were significant in Kwazulu Natal during the future as well as in Eastern Cape province during the near future.

Table 8: P value and sen slope for drought Frequency for three periods.

Province	P-value			Trend		
	1971-2000	2011-2040	2041-2070	1971-2000	2011-2040	2041-2070
Limpopo	0.496	0.0793	0.882	-0.0975	0.248	0.0236
Mpumalanga	1	0.682	0.661	0.00259	-0.0603	-0.0671
North West	0.445	0.484	0.543	0.113	-0.102	-0.106
Gauteng	0.185	0.551	0.480	0.189	-0.0864	-0.102
Free State	0.304	0.292	0.321	-0.147	-0.153	0.141
Northern Cape	0.121	0.110	0.657	-0.219	0.183	-0.0649
Eastern Cape	0.0179	0.0779	0.00513	-0.338	0.241	0.393
Western Cape	0.00764	0.0177	0.00839	-0.246	0.332	0.369

Kwazulu Natal	0.912	0.697	0.301	-0.0181	-0.0596	-0.150

Table 9: P value and sen slope for drought Frequency for three periods.

Province	P-value			Trend		
	1971-2000	2011-2040	2041-2070	1971-2000	2011-2040	2041-2070
Limpopo	0.496	0.2905	0.882	0.0629	-0.119	0.182
Mpumalanga	0.618	0.256	0.0259	0.0782	0.176	0.348
North West	0.445	0.484	0.453	0.113	-0.102	-0.106
Gauteng	0.816	0.298	0.0264	0.0389	0.164	0.341
Free State	0.305	0.292	0.319	0.147	-0.153	0.414
Northern Cape	0.121	0.199	0.657	-0.219	0.183	-0.0649
Eastern Cape	0.327	1	0.0839	0.155	0.00392	0.272
Western Cape	0.333	0.0229	0.130	0.154	-0.354	0.234
Kwazulu Natal	0.734	0.852	0.0292	-0.0547	0.0312	0.339

Table 10: P value and Sen Slope for drought severity for three periods.

Province	P-value			Trend		
	1971-2000	2011-2040	2041-2070	1971-2000	2011-2040	2041-2070
Limpopo	0.728	0.657	0.437	0.0538	-0.0302	-0.117
Mpumalanga	0.862	0.155	0.877	0.0423	-0.146	-0.0389
North West	0.353	0.471	0.0949	-0.107	-0.0505	0.254
Gauteng	0.654	0.179	0.516	-0.0584	-0.162	-0.0988
Free State	0.224	0.556	0.108	-0.156	0.0893	0.247
Northern Cape	0.357	0.196	0.119	-0.103	-0.2058	0.238
Eastern Cape	0.634	0.0380	0.148	0.104	-0.301	0.220
Western Cape	0.792	0.751	0.556	-0.0426	0.00523	0.0941
Kwazulu Natal	0.832	0.729	0.0229	0.116	0.225	0.350

5.5 Discussion

The prediction of spatial and temporal evolution of future droughts in South Africa was done using ensemble mean the regional climate model (RCA4) driven by nine downscaled CORDEX GCM models. All nine GCM models were evaluated against TRMM and CRU datasets. The results have shown that the ensemble mean performs better than all the individual models.

In most parts of South Africa an increase in drought intensity, severity, duration and frequency was predicted particularly during the future period (2041-2070). The increase in the intensity and duration was also prominent in regions of Mediterranean climate such as the South Western parts of South Africa. Nevertheless, in other regions such as parts of the North West and Free State province a decrease in drought intensity and duration was predicted.

CHAPTER 6: CONCLUSIONS, RESEACH CONTRIBUTION AND FUTURE WORK

6.1 Reseach contribution

The current study presented a framework for characterization of future droughts across South Africa. Policy makers will incorporate the findings of this work for the development of drought early warning systems. The drought early warning system will assist the decision makers in sectors such as hydrology, agriculture and other socio economic sectors to create a drought preparedness plan for near and distant future drought conditions.

6.2 Conclusion

The current and future drought conditions in South Africa were assessed in this study. The two indices used were able to capture most of the past drought episodes in South Africa. Both SPI and SPEI are useful indicators for assessing drought conditions, however where the temperature observations are available the SPEI is recommended. Spatial analysis of droughts over most parts of South Africa has shown that the North Eastern parts of the country is more likely to experience severe droughts as compared to other parts of the country.

The future drought conditions were predicted using the regional climate model RCA4. The results show significant increases in meteorological drought frequency and severity for most parts of South Africa. In most parts of South Africa, the increase in the drought intensity, frequency and severity were not significant.

6.3 Recommendations

The following recommendations were done from this study:

1. Both SPI and SPEI indices are capable of analyzing the current and future drought conditions in South Africa. However when the temperature is available the SPEI is recommended.
2. For spatial analysis of droughts in regions where observations are scares, the use of high resolution GPM data or other satellite such as Tropical Application for Meteorology using Satellite data (TAMSAT) is recommended.
3. In this study droughts were analyzed using temperature and precipitation based indices (i.e. SPI, SPEI), remotely sensed drought indices such as Normalized Difference Vegetation Index (NDVI), Vegetation Condition (TCI) and Temperature Condition Index (TCI) and can also add value to the comparison.
4. The results obtained from this study can be used by decision makers such as the Department of Water Affairs and sanitation to mitigate the impacts of droughts at regional or provincial levels.

6.4 Future work

- This work will be expanded by using other available datasets such as TAMSAT data and ECMWF reanalysis data. NCEP global ensemble will also be tested in the future to predict droughts in real-time.
- In the future bias correction methods will be applied to the model data prior to the analysis.

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