

MODELLING OF STANDARDISED PRECIPITATION INDEX USING REMOTE SENSING FOR IMPROVED DROUGHT MONITORING

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A dissertation submitted to the Faculty of Engineering and Built Environment, University of the Witwatersrand, Johannesburg, in fulfilment of the requirements of the degree of Master of Science in Engineering.

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DECLARATION

I declare that this dissertation is my own unaided work. It is being submitted for the degree of Master of Science in Engineering to the University of Witwatersrand, Johannesburg and has not been submitted before for any degree or examination to any other university.

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On this day..... of2013

ABSTRACT

The South African Weather Service (SAWS) has reported a decline in the number of rainfall observation stations due to inadequate financial resources to meet maintenance costs. This reduction in rainfall stations complicates the calculation of the rainfall-based Standardised Precipitation Index (SPI) drought index mainly owing to the sparse distribution of these stations and the high variability of rainfall. The SPI is used to inform short-term drought mitigation and relief decisions. This study investigates the determination of a spatially improved Standardised Precipitation Index (SPI) using the Normalised Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI) and topographical attributes, which makes it possible to obtain SPI in the Luvuvhu/Letaba Water Management Area on a spatial resolution of 60m×60m.

The applied approach consists of simple and stepwise linear modeling with SPI as the dependent variable and NDVI, VCI, Aspect and Elevation as independent variables incrementally added in this order. There is a significant correlation (R^2 ; 0.599) between the SPI and the NDVI for the dry season and (R^2 ; 0.473) for the wet season. After the VCI, Aspect and Elevation were added to the model, R^2 improved for the dry season, equaling to 0.696 and R^2 equals to 0.550 for the wet season. Seasonal drought maps for year 2012 obtained by the model correlated much better with the observed dryness conditions than those produced by the SAWS for five communities located widely within the study area. Decision-making for drought relief can therefore be improved substantially using the SPI model-based drought prediction method.

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
AMESD	African Monitoring of Environment for Sustainable Development
ARC	Agricultural Research Centre
AVHRR	Advanced Very High Resolution Radiometer
CSIR	Council of Scientific and Industrial Research
DEM	Digital Elevation Model
EDI	Effective drought Index
FAO	Food and Agricultural Organisation
FEWSNET	Famine Early Warning Systems Network
GIS	Geographical information System
KNP	Kruger National Park
LWMA	Luvuvhu/Letaba Water Management Area
MSS	Landsat Multispectral Scanner
NASA	National Aeronautics and Space Administration
NDVI	Normalised Difference Vegetation Index
NOAA	National Oceanic and Atmospheric Administration
PDSI	Palmer Drought Severity Index
RMSE	Root Mean Square Error
SADC	Southern Africa Development Community
SARCOF	Southern Africa Regional Climate Outlook Forum
SAWS	South Africa Weather Services
SMLR	Stepwise Multiple Linear Regression
SPI	Standardised Precipitation Index
SRTM	Shuttle Radar Topography Mission
SWSI	Standardised Water Supply Index
RMSE	Root Mean Square Error
TCI	Temperature Condition Index
UNDP	United Nations, Development Programme
USAID	United States of Agency International Development
USGS	United States Geological Survey
VCi	Vegetation Condition Index
WGS	World Geodetic System

1. INTRODUCTION

Drought is the most significant natural disaster in Southern Africa in economic, social and environmental terms (Buckland *et al.*, 2000). According to the United Nations Development Programme (UNDP) report (UNDP/UNSO, 1999), 'drought is considered by many to be the most complex but least understood of all natural hazards, affecting more people than any other hazard.'

Most regions of the world are affected by drought from time-to-time. Although it tends to be most common and severe over the central regions of continents, there are many exceptions to this. Drought has been and will continue to have some of the greatest impacts on climate. Drought has brought ancient civilisations to their knees and leads to famine, food scarcity, and loss of lives and property. Evidence suggests that the area affected by drought has been increasing on a global basis (Dai *et al.*, 2004). Furthermore, many climate predictions anticipate a further increase in drought-affected regions in the future.

The impacts from drought can be reduced provided there is forewarning. This can be on relatively short scales for weather conditions within a drought to decadal scale expectation involving natural decadal variability and climate change. Drought affects particularly vulnerable societies that have little resilience and readiness.

1.1 TYPES OF DROUGHT

The National Drought Mitigation Centre (NDMC) classifies drought by the following types: meteorological, hydrological, agricultural, and socioeconomic drought. The impacts associated with drought usually take three months or more to develop, but this time period can vary considerably, depending on the timing of the initiation of the precipitation deficiency.

1.1.1 Meteorological drought

Meteorological drought is expressed exclusively on the basis of the degree of dryness in comparison to some normal or average amount and the duration of the dry period. Intensity and duration are thus key characteristics of Meteorological drought.

1.1.2 Agricultural drought

Agriculture is usually the first economic sector to be affected by drought because the soil moisture content is often quickly depleted, especially if the period of moisture deficiency is

associated with high temperatures and windy conditions. Agricultural drought links various characteristics of meteorological drought to agricultural impacts. The focus here is on precipitation shortages, differences between actual and potential evapotranspiration, and soil water deficits. A thorough definition of agricultural drought should account for the variable susceptibility of crops at different stages of development.

1.1.3 Hydrological drought

Hydrological droughts are associated with the effects of periods of precipitation shortfall on the surface, or on subsurface water supply (for example, stream-flow, reservoir and lake levels, and groundwater) rather than with precipitation shortfalls. Hydrological droughts usually delay the occurrence of meteorological and agricultural droughts since more time elapses before precipitation deficiencies are detected in reservoirs, groundwater, and other components of the hydrologic system.

1.1.4 Socio-economic drought

Socio-economic drought associates the supply and demand of some economic good or service with elements of meteorological, hydrological, and agricultural drought. In socio-economic drought, deficiencies of precipitation are directly linked to the supply of some commodity or economic good (for example, water, hay, or hydroelectric power). Population increases can substantially alter the demand for these economic goods over time. The incidence of socio-economic drought can increase because of a change in the frequency of meteorological drought, a change in societal vulnerability to water shortages, or both. For example, poor land-use practices such as overgrazing can decrease animal carrying capacity and increase soil erosion, which in turn will exacerbate the impacts of, and vulnerability to, future droughts.

1.2 THE IMPACTS OF DROUGHT

According to Chopra (2006), the impacts of drought are diverse and often ripple through the economy. For this reason, impacts are often referred to as either direct or indirect. A loss of yield resulting from drought is a direct or first-order impact of drought. However, the consequences of that impact (for example, loss of income, farm foreclosures, and government relief programmes), are secondary or even tertiary. The impacts of drought appear to be increasing in both developing and developed countries, which in many cases suggests the persistence of non-sustainable development and population growth.

1.3 DROUGHT PREPAREDNESS AND MITIGATION

Drought is considered by many people to be strictly a natural or physical event. This view of drought provides little, if any, opportunity to change the impact of drought by applying appropriate drought management techniques. In reality, drought has both physical and social components, and it is essential that water managers and decision makers understand this.

Throughout Africa, and in particular Southern Africa, the occurrence of extreme climate conditions is equally increasing (IPCC, 2007; Chamaillé-Jammes *et al.*, 2007). This problem is compounded by a process of desertification as a result of prolonged droughts (Stringer *et al.*, 2009). Failing or lack of drought mitigation and management practices, as well as lack of institutional frameworks, increase the vulnerability of water users to drought hazard. As a result, drought risk increases substantially. The impacts of droughts are often related to agriculture, crop failure and food security. However, widespread societal impacts on drought include restrictions on the use of drinking and industrial water.

Research shows that there is considerable scope for incorporating drought mitigation measures in policy, planning and institutional strengthening. This would reduce vulnerability of drought-prone regions and would require the following: More detailed and consistent drought forecasting methods; consistent indicators for drought proneness to enforce effective drought mitigation measures at all administrative levels (local, national and trans-boundary), and effective adaptation strategies at strategic time scales.

Within Southern Africa, the Limpopo basin is particularly vulnerable to the drought's effects on crop failure. Poverty in the Limpopo Province is widespread and starvation and malnutrition are common occurrences. About one million people in the Limpopo basin currently rely on food aid (Love *et al.*, 2006). As detailed in the literature review, these people have been subject to drought for a long period and have deteriorating basic humanitarian needs. Figure 1-1 shows the Luvuvhu/Letaba Water Management Area, which is within the Limpopo province. This area is one of many that has experienced drought without drought indicators giving an early warning system to the people of living in the area. For this reason this study will use the Luvuvhu/Letaba Water Management Area as a case study area.

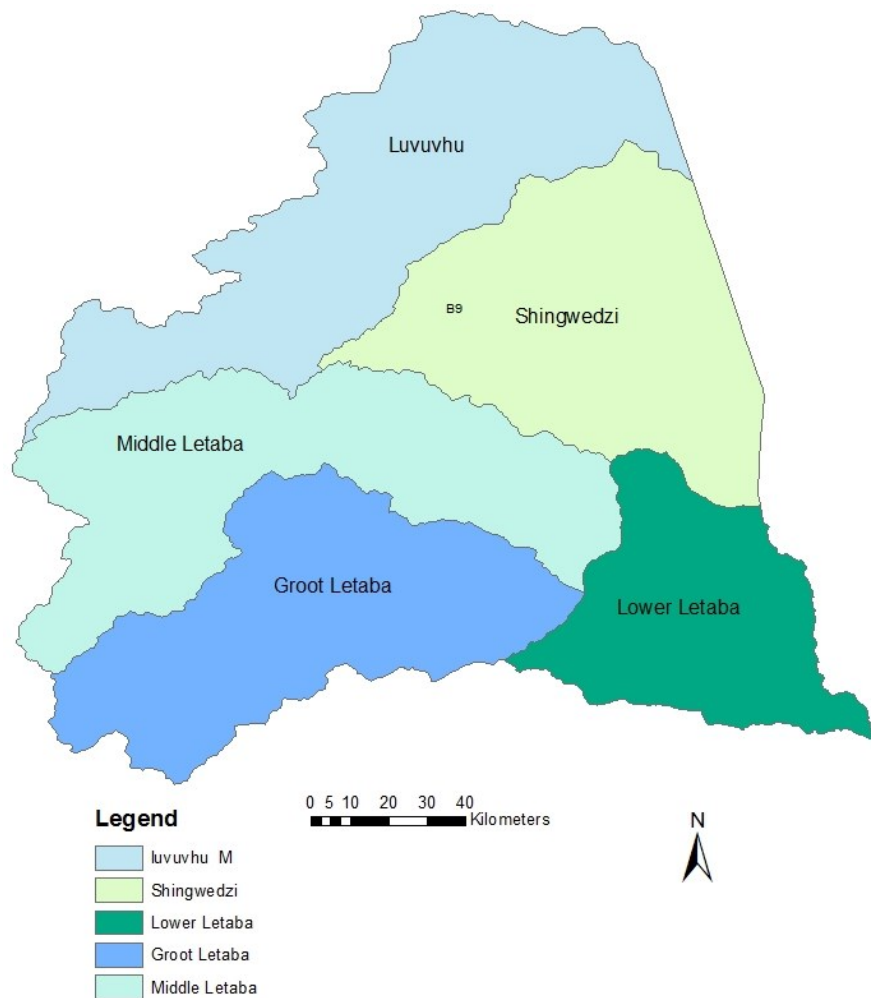


Figure 1-1: Locality of some of the districts most affected by drought in the Luvuvhu/Letaba Water Management Area

Meteorological droughts occur where the annual precipitation is between 70% and 85% of the long-term annual mean precipitation. At national level, meteorological drought is said to occur when the annual rainfall is below 75% of the long-term mean. The long term refers to a period exceeding 30 years. A deficit in runoff in rivers, surface reservoirs and ground water (as a result of rainfall) constitutes a meteorological drought. For rainfed crops, a drought is a situation of inadequate soil moisture. (US National Drought Mitigation Centre 1995; Dracup *et al.*, 1980; Zucchini and Adamson 1984; Wilhite and Glantz 1985; Rowland 1994; and Tallaksen *et al.*, 1997).

1.4 DROUGHT IMPACTS, EXPERIENCE IN MANAGING AND PLANNING FOR DROUGHTS IN LIMPOPO

Droughts differ by three essential characteristics: intensity, duration, and spatial coverage. Intensity refers to the degree of precipitation shortfall and/or the severity of impacts associated with the shortfall. Intensity is usually measured by the departure from normal of some climatic parameter (e.g., precipitation), indicator (e.g., reservoir levels) or index (e.g. Standardised Precipitation Index). Many indices and indicators are widely used to monitor drought. Another distinguishing feature of drought is its duration. In determining impact, intensity is closely linked to duration. Droughts usually require a minimum of two to three months to become established but can then continue for months or years. The magnitude of drought impacts is closely related to the timing of the onset of the precipitation shortage, its intensity, and the duration of the event. Droughts also differ with regard to their spatial characteristics.

There is a significant interval between precipitation departures and the point at which these deficiencies become evident in surface and subsurface components of the hydrologic system. This is indicated in Figure 1-2. Recovery of these components is slow because of long recharge periods for surface and subsurface water supplies.

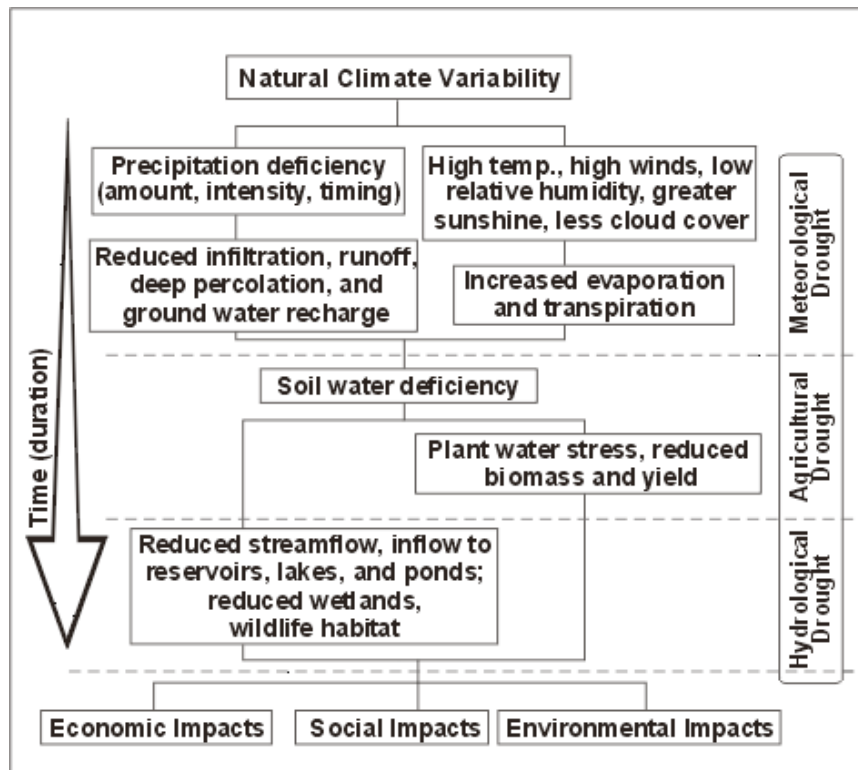


Figure 1-2: Drought types in relation to the duration of the event. The most immediate impacts of drought usually occur in the agricultural sector, followed by impacts in the water supply sector as dry conditions continue.

(Source: National Drought Mitigation Centre, University of Nebraska)

1.5 OVERVIEW OF THE STUDY AREA

The Luvuvhu/Letaba Water Management Area (WMA) is located adjacent to and shares watercourses with Zimbabwe and Mozambique. The Limpopo River demarcates the northern boundary of the WMA. The Kruger National Park (KNP) lies along the eastern boundary, and occupies approximately 35% of the Water Management Area. The Letaba Water Management Area is dominated by the irrigation sector, which represents almost 75% percent of the total requirement for water within the Water Management Area. More than half of the total water requirement within the Water Management Area is in the catchment of the Groot Letaba River. This water is mainly used for the irrigation and forestry sectors, which confirms the intensity and concentration of irrigation and afforestation in this subarea. The Luvuvhu/Mutale subarea represents a further substantial proportion of the water requirement in the Water Management Area. Surface water is the dominant source of supply in four of the five subareas. The only exception is the Shingwedzi subarea where more than half of the available water is abstracted from groundwater, while water is also transferred into the subarea from the Luvuvhu River catchment. (GOSA–DWAF, 2003).

2. LITERATURE REVIEW

2.1 DROUGHT IN LIMPOPO

Historical droughts have occurred both at regional (SADC) and local scales. The South African Weather Services and Southern Africa Regional Climate Outlook Forum provide early drought warning systems at these scales. The Limpopo Basin is identified as one of the areas in South Africa which experiences drought. This area was selected because of the need to use a geographical space and its drought experience.

2.1.1 Meteorological droughts

The following years are classified as meteorological drought periods: 1820-30, 1844-49, 1921-1930, 1946-47, 1967-73, 1982-83, 1986-87, 1991-94 and 2002-03 (Tyson, 1987 and SAWS and Department of Agriculture, 2005 (http://cnas.ucr.edu/drought-symposium/south_africa_team.html)). Campbell (1986) points out that meteorological droughts lasting between one and five years in Southern Africa, may occur at a local or regional scale. According to Tyson (1987), Southern Africa, including South Africa, has experienced meteorological droughts of varying severity over the past 300 years.

2.1.2 Agricultural droughts

As stated by GTZ (1992), the manner in which a season relates to the long-term average situation, can be determined by correlating the difference between the cumulative weekly totals of rainfall received and the long-term averages for the same period. In any given year the total annual rainfall may appear to be normal. This is because mid-season shortfalls may be levelled out by late heavy rain levels. In turn, mid-season spells may reduce crop harvest.

2.1.3 Socio-economic droughts

Benson and Clay (1994) report the following decreases: Pre-drought levels in the manufacturing (production) sector dropped by 9.3%; the actual manufacturing volume dropped by 25%; and foreign currency receipts dropped by 6%, during 1991-2. Socio-economic droughts are managed as a state of emergency. Resources are diverted from growing the economy to deal with life threats and strategic activities or resources. The most vulnerable groups include the poor, destitute, elderly, children, wildlife and livestock Nyabeze, (2004).

2.1.4 Hydrological droughts

The Tzaneen dam manager Mr J Venter in a meeting on the 5th August 2012 in a stakeholder forum explained that at the start of the 1991-92 season the cumulative effects of reduced rainfall (in the years following deficit) impacted differently on the availability of

surface and subsurface water in the different catchments. This caused surface water shortage, which in turn directly caused meteorological droughts. The cumulative effect of reduced surface water is reduced ground water recharge, which causes dried out shallow wells and boreholes. Periods of rainfall shortfall can be linked to surface or subsurface water supply deficit. These circumstances constitute hydrological droughts.

2.2 DROUGHT IMPACTS IN LIMPOPO

A USAID report (June 1994) indicated that the SADC region was struck by droughts, notably in the seasons 1982-83, 1987-88, and 1991-92. This corresponds to an average frequency of once every four or five years, despite the fact that drought periodicity is not necessarily predictable. The Food and Agricultural Organisation (FAO) (1994) identifies three drought cycles during the years 1960-1993 with lengths of 3.4, 7.1 and 5.8 years, respectively. Table 2-1 presents the impact of drought and the number of people affected from 1983.

2.2.1 Impacts of droughts between 1980/81 and 1991/92

This section reviews the impact of droughts experienced between the seasons 1980-1 and 1991-92. This review also brings together indicators to interpret possible impacts of the different levels of surface runoff deficits.

2.2.1.1 Impacts of the 1983/84 drought

The Drought and Famine in Africa report (1981-1986) indicates that 1983 and 1984 were the worst drought years, in which most of the Southern and central areas were affected. The rainy season in 1982-83 was 35 to 50% normal in the central region and 25 to 50% normal in the Southern region. As the 1982 drought continued, there were widespread livestock deaths. Water restrictions were enforced. According to FAO estimates, production in the southern provinces fell by 70-80%. This necessitated some 500,000 MT of cereals to offset the losses in 1983/84.

2.2.1.2 Impacts of the 1991/92 drought

The 1991-92 droughts are compared to the 1967-68 and 1910-11 droughts as one of the worst dry periods (Nyabeze, 2004). Comparisons of this nature indicate the drought recurrence period as it was experienced by people in different parts of the country. Commercial farming's output dropped by 60 to 70%, while communal farming dropped by between 90 and 100% of normal (Financial Gazette, 13/02/1992). Crop production was a complete failure -- even in community and household gardens. Food shortages resulted in malnutrition and increased vulnerability to disease (Nyabeze, 2004). In 1991-92, compared to

pre-drought levels, manufacturing output dropped by 25% Forestry plantations and tea estates suffered significant mortality. Inadequate irrigation water almost terminated the sugar cane industry (Benson and Clay, 1994).

2.2.1.3 Impacts of the 1993/94 drought

The Limpopo Province faced acute water problems, which necessitated the drilling of boreholes (Chronicle news bulletin, 05/09/93). According to Rowland *et al.* (1994), soil loss from water erosion was hindered during drought periods. Nevertheless, on return to normal it went up to three times the drought rates. This was aggravated by loss of plant cover and the loosening of soil during droughts. Loss of fertile soil through erosion reduced the productive capacity of land. In turn, sedimentation of some of the small to medium sized dams led to loss of live storage capacity and diminished draft.

Table 2-1: Number of people affected by drought in South Africa*

Disaster	Year	Number of people affected
Drought	2004	15,000,000
Drought	1995	300,000
Drought	1991	7, 423,000
Drought	1993	4, 354, 000
Drought	1988	1,320,000
Drought	1986	850,000
Drought	1984	840, 000
Drought	1983	760, 000

Source: *<http://www.preventionweb.net>

2.3 PURPOSES OF A METEOROLOGICAL DROUGHT INDEX

Drought indices attempt to quantify and capture the severity of drought on the landscape by assimilating data on rainfall, snowpack, stream-flow, and other water supply indicators into a comprehensible numerical value. A drought index is typically used to identify thresholds to indicate a drought's onset, severity, magnitude (duration) and (eventually) its decay (Sivakumar *et al.*, 2010).

2.3.1 Meteorological Drought Indices in use

Several indices measure how much precipitation for a given period of time has diverged from historically established norms. Though none of the major indices is intrinsically superior to the rest in all circumstances, some indices are better suited than others for certain uses. Most decision makers and resource managers find it beneficial to consult and integrate one or more indices before they make a decision in a convergence of evidence approach (Sivakumar *et al.*, 2010). The following is a brief introduction of some of the more common Meteorological Drought Indices used around the globe today.

2.3.2 Standardised Precipitation Index (SPI)

The understanding that a precipitation deficit differently impacts on groundwater, reservoir storage, soil moisture, snowpack, and stream-flow led McKee *et al.* (1993) to develop the Standardised Precipitation Index (SPI). The SPI was especially designed to quantify the precipitation deficit for multiple time scales. These time scales reflect drought's impact on the availability of different water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short scale. Groundwater, stream-flow, and reservoir storage reflect longer-term precipitation anomalies. In line with this, McKee *et al.* (1993) originally calculated the SPI for 3-, 6-, 12-, 24-, and 48-month time scales.

The SPI calculation for any location is based on the long-term precipitation record for a desired period. This long-term record is fitted to a probability distribution, which is then converted into a normal distribution. According to this distribution, the mean SPI for the location and desired period is zero (Edwards and McKee, 1997). Positive SPI values indicate greater than median precipitation while negative values indicate less than median precipitation. Since the SPI is normalised, wetter and drier climates can be represented in the same way, thus wet periods can also be monitored using the SPI.

McKee *et al.* (1993) uses a classification system to define drought intensities resulting from the SPI. McKee *et al.* (1993) defines the criteria for a drought event for any of the time scales. A drought event occurs any time when the SPI is continuously negative and reaches an intensity of -1.0 or less. The event ends when the SPI becomes positive. Each drought event, therefore, has a duration defined by its beginning and end, and intensity for each month that the event continues. The positive sum of the SPI for all the months within a drought event can be labelled the drought's "magnitude".

The SPI was designed to quantify the precipitation deficit for multiple time scales. Since it is normalised, the SPI represents wetter and drier climates in the same way. The SPI also monitors wet periods in the same way. The SPI is not very applicable to climate change analysis. This is due to the lack of temperature as an input parameter.

2.3.3 Palmer Drought Index (PDI)

The Palmer Drought index (PDI) was published in 1965 as one of the models for a drought index (Palmer, 1965). This index was designed to include antecedent precipitation, moisture supply and moisture demand and was based on the pioneering evapotranspiration work by Thornwaite (1931). In his ground-breaking paper, PDI maintains that agriculture and hydrology are more concerned with moisture shortage effects than with meteorological aspects. This statement was in response to the predominantly precipitation-based indices that were developed previously. PDI defines a drought period as a period of time (duration in months or years) during which the actual moisture supply at a given location constantly falls short of the climatically expected or appropriate moisture supply.

PDI further states that drought severity may be considered as a function of both the duration and magnitude of the moisture deficiency. Since its launch, the PDSI has been extensively used as a drought indicator for the continental USA. PDSI maps are accessible for all climatic regions of the USA from the Climate Prediction Centre at the National Weather Service's website at the following url: www.nws.noaa.gov. The PSDI ranges from values of -5 to +4, with -5.0 to 4.0 indicating extreme drought; -3.9 to -3.0 indicating severe drought; -2.9 to 2.0 indicating moderate drought; -1.9 to 1.9 indicating near-normal conditions; 2.0 to 2.9 indicating a moderate moist spell; and 3.0 to 3.9 indicating a very moist spell. This index is based on precipitation and air temperature data, as well as on the available water content of the soil (Sivakumar *et al.*, 2010).

2.3.4 Effective Drought Index (EDI)

Effective Drought Index (EDI) in its original form (Byun and Wilhite, 1999) is calculated with a daily time step. It is a function of precipitation needed for a return to normal condition, in other words it is precipitation that is needed to recover from the accumulated deficit since the beginning of drought. The EDI is an intensive measure that considers daily water accumulation with a weighing function for time passage. It calculates daily drought severity. This index is also able to diagnose prolonged droughts that continue for several years.

The EDI ranges from values -2 to 2, where -2 to -1.5 indicates extreme drought; -1.49 to -1.0 moderate drought; -0.9 to 0.9 near-normal conditions; 1.0 to 1.49 a moderate moist spell; and 1.5 to 2 a very moist spell (Smakhin and Hughes 2007). Historical data on precipitation, dam and reservoir levels is required to calculate an effective drought index. Such data is not historically available to determine the effective drought index for Luvuvhu/Letaba Water Management Area.

2.3.5 Standardised Water Supply Index (SWSI)

To complement the Palmer Index for moisture conditions across the state of Colorado, Shafer and Dezman (1982) developed the Standardised Water Supply Index (SWSI). This index depends on the season and is computed with precipitation and reservoir storage in winter. During the summer months, stream flow replaces snowpack as a component within the SWSI equation. The SWSI has been used together with PDSI to trigger the activation and deactivation of the Colorado drought plan. The SWSI is easy to calculate, yet is limited in that values between two basins or a region are difficult to compare (Doesken *et al.*, 1991) (www.drought.unl.edu).

2.4 PREVIOUS EXPERIENCE WITH SPI

Mathieu and Yves (2005) performed a retrospective analysis of the spatial extent of droughts in Southern Africa from 1901-1999. Hayes *et al.* (1999) applied the Standardised Precipitation Index (SPI) to monitor the 1996 drought in the United States of America. These researchers show how the SPI can be used operationally to detect the start of a drought, its spatial extent and temporal progression. McKee *et al.* (unpublished data, 1993) from the Colorado Climate Centre formulated the SPI in 1993. While it is quite a recent index, the SPI was used in Turkey (Komuscu, 1999); Argentina (Seiler *et al.*, 2002); Canada (Anctil *et al.*, 2002); Spain (Lana *et al.*, 2003); Korea (Min *et al.* 2003); Hungary (Domonkos, 2003); China (Wu *et al.*, 2001); East Africa (Ntale and Gan, 2003, 2004); and Europe (Lloyd-Hughes and Saunders, 2002) for real time monitoring or retrospective analysis of droughts.

Ji *et al.* (2003) studied the relationship between vegetation vigour and moisture availability with satellite sensor data for the north and central Great Plains in the United States. This was done by using the Standardised Precipitation Index and the Normalised Difference Vegetation Index for 1989-2000. The three month SPI had the highest correlation to the NDVI because vegetation response to precipitation has a time lag, and the impact of water deficits on vegetation is cumulative. The researcher suggested that the three month SPI would be best for determining drought severity and duration in vegetation cover. His

research also found that seasonality had a very significant effect on the relationship between the NDVI and SPI.

Vicente-Serrano *et al.* (2006) conducted a study in the Ebro valley in the Mediterranean region to determine spatial differences in the effects of drought on natural vegetation and agricultural crops through the joint use of the Vegetation Condition Index derived from AVHRR images, and the Standardised Precipitation Index. He demonstrated, in line with other studies (Wilhelmi and Wilhite, 2002; Wu and Wilhite, 2004), that the impact of vegetation on climate variability, including drought, can vary spatially. Likewise, he indicated that the decrease in vegetation activity in relation to drought is a normal behaviour for ecosystems.

Dutta *et al.* (2012) also performed a study to calculate agricultural drought through predicting agricultural yield via a model based on the NDVI-SPI. She used a correlation of SPI and NDVI to accept the hypothesis that there is correlation between the meteorological drought index SPI and the remotely sensed drought index NDVI derived from NOAA/AVHRR. In doing so, she subsequently found the correlation between the NDVI and crop yield.

2.5 INDICES DERIVED FROM REMOTE SENSING

According to Rouse *et al.* (1974), satellite-based drought indices such as the Normalised Difference Vegetation Index (NDVI) and the Vegetation Condition Index (VCI) (Kogan, 1995) have proved useful in detecting drought onset and in measuring intensity, duration, and drought impact in regions around the world (Anyamba *et al.*, 2001; Gutman, 1990; Ji and Peters, 2003; Kogan, 1995; Nicholson and Farrar, 1994; Seiler *et al.*, 2000; Unganai and Kogan, 1998 ; Wang *et al.*, 2001). In recent decades, optical remote sensing has demonstrated a strong potential to monitor vegetation dynamics and its variations over time. This is because optical remote sensing provides a wide spatial coverage and because its internal data sets are consistent.

Previous studies reveal a strong relationship between vegetation health (vigour), as measured by the AVHRR (Advanced Very High Resolution Radiometer) sensor (and many other optical satellites), and moisture conditions (Goward *et al.*, 2002; Nicholson *et al.*, 1994; Wang 2001).

2.5.1 Normalised Difference Vegetation Index (NDVI)

The primary sources for drought information used to support decision making in the past, were climate and meteorological data. More recently, satellite observations have demonstrated to be a valuable source of timely, spatially continuous data with improved detail for monitoring vegetation dynamics over large areas. Many prior studies of vegetation conditions base their analyses on numerical transforms known as vegetation indices (VI). These indices have been used for examining vegetation characteristics over large areas since the 1970s (Rouse *et al.*, 1974; Tucker, 1979). The advantages of using VI's instead of strictly spectral observations include minimised soil and other background effects, reduced data dimensionality, a degree of standardisation for comparison, and an enhanced vegetation signal (Curran, 1981; Godward, 1989; Malingreau, 1989). One of the more commonly used VIs, the Normalised Difference Vegetation Index (NDVI), takes advantage of the reflective and absorptive characteristics of plants in the red and near-infrared portions of the electromagnetic spectrum. Several studies have established the utility of satellite measurements to both observe and monitor drought. These studies provide analyses of the relationships between climate variables (e.g. precipitation) and satellite-derived VIs (Di *et al.*, 1994).

2.5.2 Vegetation Condition Index (VCI)

Further studies have presented drought analyses in the USA, Africa, South America, and Asia. These studies elucidate how derivatives of the NDVI can improve the ability to observe drought in time-series satellite data (Kogan, 1995; Liu and Kogan, 1996; Unganai and Kogan, 1998). One of the main advantages of the VCI is that, because it is a satellite-based drought product, it can provide near real-time data over the globe at a relatively high spatial resolution. Furthermore, the VCI uses a completely independent methodology to monitor drought, while all the other meteorological indices rely, to some extent, on station-based meteorological data. Kogan (1997) found that the VCI strongly correlated with agricultural production in South America, Africa, Asia, North America, and Europe, mainly during the critical periods of crop growth. For example, the relationship between the VCI and corn yield in some regions in Argentina was as high as 0.92 (Kogan, 1997). Unganai and Kogan (1998) achieved a more detailed analysis of the relationship between the VCI and corn yield (e.g. agricultural drought) in Southern Africa. They found that the VCI explained between 46 and 83% of the variance in corn yields. These researchers conclude that satellites can be useful to detect, monitor and map agricultural droughts and that the VCI is suitable for early assessment of corn yields in Zimbabwe (Unganai and Kogan, 1998). Gitelson *et al.* (1998) studied the relationship between the VCI and crop growth at six sites in Kazakhstan that spanned a range of climate zones. On average the VCI explained 76% of the variations in

crop density (number of plants per square meter). The VCI's performance was consistent across the six sites (Gitelson *et al.*, 1998). Dabrowska-Zielinska *et al.* (2002) also tested the suitability of the VCI and Temperature Condition Index (TCI) for modelling crop yield models in Poland.

2.5.3 Temperature Condition Index (TCI)

The Temperature Condition Index (TCI) was suggested by Kogan (1977), (Thenkabail *et al.*, 2004). This index was developed to reflect vegetation response to temperature. In other words, the higher the temperature the more extreme the drought. TCI is founded on brightness temperature and signifies the deviation of the current month's value from the recorded. Low TCI values show very hot weather and have been used for drought monitoring in Zimbabwe, USA, and China. Argentinian research in drought detection revealed that the TCI was useful to assess spatial characteristics, duration and drought severity. It was also found to be in line with precipitation patterns; moreover, the TCI has been related to recent regional scale drought patterns in South Africa (Kogan, 1998).

2.6 TOPOGRAPHICAL ATTRIBUTES

Aspect, Slope, and Elevation were demonstrated to be useful surrogates for the spatial and temporal distribution of factors such as radiation, precipitation, and temperature that affect the composition and productivity of species. Predictive models using Slope, Aspect, and Elevation can be useful for extrapolating present or historical effects to areas where observations of species composition or productivity are unavailable (Stage and Salas, 2007). Large variations in rain intensity might occur due to local wind variations brought on by small-scale topographical configurations or surface disturbances, such as high trees, buildings and windbreaks. This small-scale topographical effect is the subject of this investigation. It should be distinguished from the more well-known orographic effects, which are triggered by large-scale disturbances of the atmospheric surface layer caused by large topographical configurations. Rainfall intensity variations are significant to agricultural activities and hydrologic, erosional and ecological processes. In addition, topography can influence rainfall measurements (Poreh and Mechrez, 1984).

Hydrological applications and water resources management have created the need to determine the spatial and temporal structures of rainfall distribution by considering the topographic properties in a watershed. It is especially difficult to understand the nature of rainfall-topography relationships in mountainous regions. The fluctuations of rainfall distribution are subject to various factors concerning atmospheric conditions or topographic

features (such as moisture source, wind speed, wind direction, topographic elevation, slope orientation, barrier characteristics, scale of mountains, and other factors). A number of investigations have been conducted on the relation between such factors and precipitation distribution (e.g., Spreen, 1947; Williams and Peck, 1962; Schermerhorn, 1967; Huff *et al.*, 1975; Oki *et al.*, 1991; Johnson and Hanson, 1995).

The Normalised Difference Vegetation Index (NDVI) has been used extensively to both qualitatively and quantitatively estimate vegetation cover and growth activity. It is of critical importance to understand the relationship between the NDVI and terrain attributes so that environmental and natural resources may be protected. Climate, topography and human activities affect vegetation. In turn, vegetation creates adaptation and feedback effects for climate and human activities. Studies have revealed climatic factors, such as precipitation and temperature, as the major indicators for plant growth and development. Several studies have reported that terrain factors (including Elevation, Aspect and Slope) affect vegetation distribution and growth (Walsh, *et al.* 2001).

2.7 EXPERIENCES ON MANAGING DROUGHT CONDITIONS IN SOUTH AFRICA

In 1991-92 an infrastructure was set up to identify, assess and quantify relief needs (USAID report: Southern Africa Regional, 1994). This programme included food relief, together with livestock and wildlife rescue operations.

2.7.1 Food Relief (USAID, 1993)

- The impact of rain failure in 1991/92 was as severe in South Africa as in other countries of the region. The drought reversed the balance in grain holdings from a surplus of 1,000,000 to 2,000,000 metric tons to a deficit of 5,500,000 tons.
- As part of their all-out effort to move grain from four South African ports for domestic use and for six other countries, South African rail system experts invited neighbouring representatives of the grain boards and railways to work with them through a Grain Operations Control Centre.
- The South African ports handled an unprecedented 8.6 million metric tons of drought related commodities in thirteen months (1 April 1992 to 31 May 1993).
- Spoornet mobilised some 15,000 rail wagons to transport grain from South African ports to inland destinations.
- A Consultative Forum on Drought, established by the Independent Development Trust, the Kagiso Trust and the Rural Advice Centre, provided the venue to coordinate drought relief programmes among governmental and non-governmental organisations.

- The Water Supply Task Force of the Consultative Forum became active in July 1992. This developed out of a survey by the Rural Advice Centre and the Department of Water Affairs that disclosed that a large number of people were about to abandon their communities because of lack of water.
- The Task Force had 10,000,000 South African Rand available to help meet the immediate water needs of communities that had not been served by government programmes. The objective was to guarantee a community supply sufficient for the WHO-established minimum of 15 litres of water per person per day.
- Programmes coordinated by the Task Force serviced, repaired or installed over 300 water points serving over 700,000 people.
- The operations of the Water Supply Task Force of the Consultative Forum, in particular, confirmed the viability of partnership between government and non-governmental organisations. This enabled access by black communities to tie human and financial resources of government.

2.8 PROBLEM STATEMENT

The indecisiveness of decision makers to identify drought areas that are affected worse than others areas should be reduced. Consequently, a tool that provides precise information on drought affected areas is vitally important. It is therefore important to find a drought predicting method in these areas without observed rainfall data.

SPI application in South Africa is the only method used by the South African Weather Services to assess drought conditions in the Country and is considered the most important provider of drought information in the country to inform decisions on short-term drought management. This method currently is limited because the coarse spatial scale it uses (as shown in Figure 2-1) fails to represent the actual variability of drought conditions which is much higher. This is due to the diminishing number and sparse distribution of available rainfall stations.

Figure 2-2 shows the sparse distribution of available rainfall stations in the Limpopo in 2011. The sparse distribution of rainfall stations therefore makes it difficult to determine meteorological data based indices.

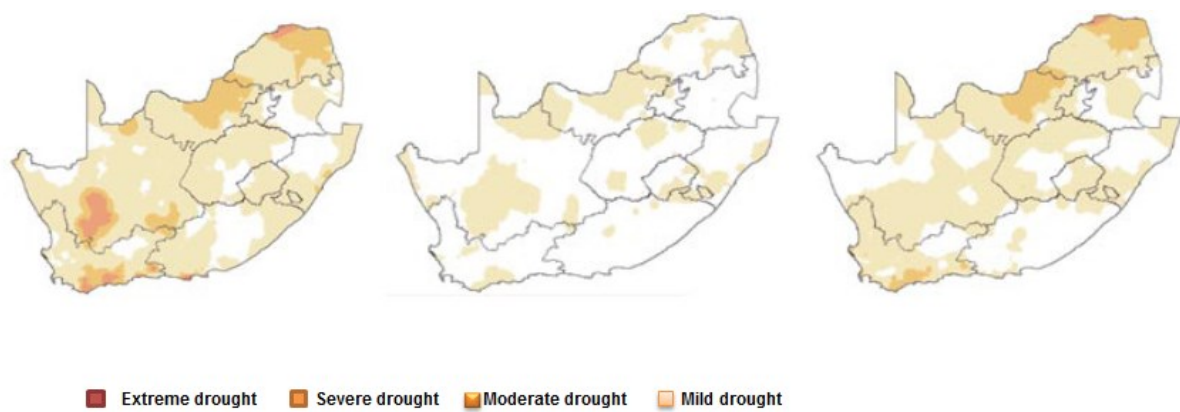


Figure 2-1: Standardised Precipitation Index (SPI) based drought maps for South Africa, November 2005 (left); September to November 2005 (middle); June to November 2005 (right)

Source: South African Weather Service

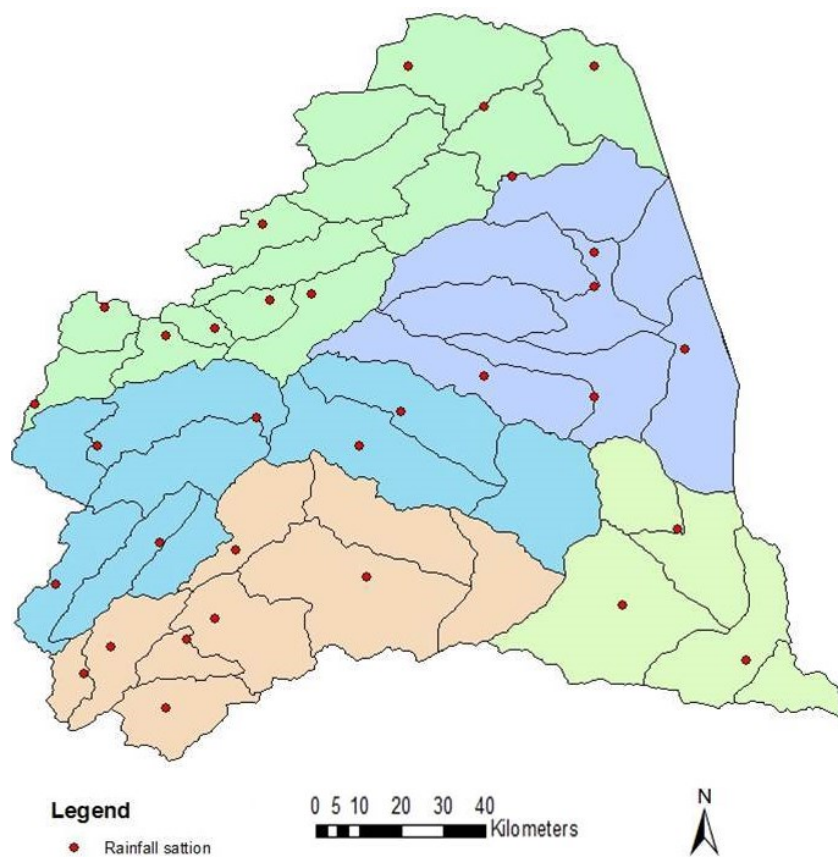


Figure 2-2: Operational rainfall stations in Limpopo in the year 2011

2.9 RESEARCH QUESTION

This study will answer the question: **How can the SPI be determined by means of NDVI, VCI and topographical attributes for locations without rainfall data?** The SPI, NDVI and VCI will be derived to establish drought severity and to find a relationship between rainfall stations based indices and satellite based indices at the same station. As mentioned in the literature review, 1983, 1984, 1991 and 1992 were severe drought periods. These drought periods began with meteorological droughts and developed into agricultural droughts. The ability of the modelled SPI to determine the drought severity will also be assessed.

2.10 OBJECTIVES OF THE STUDY

The main objective of this study is to develop a method to estimate the SPI for catchments with limited rainfall data using data for selected sub-catchments of the Luvuvhu/Letaba Water Management Area. The SPI should be obtained at an improved spatial resolution to assist in determining the extent of drought at local/community level. It is therefore important to utilise the opportunity of remote sensing for spatial data availability. This study evaluates the ability of the satellite-based vegetation indices, such as the NDVI and VCI, as well as topographic attributes (Altitude, Aspect and Slope) to predict the SPI for monitoring drought. To achieve this, the following objectives are developed:

- To derive the SPI, NDVI and VCI in order to determine the drought severity for identified periods using historical observed rainfall data and satellite images
- To determine a relationship between rainfall based indices and satellite based indices at the same station.
- To predict SPI using the NDVI, VCI, and topographical attributes at catchment scale.
- To assess the ability of the resulting model to match observed drought conditions and to compare this with the drought monitoring carried out by SAWS.

2.11 RATIONALE FOR THIS INVESTIGATION

About 70% of the population in South Africa lives in remote dry areas. Drought monitoring is based on the Standardised Precipitation Index and is done at a coarse scale that does not enable drought severity to be determined at a local (community) scale. This level of drought monitoring therefore does not enable informed drought relief decisions at community level. Furthermore, for catchments with limited rainfall data there has been no clear indication of how the SPI for drought identification can be predicted with minimal local meteorological data (Nyabeze, 2004).

3. MATERIALS AND METHODS

3.1 STUDY AREA AND DATA

3.1.1 Location

The Luvuvhu/Letaba WMA as shown in Figure 3-1 has 129 rainfall stations with available data that may be used for this study. The area is located adjacent to Zimbabwe and Mozambique and shares watercourses with these two countries, while the Limpopo River demarcates the northern boundary of the WMA. The Kruger National Park (KNP) lies along the eastern boundary, and occupies approximately 35% of the WMA.

The main rivers in the WMA are the Luvuvhu, Shingwedzi and Letaba rivers, which all flow in an easterly direction through the Kruger National Park and into Mozambique before discharging into the Indian Ocean. The Shingwedzi River first flows into the Rio des Elephantes (Olifants River) in Mozambique, which then joins the Limpopo River. The two main tributaries of the Letaba River, the Klein and Groot Letaba, have their confluence on the western boundary of the Kruger National Park, whilst the Letaba River flows into the Olifants River, just upstream of the border with Mozambique.

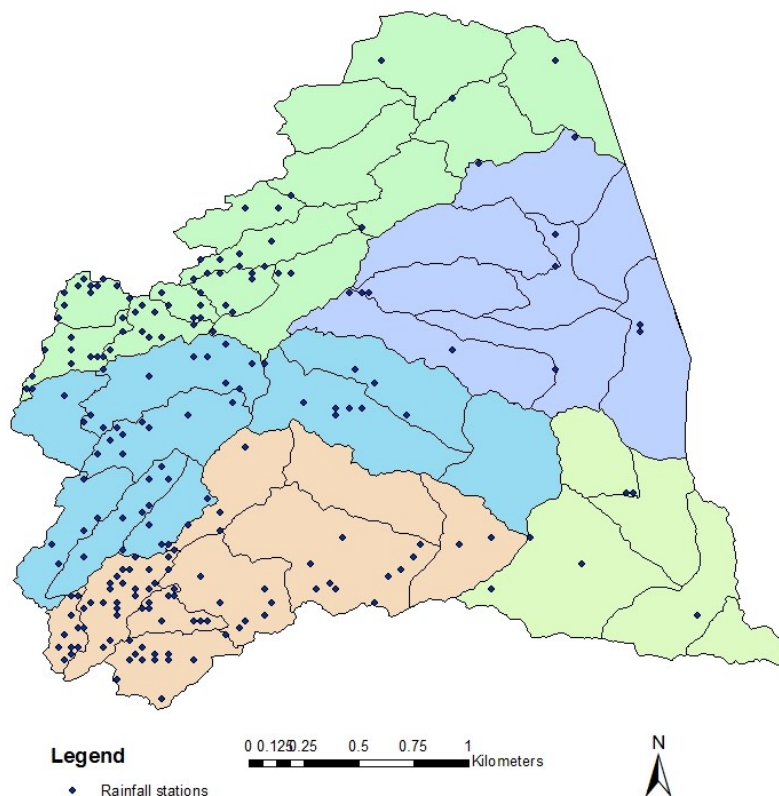


Figure 3-1: Available rainfall stations in Limpopo in year 2000 used in this study

3.1.2 Rainfall

Rainfall is strongly seasonal and occurs mainly during the summer months (i.e. October to March). Rainfall is strongly influenced by the topography. The peak rainfall months are January and February. The mean annual precipitation varies from less than 450mm on the low lying plains (northern and eastern part of the WMA) to more than 2 300 mm at Entambeni in the Soutpansberg in the mountainous areas (in the south western and north western parts of the WMA) (www.dwa.gov.za). The rainfall data used for calculating the SPI was provided by Lynch (2004). The daily and monthly rainfall datasets used were provided mainly by the South African Weather Services. **Table 3-1** presents the distribution of stations per sub-catchment. **Table 3-2** presents the critical fields in the observed metadata.

Table 3-1: Observed stations per sub-catchment

Sub-catchment	No of stations available
Groot Letaba	44
Middle Letaba	29
Lower Letaba	7
Luvuvhu	38
Shingwedzi	11

More stations are found on the eastern side of the catchment and the higher altitude is on the Middle and Groot Letaba sub-catchments. Rainfall stations at a higher altitude receive more rainfall as compared to those in low lying planes.

Table 3-2: Critical fields in the observed rainfall metadata table

FIELD	DESCRIPTION
ID	Number allocated to station for referencing in GIS
STATION_NAME	Name of station
LATITUDE	Latitude of station
LONGITUDE	Longitude of station
RECSTARTYR	First year of observed record
RECEYR	Last year of observed record
YR_OPEN	Year when station was opened

The format for observed rainfall is shown in **Appendix A**

3.1.3 Remote sensed data

3.1.3.1 Data characteristics - NDVI

Landsat Multispectral Scanner (MSS) images used in this study consist of four spectral bands with 80 meter spatial resolution. The approximate scene size is 170 km north-south by 185 km east-west. This information was retrieved from Landsat Enhanced Thematic Mapper Plus (ETM+) cloud-free images from the corresponding dates using scaled band 4 (NIR, 0.76–0.90 μm) and 3 (red, 0.63–0.69 μm) reflectances. All Landsat standard data products are Level 1 Product Generation System (LPGS) and have the following characteristics:

- Geo-TIFF output format
- Cubic Convolution (CC) resampling method
- 30-meter (TM, ETM+) and 60-meter (MSS) pixel size (reflective bands)
- Universal Transverse Mercator (UTM) map projection (Polar Stereographic projection for Antarctica)
- World Geodetic System (WGS) 84 datum
- MAP (North-up) image orientation
- Immediate for scenes already processed and ready for download. Landsat 7 takes 1 to 3 days to process data and make available for download.

Landsat scenes were processed with the Standard Terrain Correction (Level 1T). However, some scenes do not have the ground-control or elevation data required to perform these corrections. In these cases, the best level of correction is applied.

- Standard Terrain Correction (Level 1T) provides systematic radiometric and geometric accuracy by incorporating ground control points while employing a Digital Elevation Model (DEM) for topographic accuracy. The geodetic accuracy of the product depends on the accuracy of the ground control points and the resolution of the DEM used:
- The ground control points used for Level 1Terrain correction originate in the GLS2005 data set. The DEM data used for terrain correction include the following: Shuttle Radar Topography Mission (SRTM), National Elevation Data (NED), Digital Terrain Elevation Data (DTED), and Global Topographic Data (GTOPO 30).

3.1.3.2 Data characteristics - VCI

Remotely sensed composite NDVI images from the African Monitoring of Environment for Sustainable Development (AMESD) database (sourced through the Agricultural Research Centre) (ARC) were used to calculate the VCI. These images followed the process in Figure 3-4 for specific drought periods. The following parameters were applied:

- Normalised Difference Vegetation Index, derived from the visible and near-infrared channel reflectances (0.58 to 0.68 μm and 0.73 to 1.10 μm , respectively);
- Elevation, meters -1500 to 10000;
- Land Sea Mask 0 to 1
- Latitude degrees -90 to 90
- Longitude degrees -180 to 180
- Temporal Coverage: July 13, 1981 to December 31 1999
- Temporal Resolution: 10-day composites
- Spatial Coverage: Continental;

The above data was collected by the Advanced Very High Resolution Radiometer (AVHRR) flown on National Oceanic and Atmospheric Administration (NOAA) -series satellites.

(www.nasa.com/GES-DAAC/PAL/vegetation/pal_ndvi.html#201 and www.vgt4africa.org/VGTExtract/Windows/VM/setupVGTExtract_VM.exe)

An image library was created for the data collected and applies to the following periods: January to March 1983, 1984, 1991 and 1992, and June to August 1983, 1984, 1991 and 1992.

3.1.4 Topographical attributes

3.1.4.1 Land Surface configuration

The fluctuations of rainfall distribution depend on various factors concerning atmospheric conditions or topographic features, i.e., moisture source, wind speed, wind direction, topographic elevation, slope orientation, barrier characteristics, scale of mountains, and other factors. Investigations were conducted on the relation between such factors and precipitation distribution (e.g. Spreen, 1947; Williams and Peck, 1962; Schermerhorn, 1967). Studies report that the spatial and temporal variability of vegetation indices is closely related to the contribution of geographical resources to the amount of vegetation. This contribution fluctuates considerably and depends mainly on climate, soils, vegetation type and topography of an area (Di *et al.*, 1994; Ichii *et al.*, 2002).

Land surface configuration significantly influences the response of vegetation during different seasons. Slopes facing different directions have different amounts of rainfall, wind and sunlight, which in turn impacts on vegetation. Land surface configuration

- Influences vegetation through its effect on temperature, wind movement, etc. In a hills and valley country, sunlight stretches over the valley late in the morning and disappears early in the afternoon.
- The shade of the neighbouring hills makes a valley colder in winter and that of radiated heat makes the valley hot. Consequently, seasonal temperatures of the valley differ from the temperatures on the hills.
- It also affects wind movements and has a greater impact on humidity. It follows that temperature variance eventually affects the vegetation of the site.

3.1.4.2 Altitude

Large variations in rain intensity might occur due to local wind variations affected by altitude (Poreh *et al* , 1984). These variations may also be caused by:

- Altitude produced by small-scale topographical configurations, which in turn affects vegetation through solar Radiation, temperature and rainfall.
- In the same way, rainfall affected by altitude will affect the temperature and moisture, and cause a change in the nature of vegetation.

3.1.4.3 Slope

Slope influences run-off and drainage and also has a great impact on the moisture regime of the soil. The following general rule applies: The steeper the slope, the greater the run-off, and the better the drainage.

- Slope alters the intensity of insolation, temperature and moisture of the surface soil.
- Slope also influences erosion and soil depth. The greater the slope, the greater the erosion. Soil depth in the hills varies with increasing slope.
- Slope influences the vegetation of the site in that it affects the run-off, insolation, temperature, moisture and depth of soil.

3.1.4.4 Aspect

Aspect is the direction towards which a slope faces with regard to weather conditions, especially the sun and wind. Different aspects receive insolation differently. The eastern slope is open to the sun in the earlier part of the day. On the other hand, the western aspect has a desiccating effect due to the midday sun.

Aspect, Slope, and Elevation have been established as useful surrogates for the spatial and temporal distribution of factors such as radiation, precipitation, and temperature that influence species composition and productivity. Predictive models that use Slope, Aspect, and Elevation can be useful for extrapolating present or historical effects to areas (Stage and Salas 2007).

Table 3-3: DEM parameters and definitions

Parameter	Definition
Tile size	3601 x 3601 (1°-by-1°)
Posting interval	1 arc-second
Geographic coordinates	Geographic latitude and longitude
DEM output format	Geo-TIFF, signed 16 bits, and 1m/DN Referenced to the WGS84/EGM96 geoid
Special DN values	-9999 for void pixels, and 0 for sea water body

3.2 METHODOLOGY

To achieve the set out objectives, different parameters were required as data for the modelling. A SPI spread-sheet model was set up to identify the severity of drought during the period set out in the literature review in Section 2.2. Landsat images were used to determine vegetation cover during the same periods at the locations of the rainfall stations. These values were used to formulate and calibrate a model for SPI and determined the dryness of the area relative to the SPI value of the same point.

The schematic presentation of the methodology shown in Figure 3-2 involved the meteorological data process to determine the SPI (meteorological drought), the remote sensing data for determining NDVI and VCI (agricultural drought). GIS analysis was used to determine Aspect and Slope.

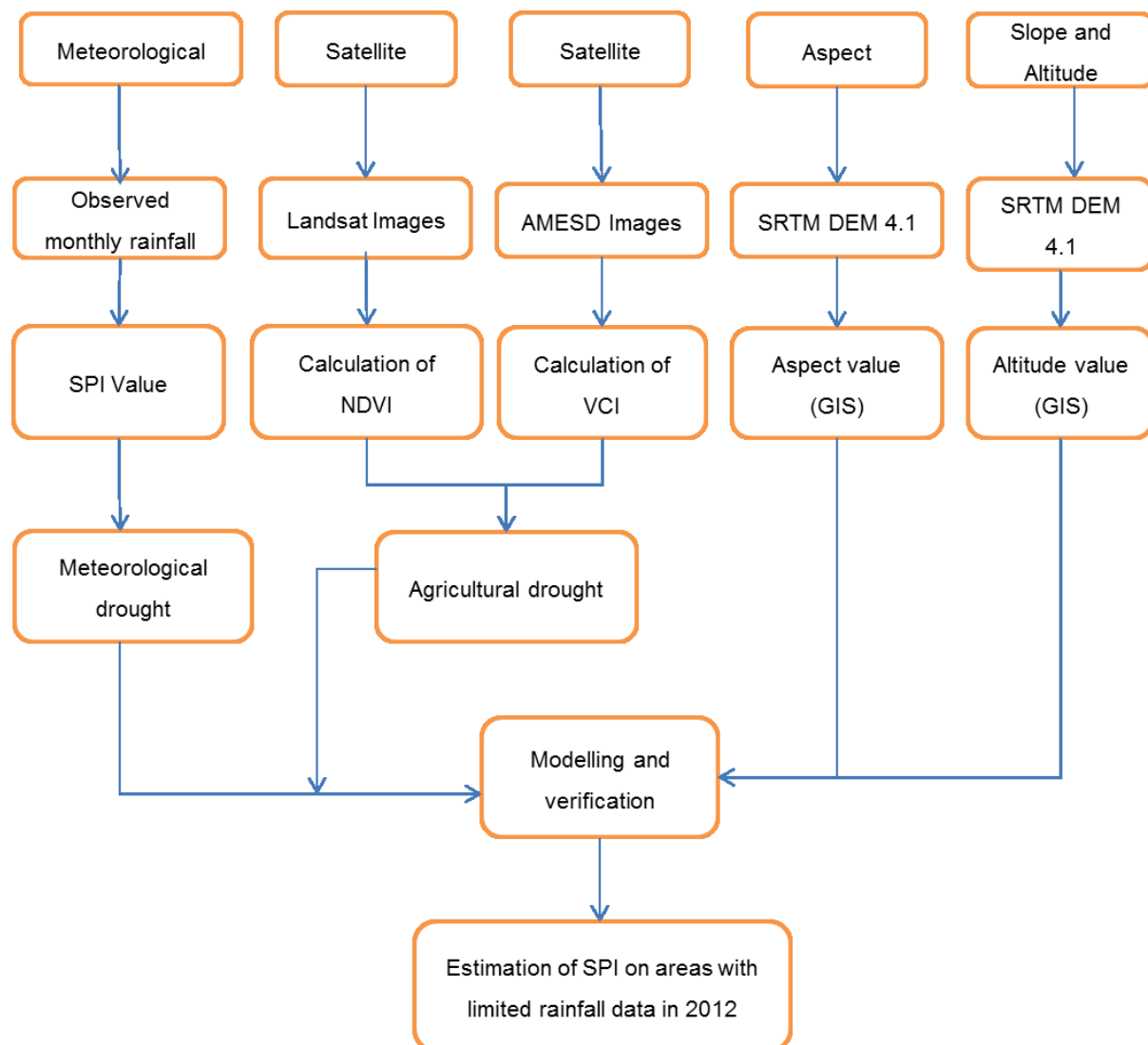


Figure 3-2: Schematic presentation of Methodology

In order to develop the model, correlation and multiple regression techniques were used to verify if there was a correlation between the SPI, NDVI, VCI, Aspect, Altitude and Slope in the Luvuvhu WMA between 1983, 1984, 1991 and 1992. The SPI, NDV, VCI, and Aspect were then used to produce SPI maps with a finer spatial resolution that could be applied for drought-related decision making at local/community level.

3.2.1 Standardised Precipitation Index– SPI

The South African Weather Services (SAWS) issues drought information using the SPI to determine the drought severity in South Africa. This is done on a monthly and three-monthly time scale. In this study, the SPI series was computed for the selected 129 weather stations for the period 1960 to 2000, at a temporal scale of three months. The aim was to identify the drought characteristics for both the wet and dry season. The SPI was used to describe the drought events affecting agricultural practices and to characterise seasonal drought due to a rainfall deficit during the primary rainy season. The three month SPI calculated for March and August uses the precipitation total for January, February, March and June, July and August respectively. A SPI computation involves fitting a gamma probability density function to a given frequency distribution of precipitation totals of a station. This was set up using equations from 3.1 to 3.11 in a Microsoft Excel spread-sheet. An example of this set-up is presented in Table 3-4 and the SPI values determined for the selected catchments are set out in Appendix B.

Table 3-4: Example of SPI calculation from spread-sheet per year

Year	Precipitation	Log _e precipitation	Gamma transform equation	t transform equation	SPI
1961	447.00	6.1026	0.5333	1.2346	0.0834
1962	426.00	6.0544	0.4614	1.2438	-0.0967
1963	271.67	5.6046	0.0489	2.4571	-1.6563
1964	245.67	5.5040	0.0241	2.7297	-1.9761
1965	493.33	6.2012	0.6783	1.5060	0.4625
1966	495.00	6.2046	0.6830	1.5158	0.4757

Usually, a drought event is defined as a period in which the SPI is continuously negative and where the SPI reaches a value of -1.0 or less. SPI values are usually classified in ranges, with values between -1.0 and 1.0 defined as near-normal conditions. Values between -1.0 and -1.50 are moderately dry, values from -1.50 to -2.0 are severely dry, and any value less than -2 is extremely dry. At the other end, values between 1.0 and 1.50 are moderately wet, 1.50 to 2.0 values are very wet, and values greater than 2 are extremely wet conditions (McKee *et al.*, 1993).

Thom (1966) found the gamma distribution to fit climatological precipitation well. The gamma distribution is defined by its frequency or probability density function:

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \dots\dots\dots 3.1$$

where x , α and $\beta > 0$ and α is a shape parameter, β is a scale parameter, x is the amount of precipitation and $\Gamma(\alpha)$ is the gamma function defined as:

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \dots\dots\dots 3.2$$

The alpha and beta parameters of the gamma probability density functions are estimated for each station and each timescale of interest (3 months, 12 months, 4 weeks, etc.), and for each time period division. From Thom (1966), the maximum likelihood solutions are used to optimally estimate α and β :

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \dots\dots\dots 3.3$$

$$\beta = \frac{x}{\alpha} \dots\dots\dots 3.4$$

Where:

$$A = \ln(x) - \frac{\sum \ln(x)}{n} \dots\dots\dots 3.5$$

n = number of precipitation observations.

The resulting parameters are then used to find the cumulative probability of an observed precipitation event for the given month and time scale for the station in question. The cumulative probability is given by:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-x/\beta} \dots\dots\dots 3.6$$

letting $t = x/\beta$, this equation becomes the simpler gamma function:

$$G(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\alpha-1} e^{-t} \dots\dots\dots 3.7$$

The gamma function is undefined for $x=0$, but precipitation distributions may contain values of zero. Thus, the cumulative probability becomes:

$$H(x) = q + (1 - q)G(x) \dots\dots\dots 3.8$$

where q is the probability of zero rainfall. If m is the number of zeros in a precipitation time series, Thom (1966) states that q can be estimated by m/n . The cumulative probability, $H(x)$ is then transformed to the standard normal random variable z with a mean of zero and a variance of one; this is the value of the SPI.

This is an equiprobability transformation, which Panofsky and Brier (1958) state has the essential feature of transforming a variate from one distribution (i.e. Gamma) to a variate with a distribution of prescribed form (i.e. standard normal). In this distribution the probability of being less than a given value of the variate will be the same as the probability of being less than the corresponding value of the transformed variate. In other words, it is transformed to a z -score, where the z term is the SPI value. This z -score is more easily obtained computationally using an approximation provided by Stegun (1965) that converts cumulative probability to the standard normal random variable z :

$$SPI = -\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \text{ for } 0 < H(x) \leq 0.5 \dots\dots\dots 3.9$$

$$SPI = -\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \text{ for } 0.5 < H(x) < 1 \dots\dots\dots 3.10$$

Where;

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \quad \text{for } 0 < H(x) \leq 0.5 \dots\dots\dots 3.11$$

$$t = \sqrt{\ln\left(\frac{1}{(1-H(x))^2}\right)} \quad \text{for } 0.5 < H(x) < 1 \dots\dots\dots 3.12$$

Where $c_0=2.515517; c_1=0.802853; c_2=0.010328; d_1=1.43788; d_2=0.189269; d_3=0.001308$.

Theoretically, the SPI represents a z-score, or the number of standard deviations above or below the mean, assuming normal distribution. This assumption is not valid for short time scales, since the distribution is skewed. The SPI also normalises with regard to location and time. It does not only account for frequency distribution and variation of precipitation at a station. It can be computed at any number of timescales depending upon the impacts of interest to the analyst. Additionally, the SPI represents a cumulative probability with regard to the base period for which the gamma parameters were estimated for any location or timescale. A functional and quantitative definition of drought can be developed for each time scale using the SPI as the indicator (McKee et al., 1993).

3.2.2 Normalised Difference Vegetation Index - NDVI

The Landsat Multispectral Scanner (MSS) images obtained through a satellite's row and path from United States Geological Survey (USGS) data were available in GEO-tiff format. Through a three week application and download process, transformation into image format was done by Landsat imagery's department for each season. At that point this ten day image composite dataset was downloaded and stacked using ENVI software. Each stacked layer for each period contained four layers representing six fortnights (January–March) of wet season and (June – August) of dry season. Atmospheric correction was applied to these stacked layers. Surface reflectance was done to show season comparison. Using the ENVI software the images were processed to arrive at drought indicators for Normalised Difference Vegetation Index (NDVI) for specific drought periods for each weather station location. These became the model generation locations. The composite NDVI data was divided into groups to be analyzed for 1983, 1984, 1991 and 1992. The weather station's NDVI value was extracted for each season for the selected catchments as set out in Appendix B. The Geographical information System (GIS) was used for 129 stations in the analysis.

More recently satellite observations have proved to be a valuable source of timely, spatially continuous data with improved detail to monitor vegetation dynamics over large areas. The NDVI is a vegetation greenness indicator that uses the visible and near-infrared bands of the electromagnetic spectrum (Rouse 1974). Healthy vegetation will absorb most of the electromagnetic energy in the red region, and highly reflect in the near-infrared region. NDVI values range between -1 to 1 where -1 represents water or snow; values around zero represent bare soil and values closer to 1 green vegetation. Healthy vegetation will usually absorb most of the visible light that falls on it, and reflect a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum (Holme *et al.*, 1987). Because we know plant behaviour across the electromagnetic spectrum, we can derive the NDVI information by focusing on the satellite bands that are most sensitive to vegetation information (near-infrared and red). The higher the difference between near-infrared and red reflectance, the higher the presence of the green vegetation.

The following equation was used for calculating NDVI using ENVI software:

$$NDVI = \frac{NIR-RED}{NIR+RED} \dots\dots\dots 3.13$$

Where: NIR is near-infrared

RED is red reflectance

The temporal variations in the NDVI reflect the vegetation's response to weather variability (Potters and Brooks, 1998). Consequently, this index has been widely used to monitor ecosystem, and to detect spatial extent of drought episodes and their impact (Di *et al.*, 1994, Kogan, 1995, 1997; Marsh *et al.*, 1992). Figure **3-3** shows the steps followed to acquire the NDVI data in order to detect drought and to set up the model.

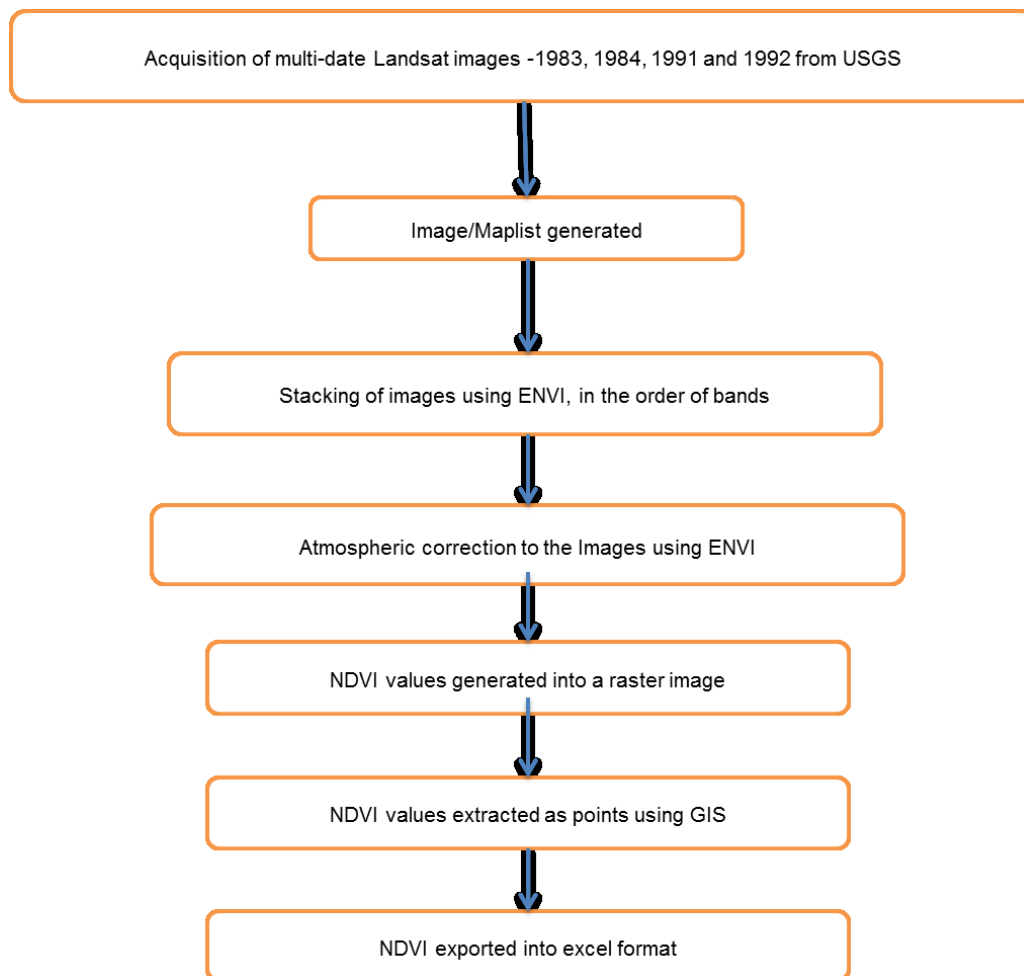


Figure 3-3: Steps followed in generating NDVI data from Landsat Satellite images

3.2.3 Vegetation Condition Index - VCI

The NDVI derived from the AVHRR on board of the NOAA was used to calculate the VCI. Because AVHRR provides imagery with high temporal resolution (daily) and large area coverage, it is convenient for mapping vegetation vigour time series at global or regional levels (Ji and Peters 2003). The African Monitoring of Environment for Sustainable Development (AMESD) database for the NDVI was sourced through the Agricultural Research Centre (ARC). The VCI was calculated, as it requires minimum and maximum NDVI values. The NDVI images used for the study were from 1981-1999. The AMESD drought monitoring system software available at ARC is capable of internally calculating the minimum and maximum values. Consequently it was used to calculate VCI. The period to be evaluated was specified on the software and run for VCI values using the equation 3.13. The composite VCI data produced was divided into groups for analysis for 1983, 1984, 1991 and 1992 as these periods represent mainly the rainy and dry season (January, February, March and June, July, August). The weather station VCI value was extracted for each season using

the Geographical information System (GIS) for the 129 stations used in the analysis for the selected catchments as set out in Appendix B.

Although the NDVI has been extensively used in the past for vegetation monitoring, it is often very difficult to interpret for vegetation condition, especially when comparing different ecosystems. From the NDVI alone, one cannot isolate weather related NDVI changes from other changes related to geographic factors such as soils, topography, vegetation type and climate. To separate the short-term weather signal in the NDVI data from the ecological signal, Kogan (1990) proposed the Vegetation Condition Index (VCI), which is derived from the NDVI as shown below

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} * 100 \dots\dots\dots 3.14$$

Where $NDVI_{min}$ and $NDVI_{max}$ are the absolute multi-year minimum and maximum NDVI values for each pixel. The VCI has shown good results in drought detection, tracking and mapping, as well as in estimating drought impact on vegetation elsewhere (Kogan, 1995). The VCI provides accurate drought information not only for well defined, prolonged, widespread and intensive droughts but also for very localised and short term droughts (Kogan, 1995).

The VCI shows how close the NDVI of the current month is to the minimum NDVI calculated from the long-term record. The condition/health of the ground vegetation presented by VCI is measured in percentage. The VCI values around 50% reflect fair vegetation conditions. The VCI values between 50 and 100% indicate optimal or above normal conditions. At the VCI value of 100%, the NDVI value for this month (or week) is equal to maximum NDVI. Different degrees of a drought severity are indicated by VCI values below 50%. Kogan (1995) illustrates that the VCI threshold of 35% may be used to identify extreme drought conditions. The VCI value close to 0% reflects an extremely dry month, when the NDVI value is close to its long term minimum. Low VCI values over several consecutive time intervals point to drought development.

Figure 3-4 shows the steps followed in acquiring VCI data in order to detect drought and to set up the model.

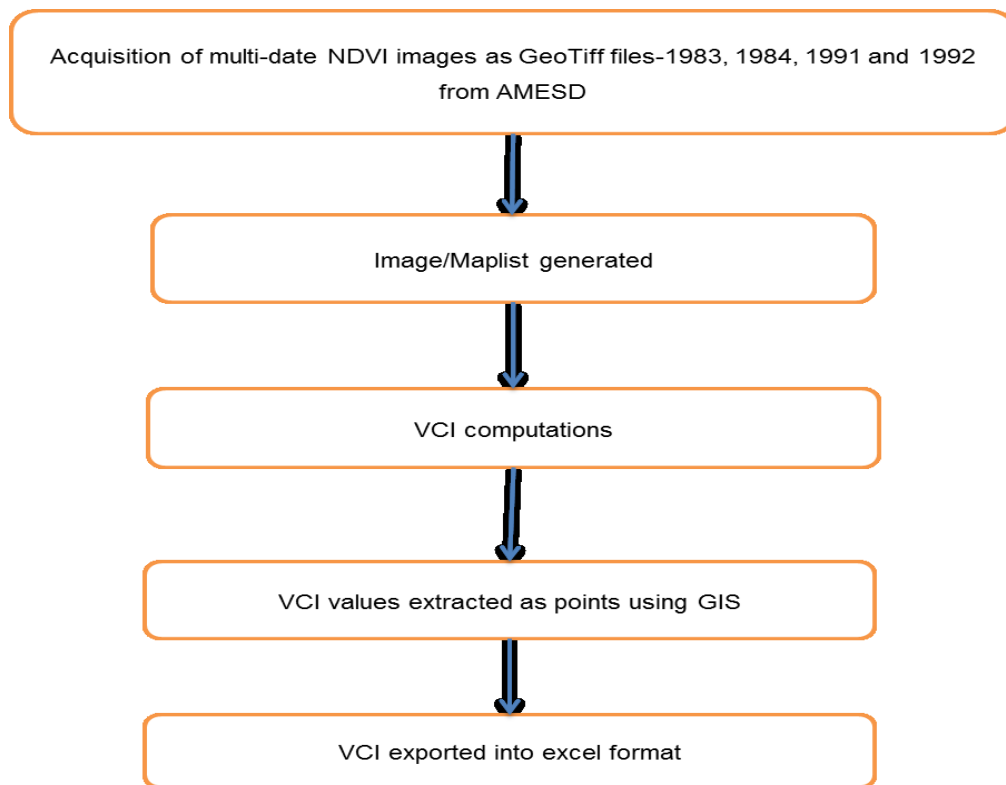


Figure 3-4: Steps followed in generating VCI data from AMESD images

3.2.4 Spatial representativeness: Scaling from point to pixel

One of the fundamental characteristics of a remotely-sensed image is spatial resolution. This is also known as the area size on the ground from which the measurements that comprise the image are derived (Townshend, 1980). A comprehensive study of the effect of spatial resolution on classification accuracy was carried out by Markham and Townshend (1981). Their conclusions represent the culmination of the results of many earlier studies. They concluded that observed classification accuracies were the result of a trade-off of two factors. The spatial resolution of a remotely sensed measurement is determined by the sensor's instantaneous field of view (IFOV), the area of the target which is viewed by a sensor in an instant of time. With imaging sensors, remote-sensing methods regularise continuous landscapes into a grid of equally sized and regularly spaced data. This data is expressed as a pixel size (Fisher, 1997). It is anticipated that there will be some degree of dependence between pixels. Using this definition, spatial resolution is analogous to scale (Woodcock and Strahler, 1987). Scale is a fundamental concept in remote sensing. It also plays an important role in determining the type and quality of information that can be extracted from an image. The first factor is boundary pixels' influence on classification results. As spatial resolution becomes finer, the proportion of pixels falling on the boundary of objects in the scene will decrease. It is assumed that land cover is spatially dependent

both within and between pixels. This assumption is realised on condition that the intrinsic scale of spatial variation in each land cover class is the same as or greater than the scale of sampling imposed by the image pixels (Atkinson, 1997). Spatial correlation is said to happen when the presence, absence, or degree of a certain characteristic influence the presence, absence, or degree of the same characteristic in neighbouring units (Cliff and Ord, 1973). This condition is specifically important in accuracy assessment if an error in a certain location can be found to positively or negatively influence errors in surrounding locations (Campbell, 1981). Work by Congalton (1988) on Landsat MSS data from three areas of varying spatial diversity (i.e., an agriculture, a range, and a forest site) present a positive influence in as much as 30 pixels (over 1 mile) away.

For correction of possible errors resulting from the scaling down of information from a point to remote sensing satellite the following assessment was done in this study: The relationship was found between a value of a single pixel that represents a point rainfall station to the average value for pixels that surrounds the same station. This verification was done to firmly conclude whether it is good enough to use a 60m x 60m pixel for the analysis particularly in this study. This process was done for thirty stations to determine the variation in representation of a pixel value for NDVI which was assumed to have same effect as the VCI at a station. NDVI values extracted from the images were point values. The assumption was that a single value in a pixel will give a fair representation of the surroundings.

To have allowable confidence to this assumption, the relationship between the pixels was investigated using R^2 to assess the deviation from a single pixel to surroundings. This was done using a 60m x 60m pixel value and the average of pixel values on a wider area. This was done at 180 x 180m, 300 x 300m, 420 x 420m, 540 x 540m, 660 x 660m, 780 x 780m, 900 x 900m and 1020 x 1020m.

3.2.5 Topographical attributes from maps and GIS

The attributes describe the configuration of the ground (its Altitude, Slope and Aspect) and also affect vegetation through climate (precipitation), soil formation processes, and soil moisture and soil nutrients. Slope affects the vegetation of the site by affecting the run-off, insolation, temperature, moisture and depth of soil.

Atmospheric and soil moisture content is influenced by climate, topography and geologic substrate as reviewed by Venter *et al.* (2003) and Mutanga *et al.* (2004). Digital elevation data used to compute values was sourced through the Council of Scientific and Industrial Research (CSIR) from SRTM 4.1 Digital Elevation Model (DEM) with its relatively high

spatial resolution of 90 m. Slope and Aspect were derived from the DEM using ArcGIS 10x. The ASTER GDEM with parameters shown in Table 3-3 were used in this study and made available by the Earth Observation Department at the CSIR. It covers land surfaces between 83°N and 83°S and is comprised of 22,600 1°-by-1° tiles. The ASTER GDEM is in Geo-TIFF format with geographic latitude/longitude coordinates and a 1 arc-second (approximately 30 m) grid. It is referenced to the WGS84/EGM96 geoid. Pre-production estimated accuracies for this global product were 20 m at 95 % confidence for vertical data and 30 m at 95 % confidence for horizontal data.

http://www.gdem.aster.ersdac.or.jp/ASTER_GDEM_Validation_Summary_Report

An image library was created for data collected (applied for January to March 1983, 1984, 1991 and 1992, and also June to August 1983, 1984, 1991 and 1992).

- Image layers were stacked together, based on their band from band 1 to band 4.
- An atmospheric correction was applied to the images to convert radiance to reflectance, and further optimise them for year to year comparison.
- The NDVI raster image was derived using ENVI software.

3.2.6 Modelling- Stepwise Multiple Linear Regression

To assess the possibility of predicting SPI, the researcher needed to find a model that would fit the NDVI, VCI, SPI and topographic attributes in it. If these variables could be modelled to come up with the best possible model that could predict SPI, then the model would subsequently be used to predict areas with limited rainfall data using available remotely sensed data. The regression technique selected for data analysis was Stepwise Multiple Linear Regression (SMLR), which has also been used by Grossman *et al.*, 1996; Martin and Aber, 1997; Kokaly and Clark, 1999; Huang *et al.*, 2004; and Schlerf *et al.*, 2010. Truly non-linear models are rarely absolutely necessary and most often arise from a theory about the relationships between the variables rather than from an empirical investigation (Marinova, 2010). Model construction and validation are critical in predicting a dependent variable given the independent variable as it helps to assess the reliability of models before they can be used in decision making. Jannath and Tsuchido, 1988; Hinkely, 1997; and Efron, 1998 considered the application of the bootstrapping method to the regression models from a model based resampling approach.

Hollander and Wolfe (1973); and Lehman (1998) implemented R programming language by means of correlation matrices. The aim was to assess the relationships between environmental variables and grass nutrient concentrations and to help the interpretation of

the integrated modeling outputs. This non-parametric correlation was used because it handles both continuous and categorical data sets irrespective of their statistical distribution. Also Lehman (1998) quantified the relationship between remote sensing and environmental variables since it can be applied for both categorical and continuous data. Based on the previous work done, the linear model is much simpler than other possible forms and so is the preferred form.

A statistical regression model was used to determine the relationship/correlation between the NDVI, VCI, SPI and topographic attributes (Slope, Aspect and Altitude), implemented in R statistical programming language see appendix C. A multivariate parametric regression technique, such as Stepwise Multiple Linear Regression (SMLR) was also implemented in R. SMLR is the step by step iterative construction of a regression model that involves an automatic selection of independent variables. Stepwise regression can be achieved either by trying out one independent variable at a time and including it in a regression model, or by including all independent variables and eliminating those that are not statistically significant (Cheng, 2004). For multivariate analysis, the dependent variable was SPI and the independent variables were the NDVI, VCI, and the topographical attributes.

The first step was to use a uni-variate analysis with a combination of SPI and NDVI, SPI and VCI, to assess the prediction capability of vegetation indices. The second step was to perform a multivariate analysis using stepwise multiple linear regression (SMLR). SPI prediction model was developed based on NDVI, VCI, and topographical features. The significant variables were selected according to lowest Akaike Information Criterion (AIC) (Sakamoto et al., 1986). AIC is a measure of uncertainty for the range of values. The model with the smallest AIC is deemed the best since it minimises the difference from a given model to a true model (Beal 2005; Sakamoto et al, 1986; An and Gu, 1989).

In this study AIC was used to select important variables. Less significant variables were removed. The selected variables were then used in bootstrapping to improve the estimation accuracy for SPI. This process was done for both the wet and dry seasons of 1983, 1984, 1991 and 1992. To develop a robust model, 1983, 1984 and 1991 for the wet season and 1984, 1991 and 1992 for the dry season models were selected. The selection was based on R² and RMSE and combined to provide a robust model to predict SPI.

Linear Model

Linear models were developed in R statistical programme, which can be used as a matrix-based programming language or as a standard statistical package. According to Faraway (2002), the main features of R include powerful data analysis and graphical tools, manipulation of matrices, and data handling and storage.

One very general form for a linear model would be

$$Y = f(X_1, X_2, X_3) + \varepsilon \quad 3.15$$

Where Y is the output, X are different parameters, f is some unknown function and ε is the error in this representation which is additive in this instance. Since the researcher does not have enough data to try to estimate f directly, the linear model has been widely used previously (Section 3.2.6), has been adopted. The linear model takes the form;

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad 3.16$$

Where β_i , $i = 0, 1, 2, 3$ are unknown parameters β_0 is the intercept term. Thus the problem is reduced to estimating four values rather than the complicated infinite dimensional f .

3.2.6.1 Model structure and regression analysis

Faraway (2002) states that given the structure of R as a linear model, the matrix representation of the model with two or more variables (from equation 3.16) may be written as:

$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \varepsilon_i \quad 3.17$$

but the use of subscripts becomes inconvenient and conceptually obscure. The matrix representation for regression becomes

$$y = X\beta + \varepsilon \quad 3.18$$

where $y = (y_1, \dots, y_n)^T$, $\varepsilon = (\varepsilon_1, \dots, \varepsilon_n)^T$, $\beta = (\beta_0, \dots, \beta_3)^T$ and

$$X = \begin{pmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ \dots & \dots & \dots & \dots \\ 1 & x_{n1} & x_{n2} & x_{n3} \end{pmatrix}$$

Considering parameters that were to be used as data for the study i.e. SPI, NDVI, VCI, aspect and elevation, six linear models were used to model SPI as a function of the NDVI, VCI, Aspect and Elevation. Equation 3.19 and 3.20 evaluates the model relationship between SPI (y_i) and NDVI (X_{1i}) or VCI (X_{2i}) at a point rainfall station.

In Equation 3.21, VCI (X_{2i}) is added to find relationship between SPI and NDVI combined with VCI. Equation 3.22 adds aspect (X_{3i}) into the model to find relationship between SPI and NDVI, VCI and aspect. Equation 3.23 models VCI (X_{2i}) and Topographical attributes (X_{3i}) and (X_{4i}), lastly equation 3.24 combines all the parameters to model SPI and other parameters. The analysis involved 129 stations to allow proper comparison with available data for SPI as shown in equation 3.25

$$y_i = \beta_0 + \beta_1 X_{1i} \quad 3.19$$

$$y_i = \beta_0 + \beta_1 X_{2i} \quad 3.20$$

$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} \quad 3.21$$

$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} \quad 3.22$$

$$y_i = \beta_0 + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} \quad 3.23$$

$$y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} \quad 3.24$$

Where y_i = SPI Value at station i , X_{1i} = NDVI value at station i , X_{2i} = VCI value at station i ,

X_{3i} = Aspect value at station i and X_{4i} = Elevation value at station i .

$$\text{and } Y_i = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{129} \end{pmatrix}, \quad X_{1i} = \begin{pmatrix} X_{1,1} \\ X_{1,2} \\ \vdots \\ X_{1,129} \end{pmatrix}, \quad X_{2i} = \begin{pmatrix} X_{2,1} \\ X_{2,2} \\ \vdots \\ X_{2,129} \end{pmatrix}, \quad X_{3i} = \begin{pmatrix} X_{3,1} \\ X_{3,2} \\ \vdots \\ X_{3,129} \end{pmatrix}, \quad X_{4i} = \begin{pmatrix} X_{4,1} \\ X_{4,2} \\ \vdots \\ X_{4,129} \end{pmatrix}, \dots 3.25$$

Bootstrapping

Bootstrap permits simulation of needed test data sets that mimic the initial data set. Model validation is then carried out by repeating the model formulation procedure on the bootstrap samples. Bunke and Droge (1984), Efron and Tibshirani (1997), performed validation by means of a bootstrapping technique because of the small sample sizes involved. A similar approach was used in this study to assess the model accuracy. Bootstrapping iteratively resamples the data set to be used for model development. This makes it a good technique to assess model accuracy; (Verbyla and Litvaitis, 1989). The advantage of bootstrapping is that it can be used efficiently when only a limited number of samples are available. The idea is to take multiple resamples of your original dataset, then compute the statistic of interest on each resample. A data point is drawn at random from the data set. The regression is performed with 70% of the data set. It validates with 30% and is then thrown back to the original dataset. A second data point is drawn and the same process is repeated a thousand times. The results of reiterated samples are then used to find the stronger correlation and eliminate statistically insignificant variables. In this study for NDVI, VCI, Aspect and Elevation, SMLR was integrated with bootstrapping to derive calibrated and validated models. SMLR was integrated with bootstrapping via R programming.

Bootstrapping with SLMR used 1000 iterations. Only significant parameters using AIC were used in the model development. The parameters were selected by means of the conventional rule for selecting independent variables in SMLR. Confidence intervals often have a duality with two-sided hypothesis tests. A 95% confidence interval contains all the null hypotheses that would not be rejected at the 5% level. That is, if $p < 0.05$, it is accepted and if $p > 0.01$ then it is rejected. For SMLR, the retrieval accuracy was defined by the bootstrapped mean of the coefficient of determination (R^2) and the root mean square error (RMSE). The confidence interval at a 95% confidence level was calculated for both R^2 and RMSE. The highly accurate bootstrapped model was applied to the NDVI, VCI and Aspect and Elevation images to map the predicted SPI's.

3.2.7 Assessing the performance of the SPI model

As indicated in Section 2.8, the approach of predicting SPI using meteorological data by SAWS may not give a conclusive/holistic picture of the extent of drought in a particular catchment because of the sparse distribution of available rainfall data. The safe use of the more spatially-precise SPI model results however first requires verification ideally based on observed drought conditions for a period not applied in model development. For this, year 2012 was selected. Regression models for the wet and dry season models that had been developed were used to develop SPI images for year 2012. This was done by first developing the NDVI and VCI images for both the wet and the dry season for 2012. Similar steps were followed as what was explained in Section 3.2.2 and 3.2.3. The coefficients of variables from the model were applied to the NDVI, VCI and aspect images on GIS to develop an SPI map for 2012. The wet and dry season maps developed were then classified using the same criteria as used by SAWS; 0.20 and below as extremely dry; 0.21 to 0.35 as severely dry; 0.36 to 0.40 as moderately dry; 0.41 to 0.49 as somewhat dry; 0.50 to 0.65 as normal conditions; 0.66 to 0.80 as wet conditions; and 0.80 and above as very wet conditions.

Areas with the same classification were mapped together to allow comparison with SAWS maps. Five communities that are well spread out within Limpopo; Tzaneen, Mandlakazi, Ga-Modjadi, Thohoyandou and Giyani were selected for the verification. These communities were visited for detailed field observations of the drought conditions in 2012 for the wet and dry season. As shown on appendix D, field visits were done through the assistance of the Catchment Management Agency which had meetings with water users. An opportunity to present and ask questions to water users was given to the researcher during the meetings. This required significant amount of time as the meetings were spread all over the study area. These meetings were accompanied by field visits to farms and sources of water supply. Stakeholder meetings were also held by the Department of Water Affairs to address issues of water availability to water managers and water users in the study area and the researcher would also make use of these opportunities to interact with water users and water managers and obtain information on the drought conditions and on the performance of available drought indicators.

4. RESULTS AND DISCUSSION

4.1 STANDARDISED PRECIPITATION INDEX– SPI

1983, 1984, 1991 and 1992 were the years identified as drought years. The Letaba Ranch station, which is in the Middle Letaba sub-catchment, was selected to demonstrate the ability of the SPI to locate drought over a 30 year period that include the known years of drought. This was done for the wet season as shown in Figure 4-1. Though it was the wet season a -1.189 SPI value was obtained in 1983. This identifies moderately dry conditions and an SPI value of -1.606 in 1992. In turn, this identifies a very dry condition despite it being a wet season.

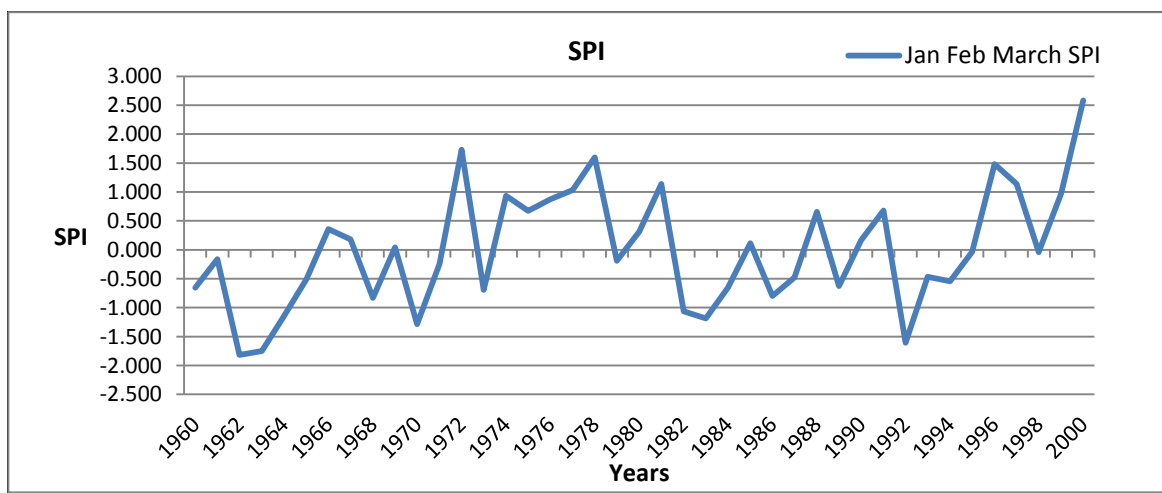


Figure 4-1: January to March Standardised Precipitation Index 1960 - 2000 for Letaba Ranch station

The dry season shown in Figure 4-2 recorded in 1992 severe dry conditions of -2.269. These conditions were previously seen in 1969 and 1972. In 1983 and 1984 the dry season was as close to normal as in other years.

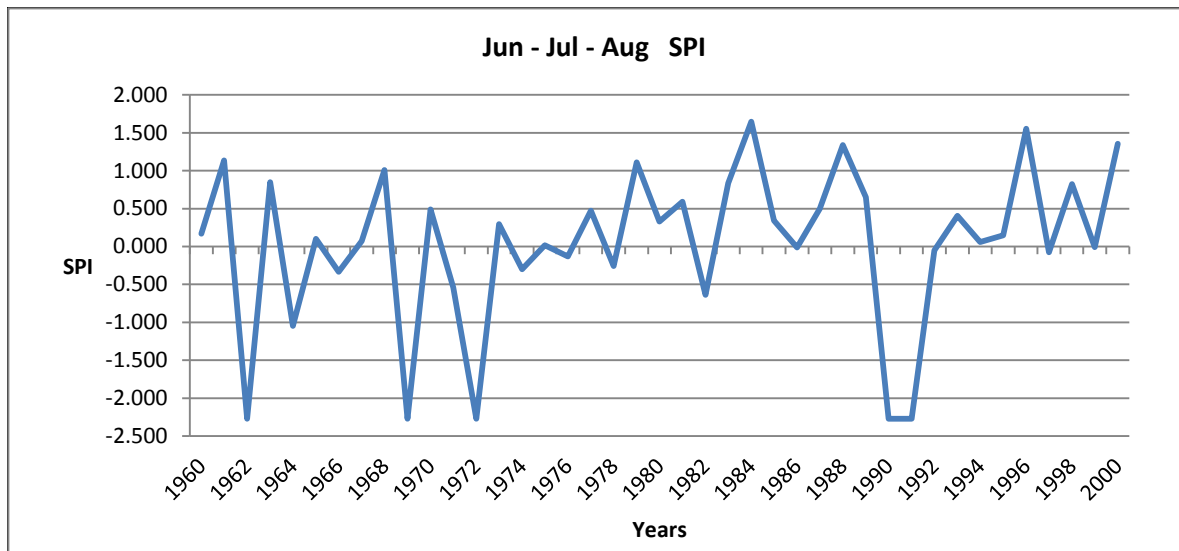


Figure 4-2: June to August Standardised Precipitation Index 1960 – 2000 for Letaba Ranch station

The annual SPI, which assesses the overall wetness and dryness of the year, shows that 1983 and 1984 were dry years while 1991 and 1992 were the worst of dry years experienced in the period (Figure 4-3).

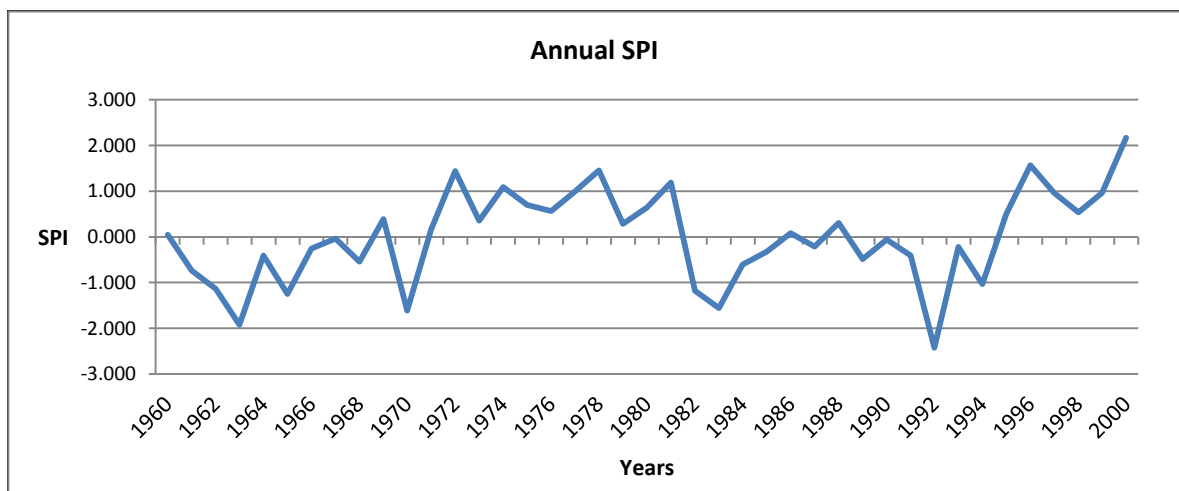


Figure 4-3: Annual Standardised Precipitation Index 1960 – 2000 for Letaba Ranch station

The graphs from Figure 4-4 to Figure 4-11 show the SPI point values at various rainfall stations for the years of drought. This indicates the dryness and wetness of the surrounding areas during the specific years.

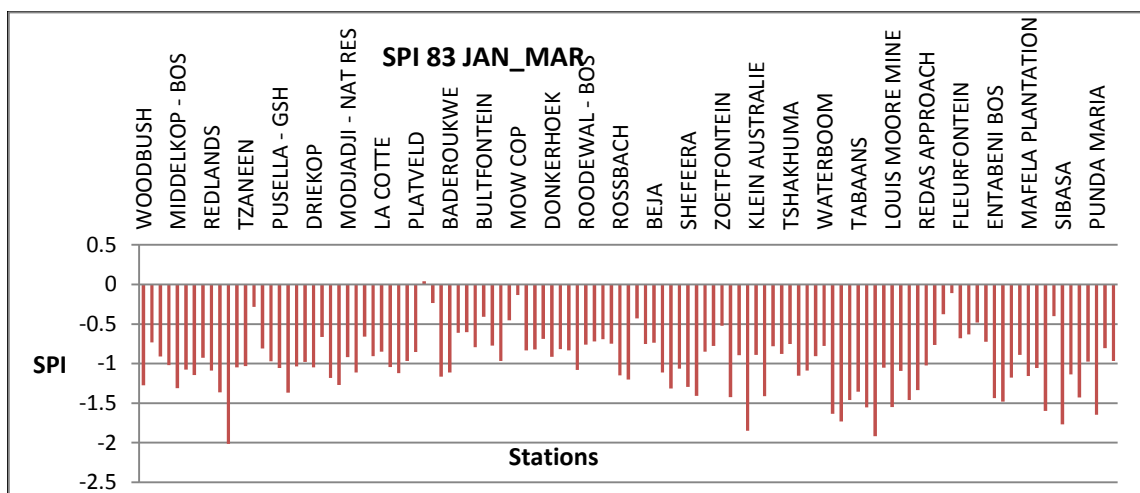


Figure 4-4: January to March: Standardised Precipitation Index 1983

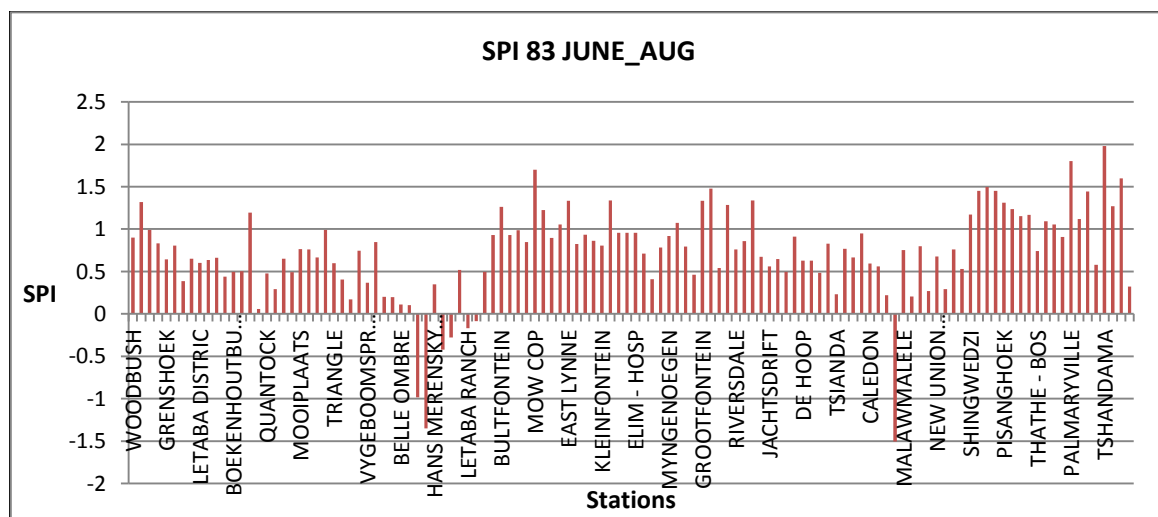


Figure 4-5: June to August: Standardised Precipitation Index 1983

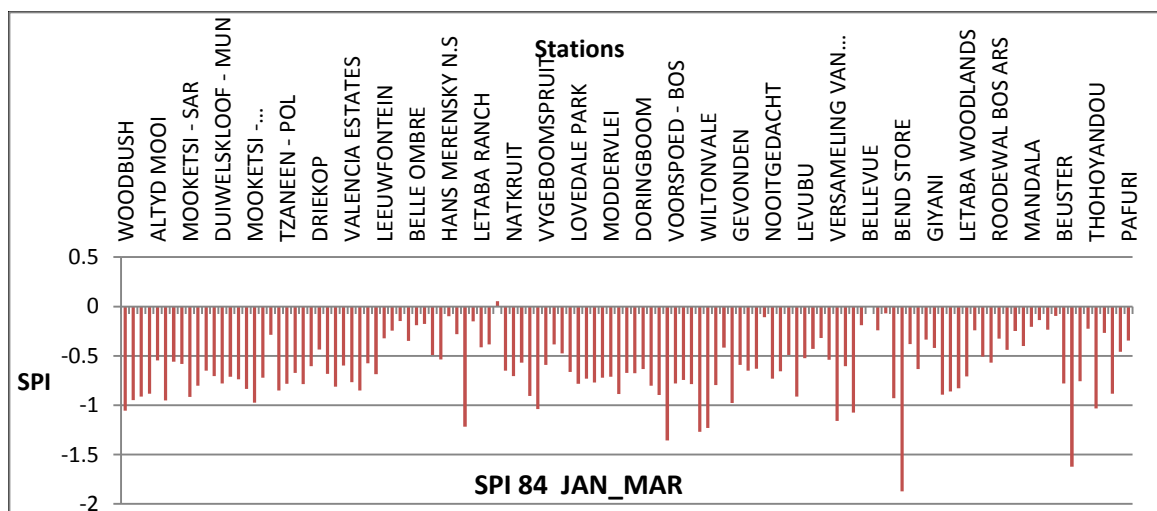


Figure 4-6: January to March: Standardised Precipitation Index 1984

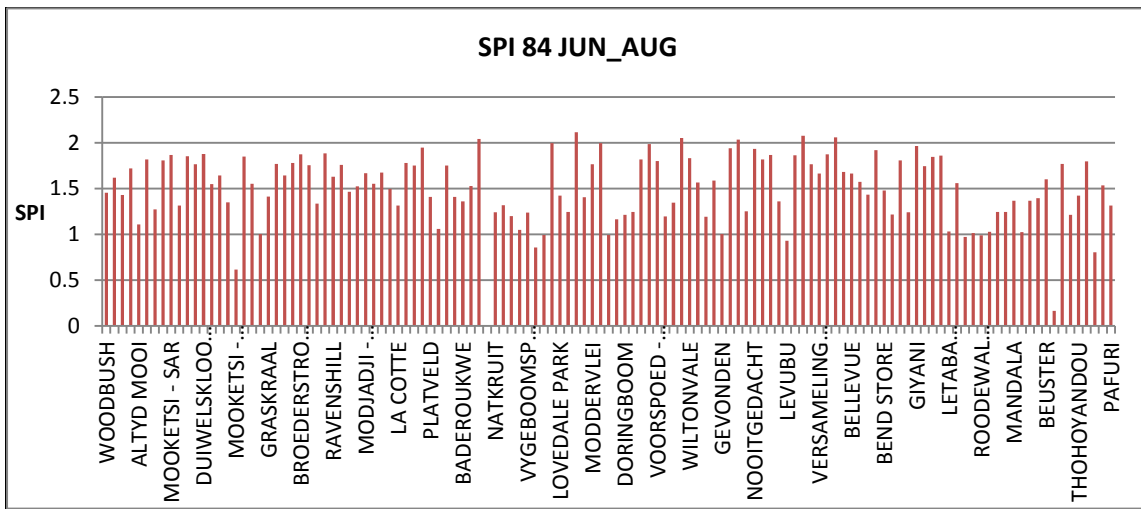


Figure 4-7: June to August: Standardised Precipitation Index 1984

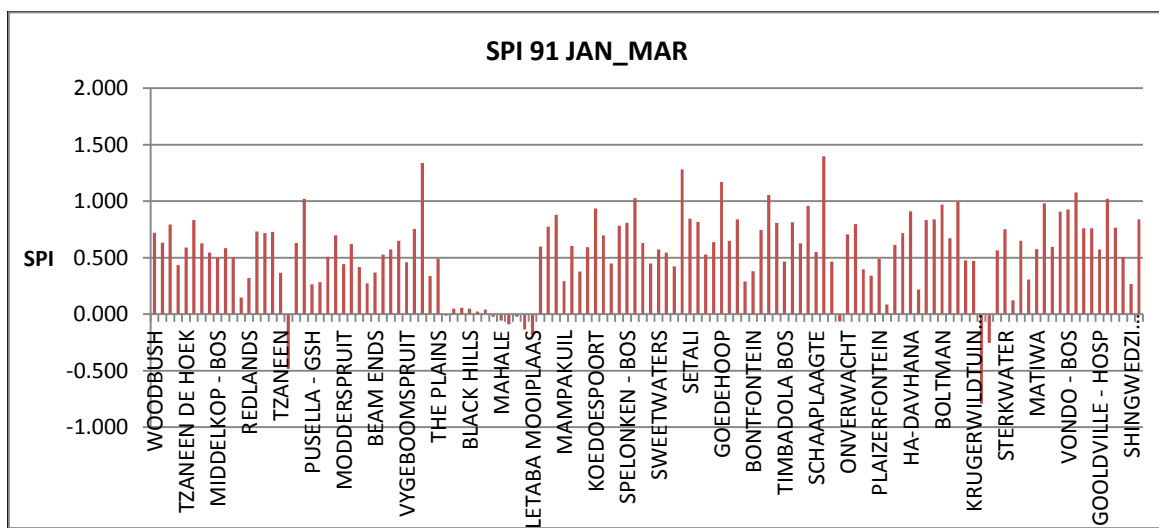


Figure 4-8: January to March: Standardised Precipitation Index 1991

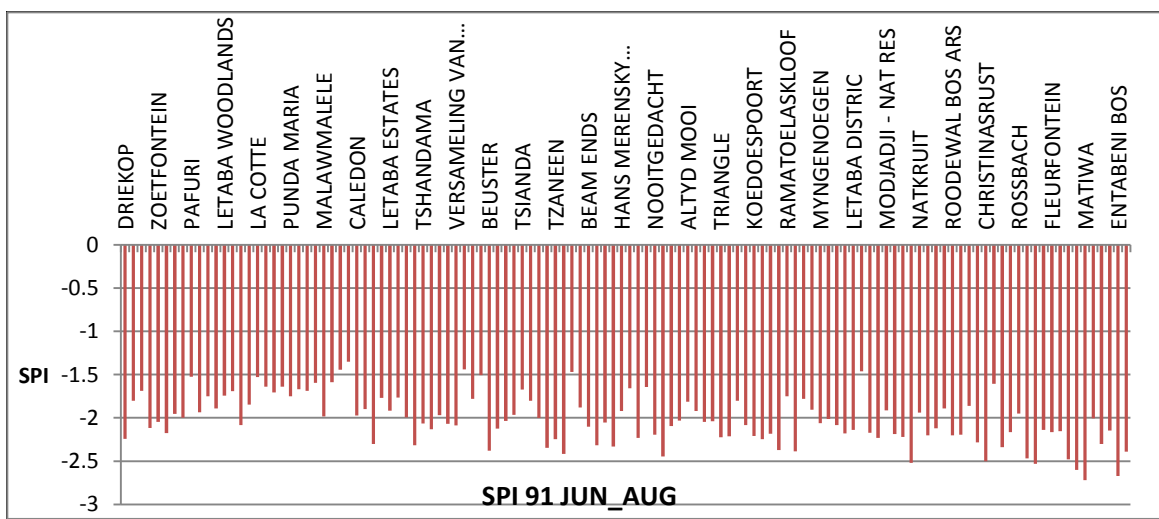


Figure 4-9: June to August: Standardised Precipitation Index 1991

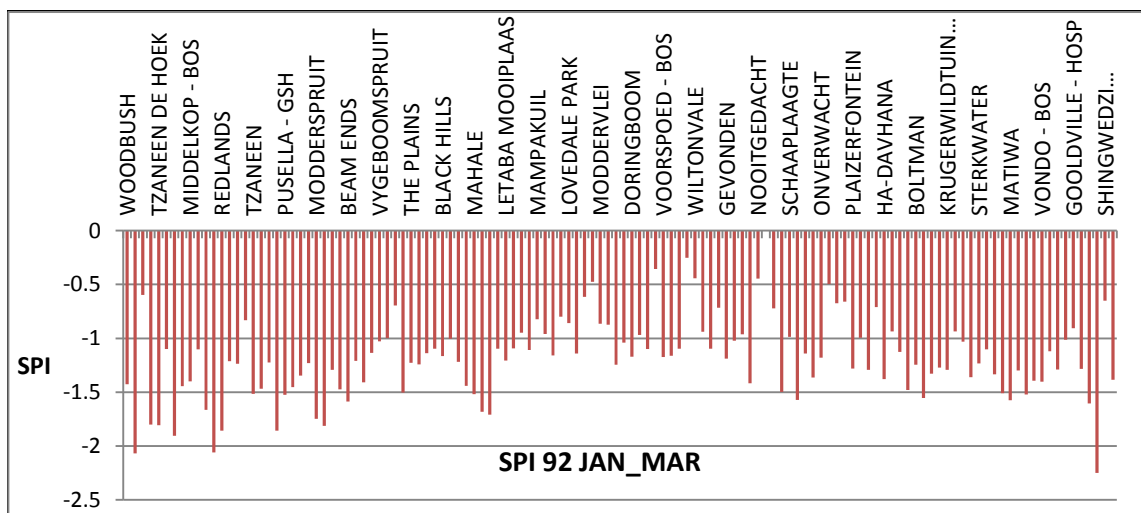


Figure 4-10: January to March: Standardised Precipitation Index 1992

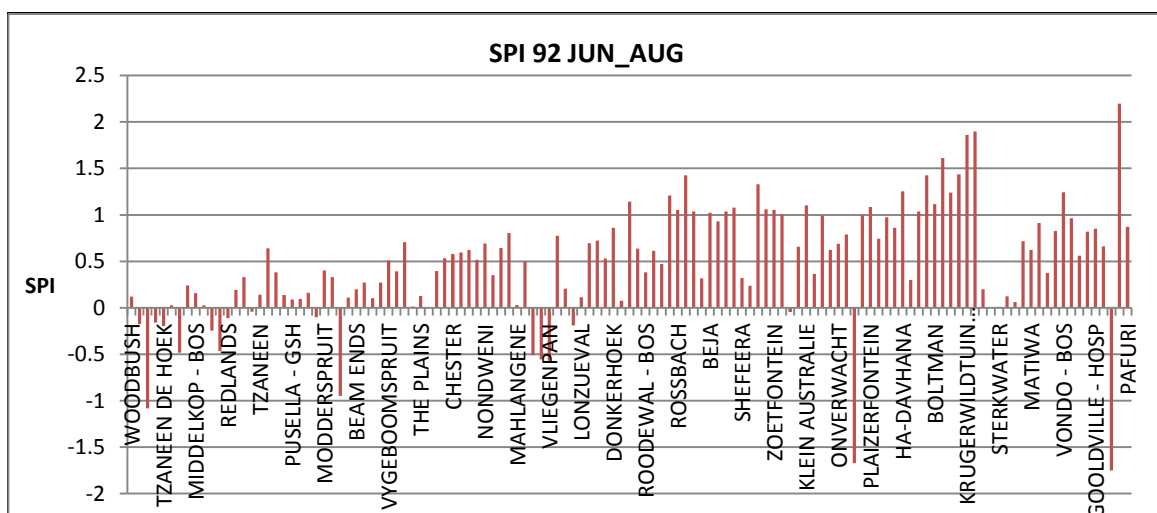


Figure 4-11: June to August: Standardised Precipitation Index 1992

Figure 4-4 to Figure 4-11 show both negative and positive SPI values for the years that were selected, as these periods are known to have experienced drought. The positive SPI's in some of the months may be the result of late rainfall. This resulted in agricultural drought for rain-fed agricultural farmers since these rains may have come too late. Graphs for 1984, 1991 and 1992 show moderate to severe drought during the wet season in the region. For 1983 and 1984 normal dry conditions are seen. The South African Weather Services could not produce or retrieve drought monitoring maps or information from literature for the drought conditions for these years.

4.2 NORMALISED DIFFERENCE VEGETATION INDEX - NDVI

Figure 4-12 to Figure 4-19 show the spatial variation of NDVI in the catchment area. The greener areas suggest healthy vegetation during the period of study. Areas which are brown to red indicate dryness of the area with the NDVI values approaching zero. The expectation is that if there is a wet season, the maps should show greenness only and winter should show dryness. Evidently Figure 4-12, Figure 4-14, Figure 4-16 and Figure 4-18 show that most parts of the area of study had dry conditions despite it having been a wet season. Figure 4-12, Figure 4-14, Figure 4-16 and Figure 4-18 show normal dry conditions during the dry season. This agrees with the meteorological and agricultural drought that was experienced by the region during these periods. Stations which were found outside the image were not used in this analysis.

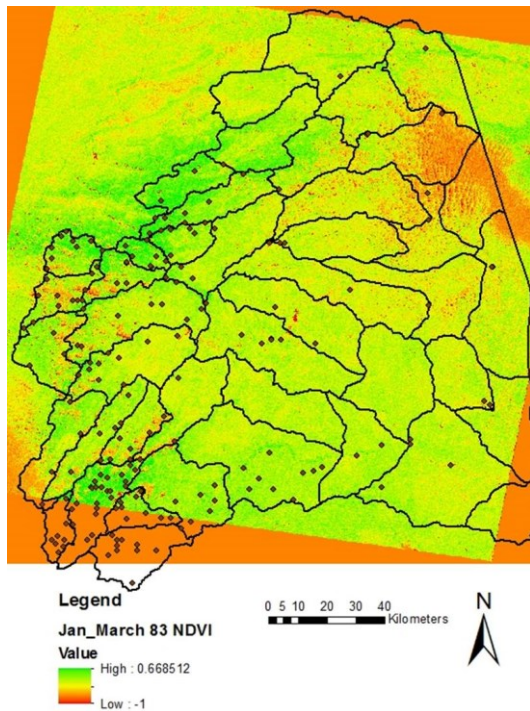


Figure 4-12: NDVI January to March 1983

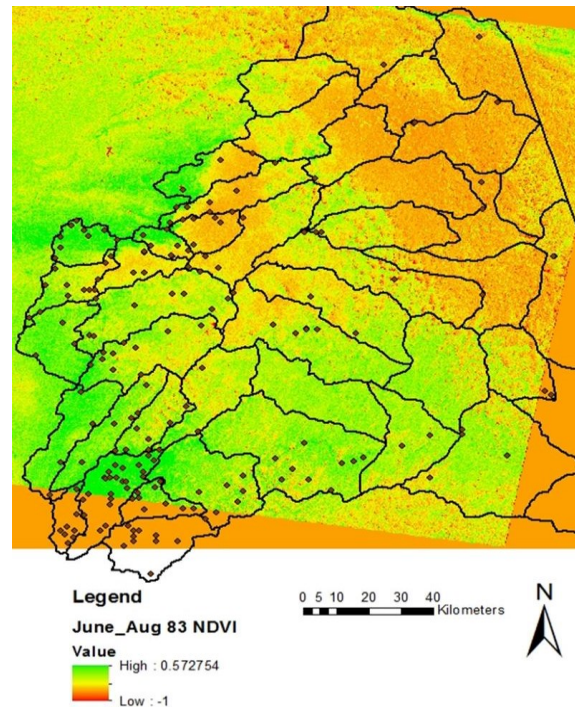


Figure 4-13: NDVI June to August 1983

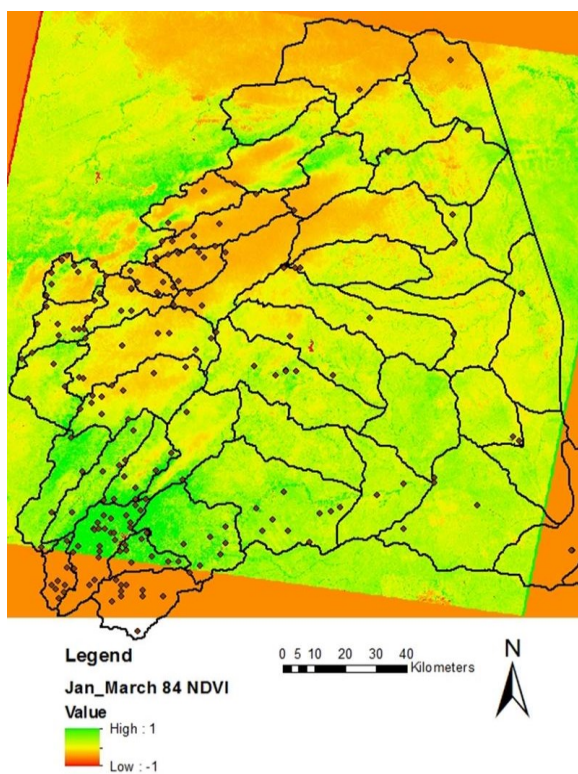


Figure 4-14: NDVI January to March 1984

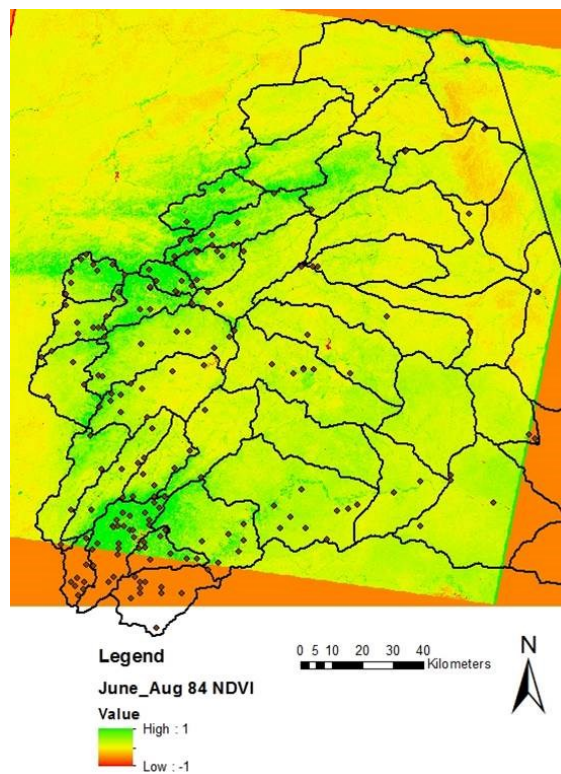


Figure 4-15: NDVI June to August 1984

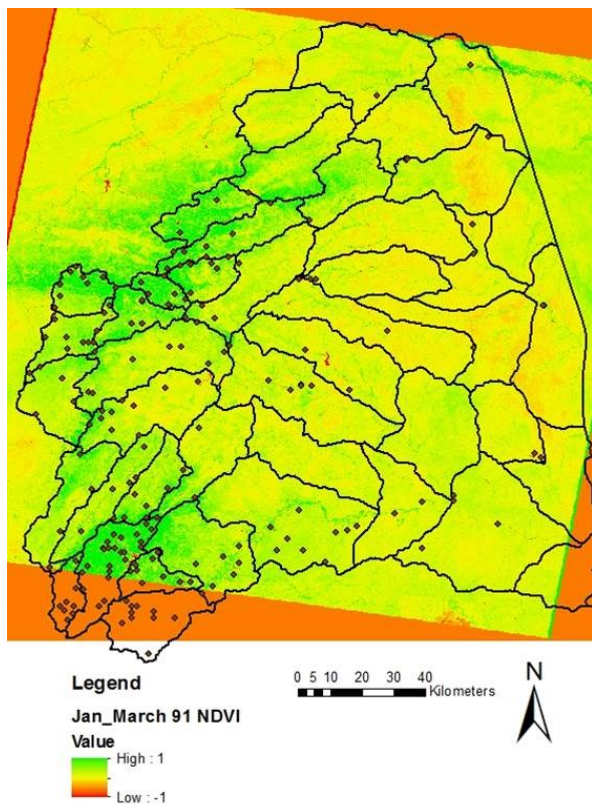


Figure 4-16: NDVI January to March 1991

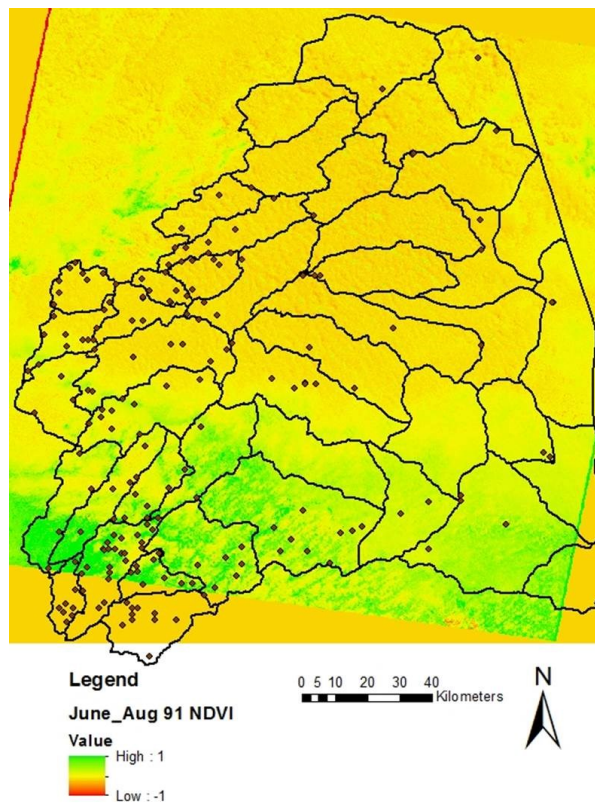


Figure 4-17: NDVI June to August 1991

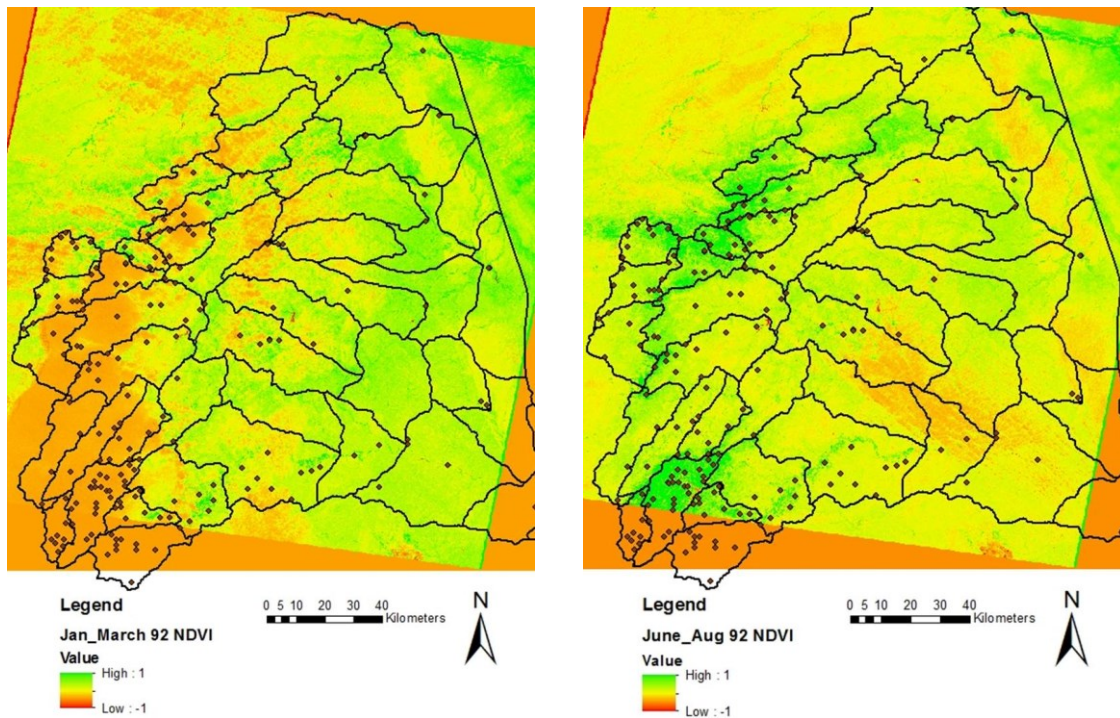


Figure 4-18: NDVI January to March 1992 Figure 4-19: NDVI June to August 1992

Graphs of NDVI for 1983, 1984, 1991 and 1992 in Figure 4-20 to Figure 4-27 show point NDVI values at the rain gauge stations. These values were extracted from the processed NDVI maps for each rainfall station. Different stations recorded different NDVI values and more stations showed low NDVI values. This indicates little vegetation and can be interpreted as severe drought during the wet season in the region. The years 1983, 1991 and 1992 show normal dry conditions. This agrees with the SPI value for 1983, 1984 and 1992.

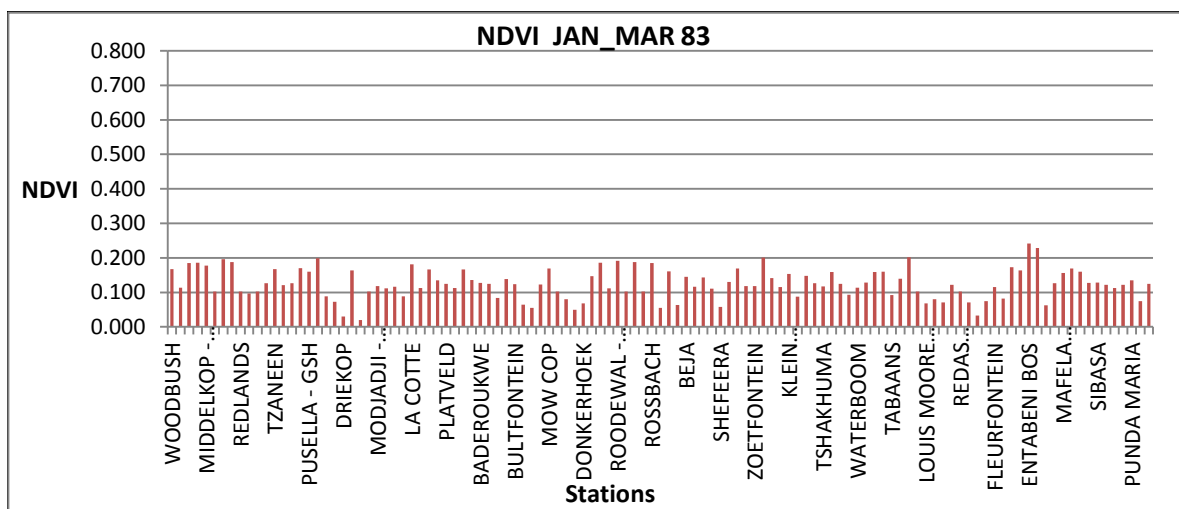


Figure 4-20: January to March: Normalised Difference Vegetation Index 1983

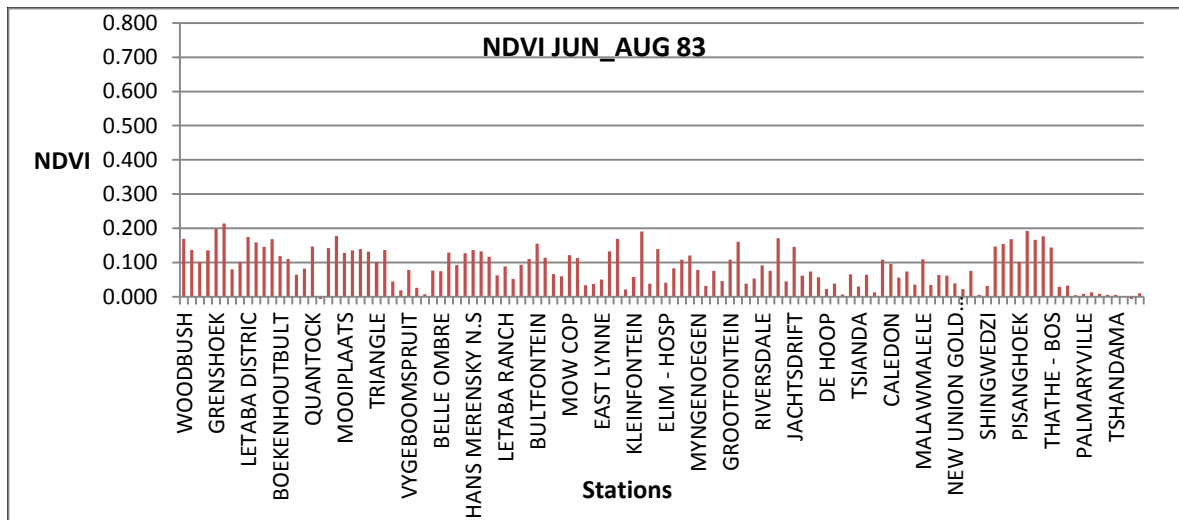


Figure 4-21: June to August: Normalised Difference Vegetation Index 1983

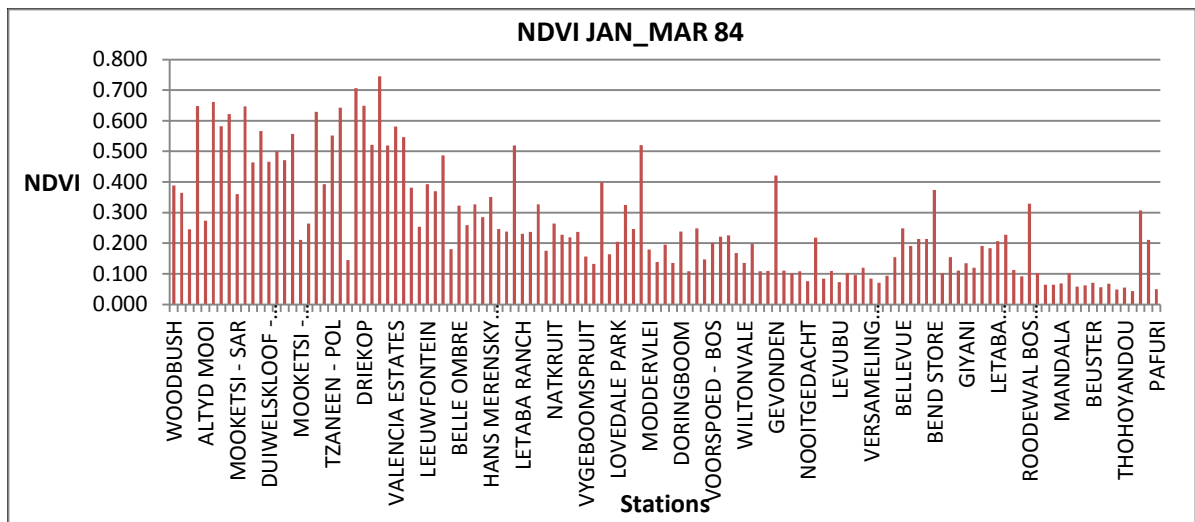


Figure 4-22: January to March: Normalised Difference Vegetation Index 1984

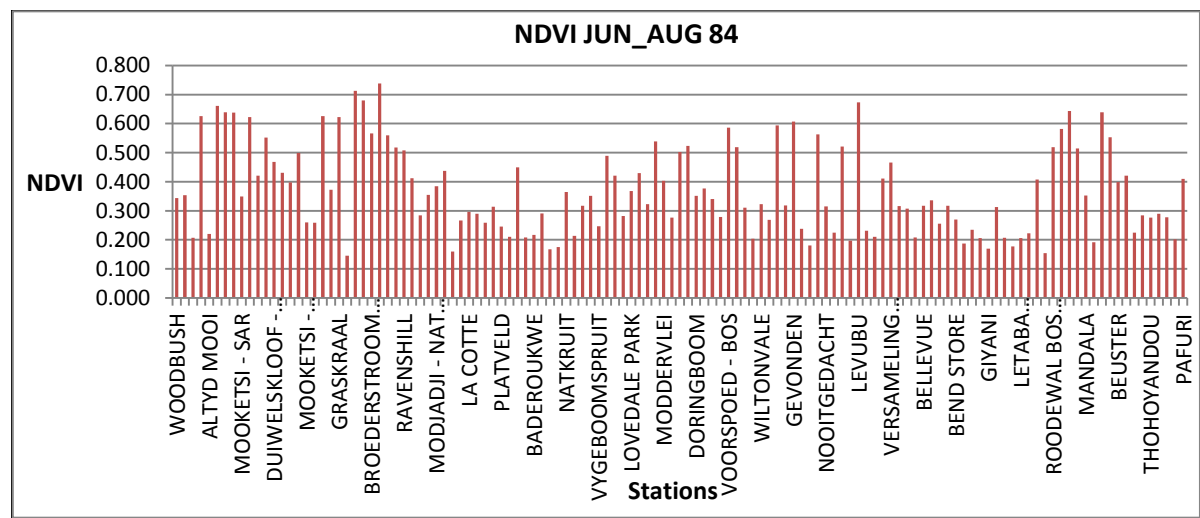


Figure 4-23: June to August: Normalised Difference Vegetation Index 1984

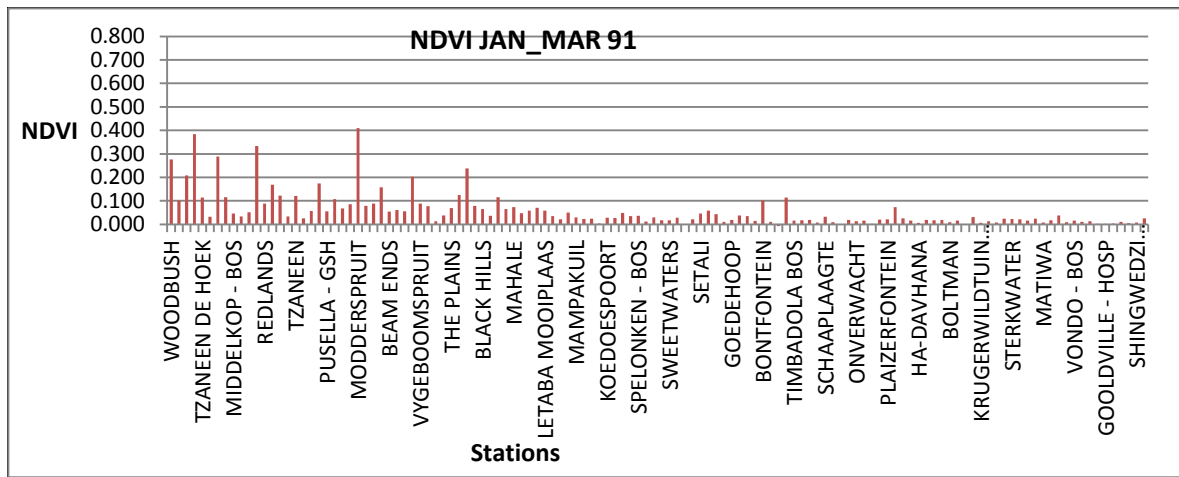


Figure 4-24: January to March: Normalised Difference Vegetation Index 1991

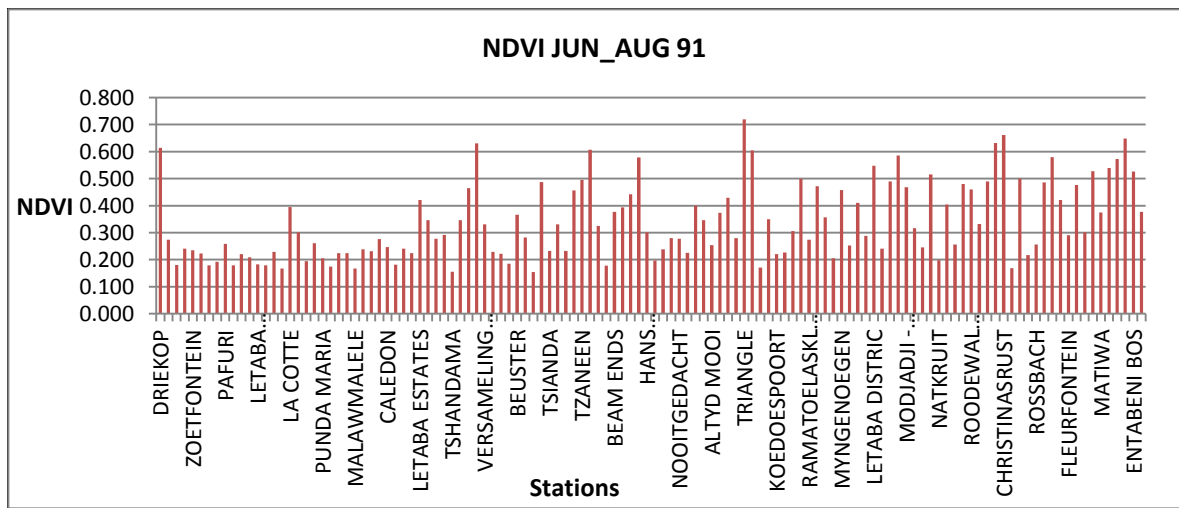


Figure 4-25: June to August: Normalised Difference Vegetation Index 1991

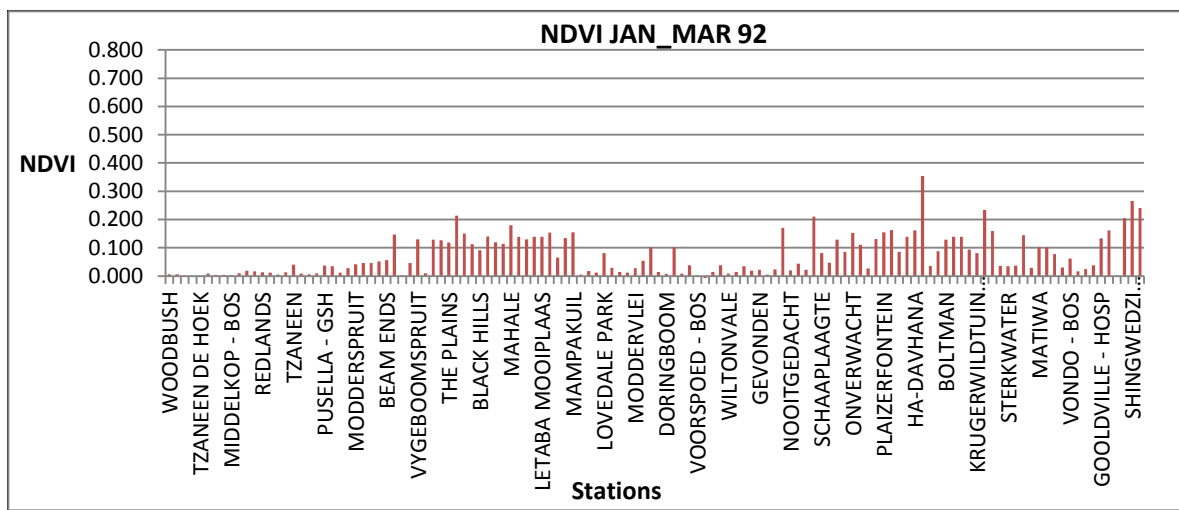


Figure 4-26: January to March: Normalised Difference Vegetation Index 1992

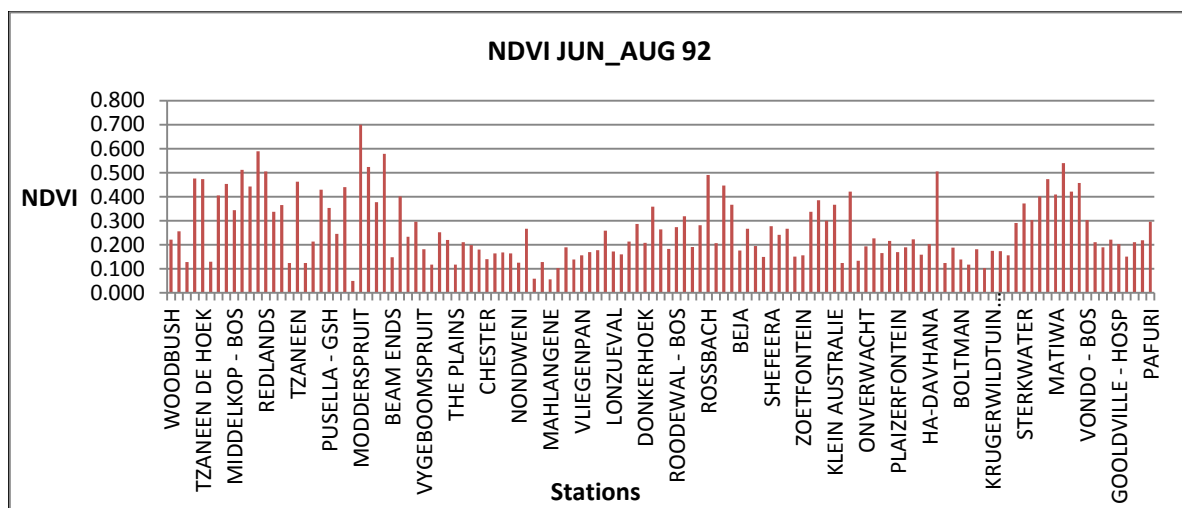


Figure 4-27: June to August: Normalised Difference Vegetation Index 1992

The extracted NDVI values show a degree of dryness for the wet season and a somewhat normal condition in the 1980's. In 1991 and 1992 there is evidence of severe dry conditions, which resulted into drought. Rainfall stations are at different locations and for those that recorded green vegetation, the NDVI value is above 0.500. This confirms that we cannot generalise the extent of drought in the area based on a single value whilst communities may have been impacted differently. The pattern of the NDVI for the wet season 1983, 1991 and 1992 does not correspond with the expected regional rainfall. A lot of rain is expected during the January, February and March period and the expectation is thus greener vegetation. Vegetation is mainly pronounced in 1984 for the wet season, even though it is known that this was a dry year, and rains were expected to have arrived late.

4.3 VEGETATION CONDITION INDEX - VCI

Figure 4-28 to Figure 4-35 show the VCI images processed by the AMESD database. It shows very dry conditions in 1984 and 1991 for the wet and dry season. Magezi *et al.* (2008), Berhan *et al.* (2011), and Hadžibegović *et al.* (2005), confirm that white areas on the maps represent pixels that include water bodies and clouds. These areas may also represent areas where there had been no vegetation in the past. A similar assumption was made for the images used in this study. These images were used to extract VCI point values in the same position as the NDVI and SPI. Considering the long term mean of the NDVI for the area of study, these images depict severely dry conditions for the better part of both the wet and dry season for the said periods.

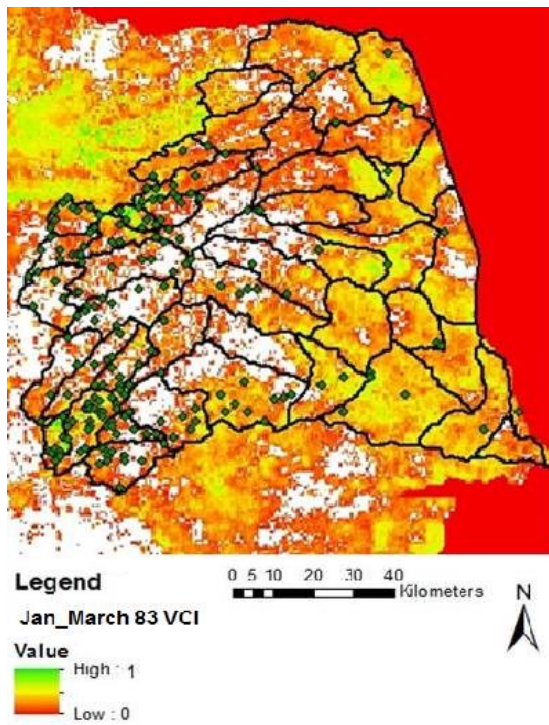


Figure 4-28: VCI January to March 1983

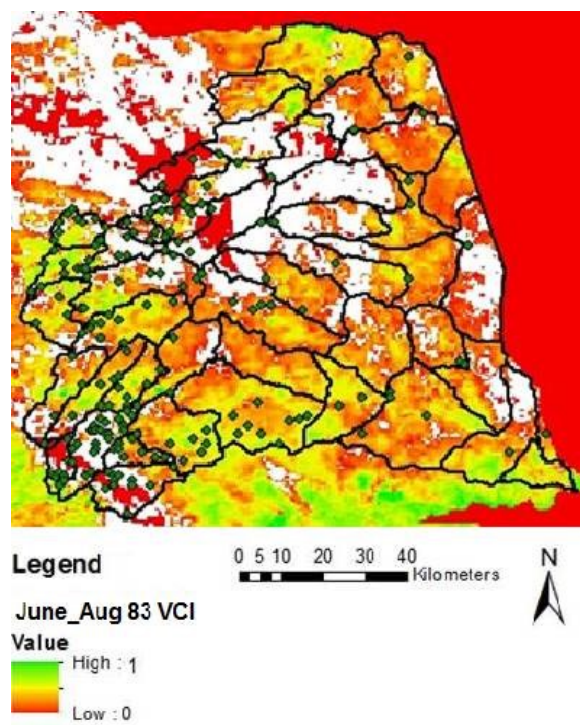


Figure 4-29: VCI June to August 1983

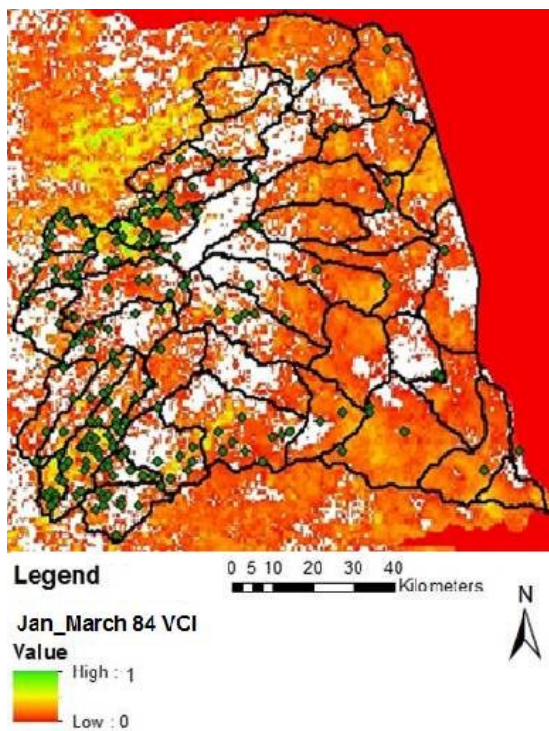


Figure 4-30: VCI January to March 1984

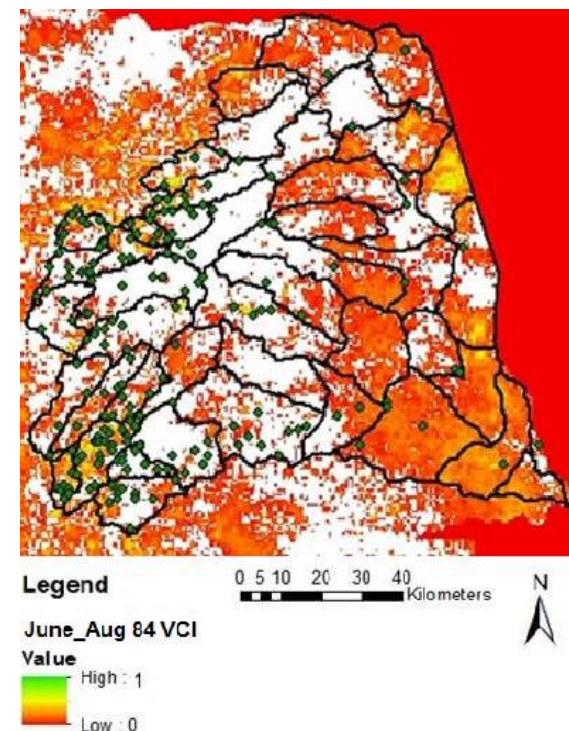


Figure 4-31: VCI June to August 1984

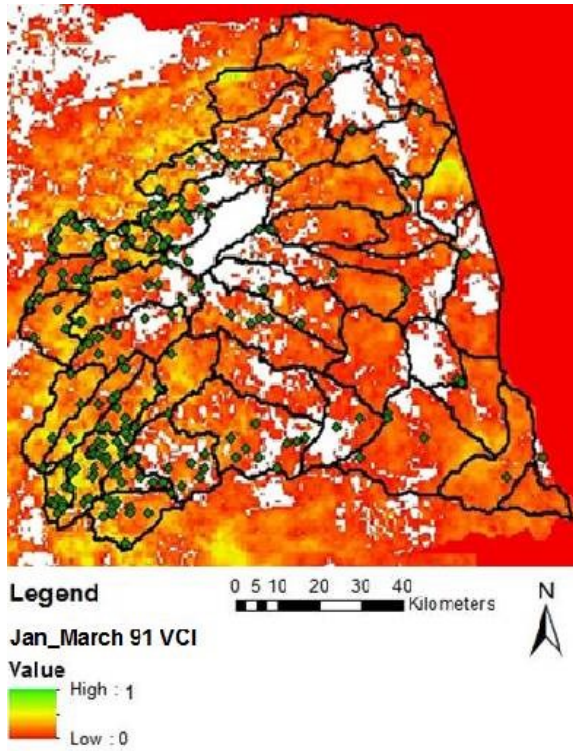


Figure 4-32: VCI January to March 1991

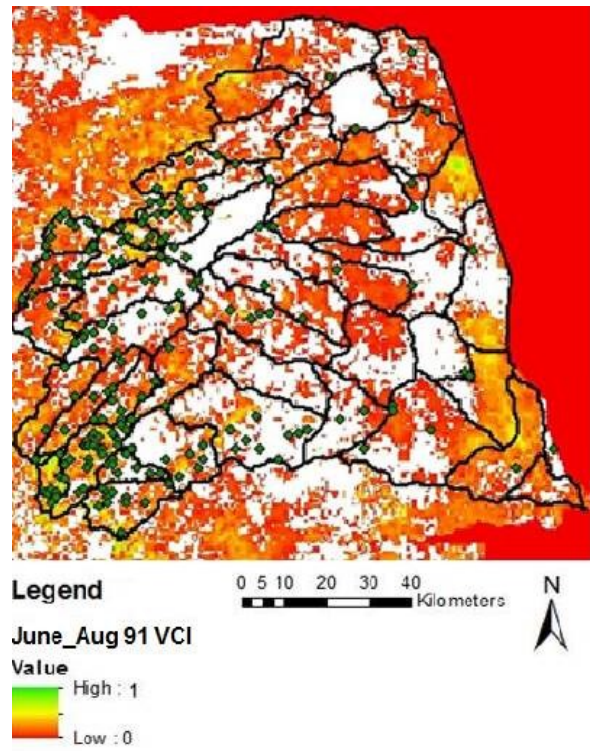


Figure 4-33: VCI June to August 1991

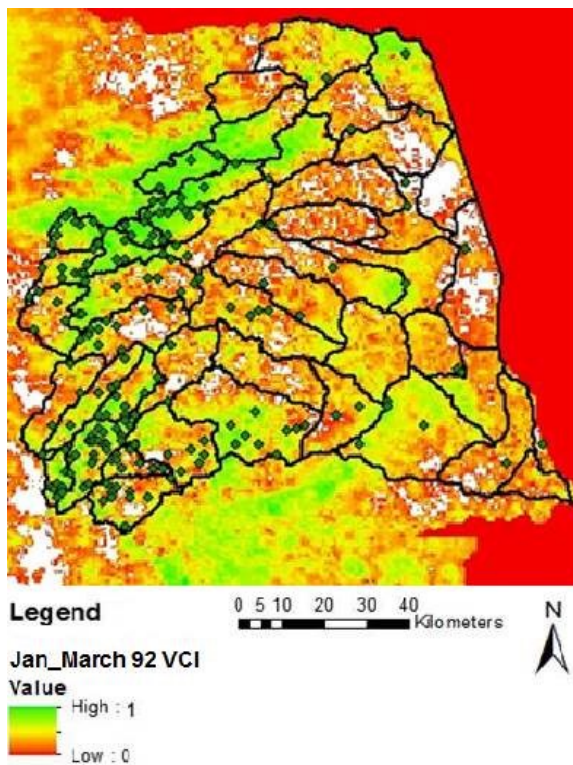


Figure 4-34: VCI January to March 1992

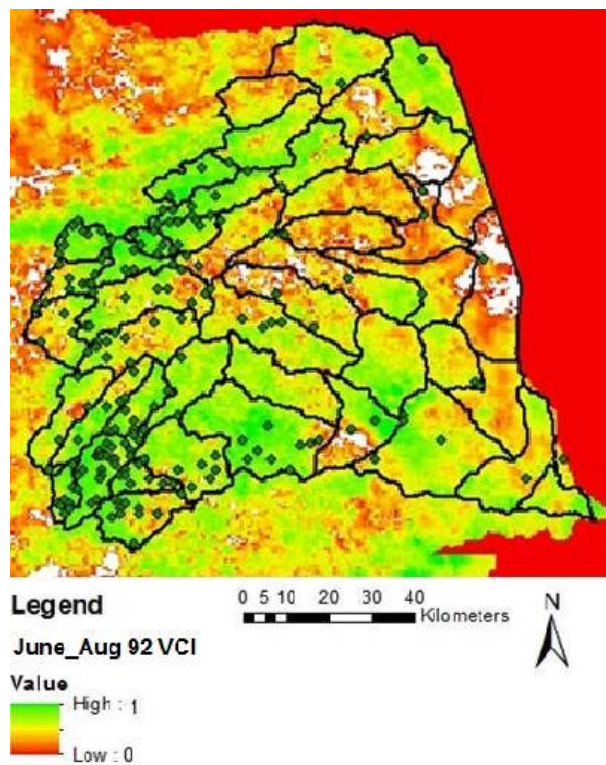


Figure 4-35: VCI June to August 1992

Figure 4-36 to Figure 4-43 show extracted point VCI values at the locations of the 129 raingauge stations. Similarly to NDVI, most stations recorded low VCI values whilst there are a few that show possible greenness in the some areas. Consistently low VCI values indicate a drought period. Accordingly, in 1984 and 1991 very low VCI values are seen. This corresponds to the severe dryness of that time as vegetation experienced stress and loss of health. The VCI maps shown above indicate that agriculture was severely affected during these periods due to failure or late commencement of rainfall. Some areas around Tzaneen and Thohoyandou had VCI values higher than 35% (in other words displaying close to normal conditions).

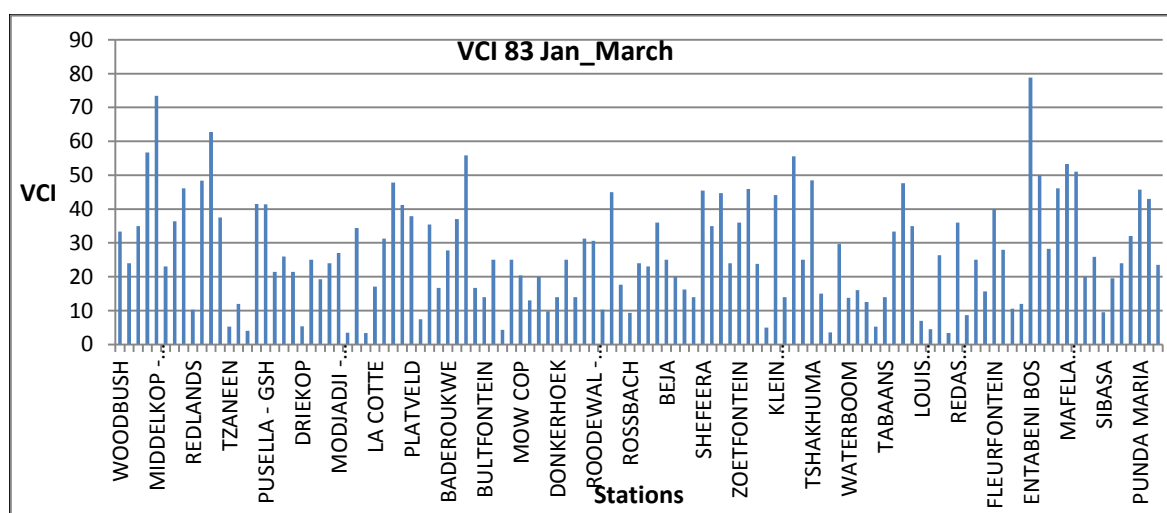


Figure 4-36: January to March: Vegetation Condition Index 1983

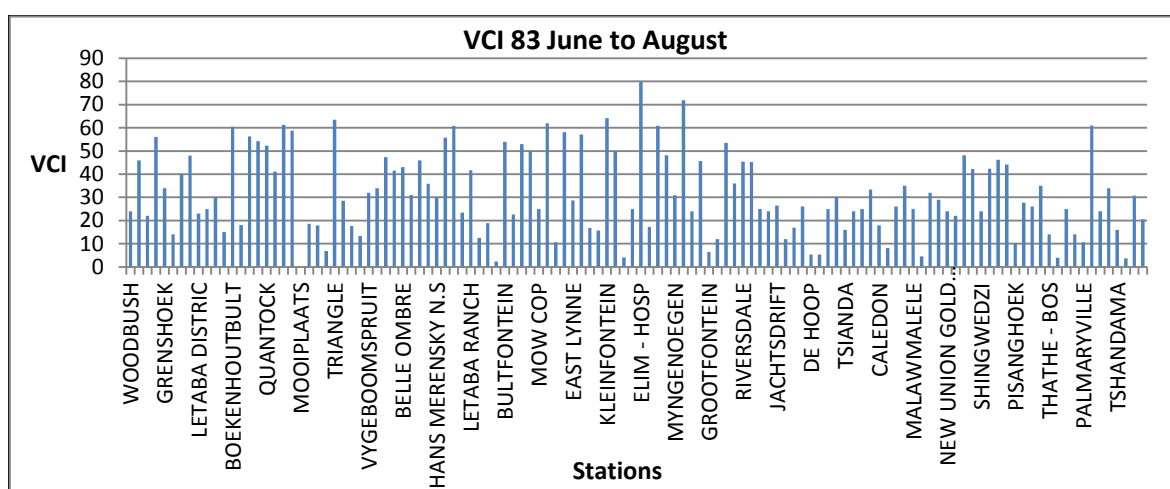


Figure 4-37: June to August: Vegetation Condition Index 1983

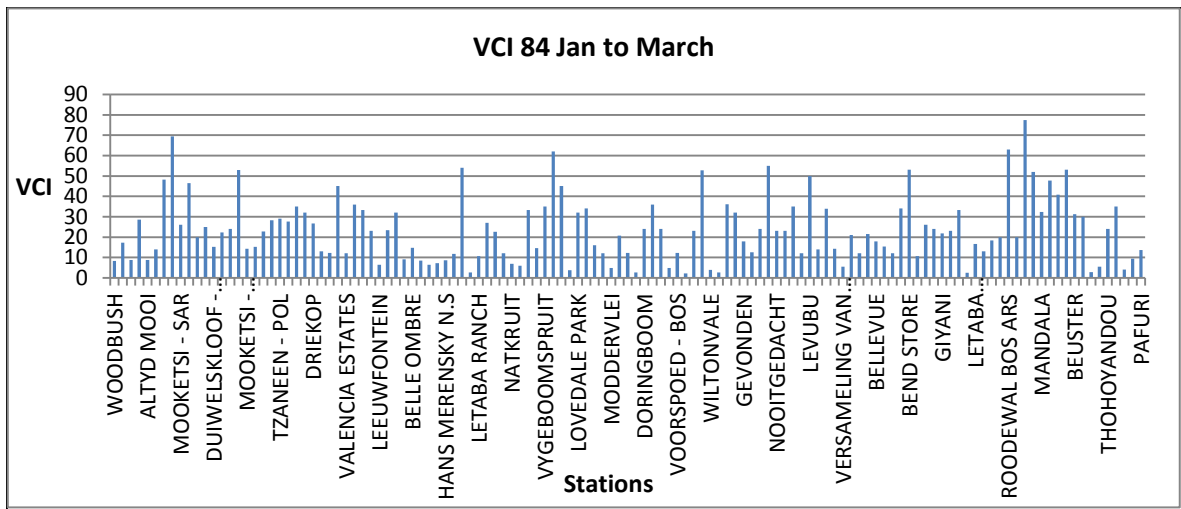


Figure 4-38: January to March: Vegetation Condition Index 1984

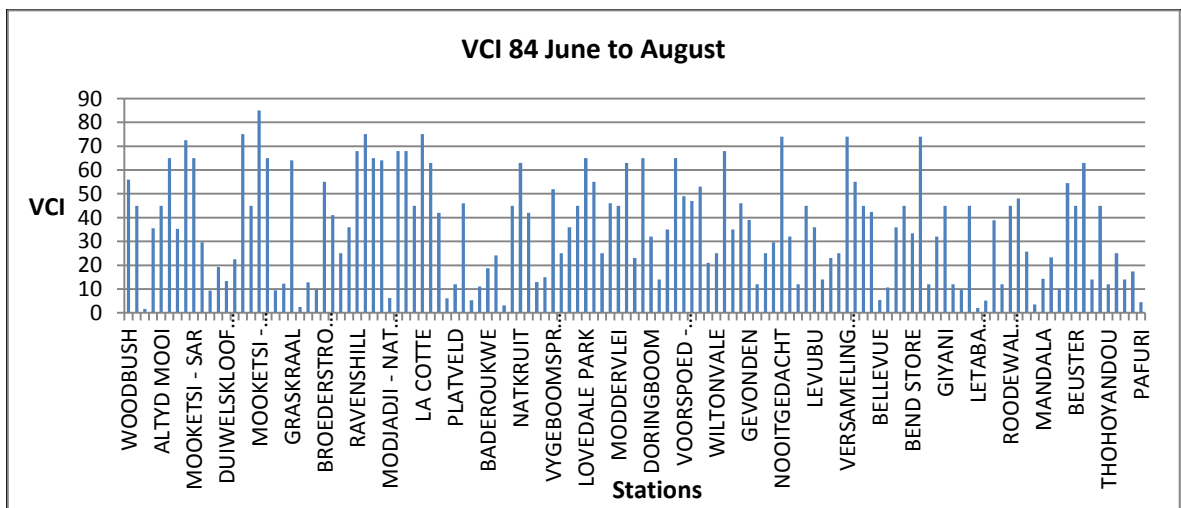


Figure 4-39: June to August: Vegetation Condition Index 1984

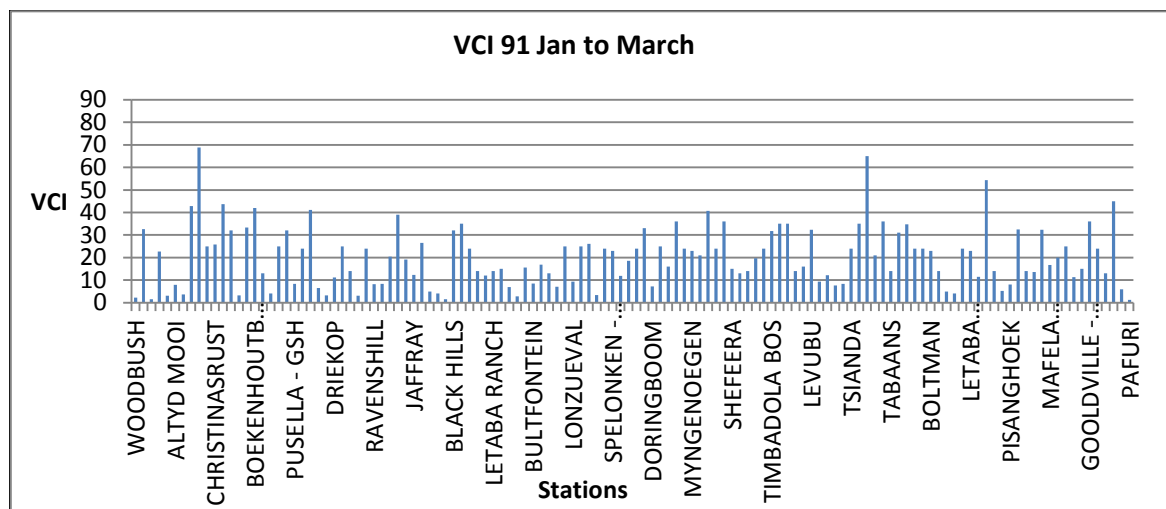


Figure 4-40: January to March: Vegetation Condition Index 1991

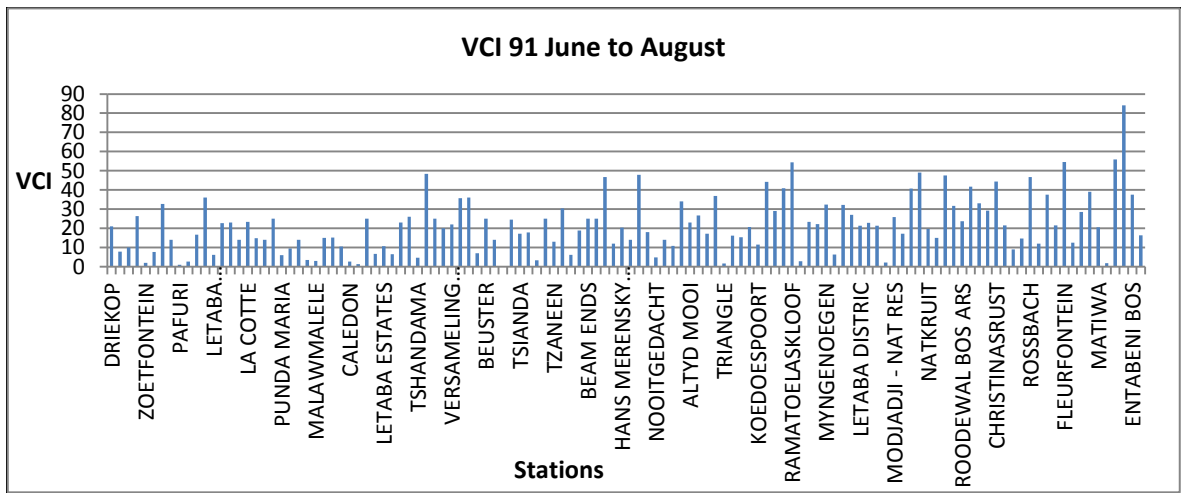


Figure 4-41: June to August: Vegetation Condition Index 1991

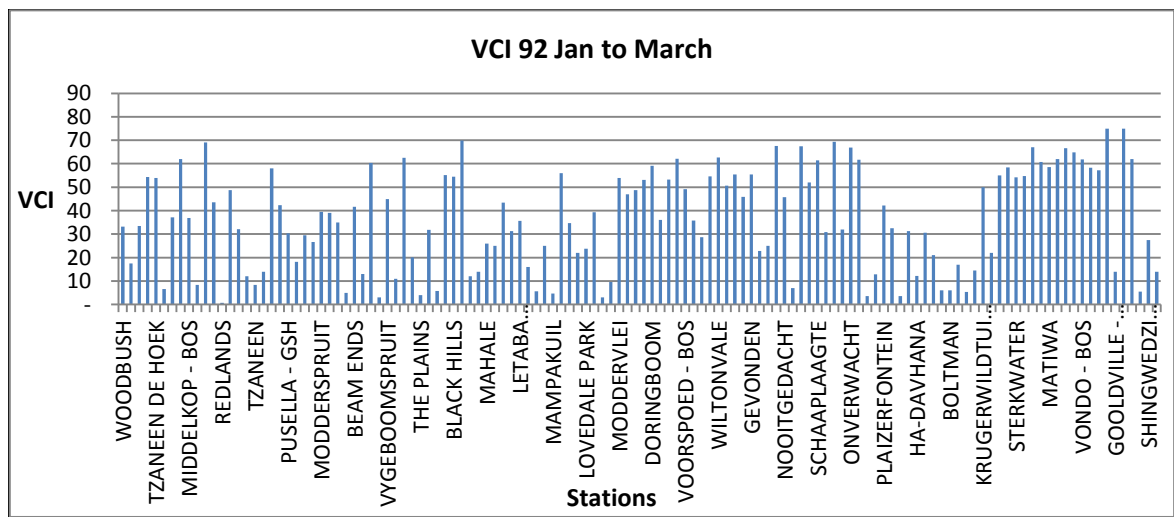


Figure 4-42: January to March: Vegetation Condition Index 1992

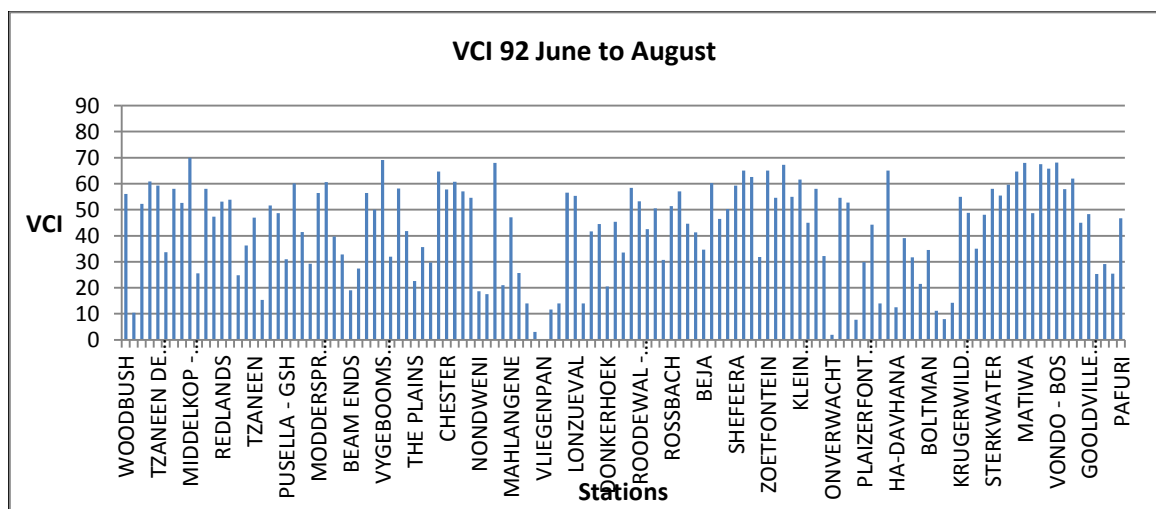


Figure 4-43: June to August: Vegetation Condition Index 1992

Figure 4-36 to Figure 4-43, for 1983, 1984 and 1991, show severe drought during the wet season for the area of study although it is a wet season. The 1991 dry season shows extremely dry conditions. The 1983 and 1992 seasons respectively show normal drought conditions for the dry season. This partially deviates with the SPI value for 1991 (where late rains were received during the wet season) but agrees with the SPI value for years 1983, 1984 and 1992. The image shows the delayed growth response of vegetation in 1984 and 1991 due to the prolonged dry spells.

4.4 SCALING FROM POINT TO PIXEL

Figure 4-44 shows the analysis of the effect of grid size on NDVI by correlating NDVIs from a 180m x180m grid with those from the station pixel of 60m x60m. This is done for thirty rainfall stations. The relationship R^2 is for the average NDVI value in the grid compared with the pixel value where the rainfall station is located. The same process was done for stations with the grid size increased as shown in Figure 4-45.

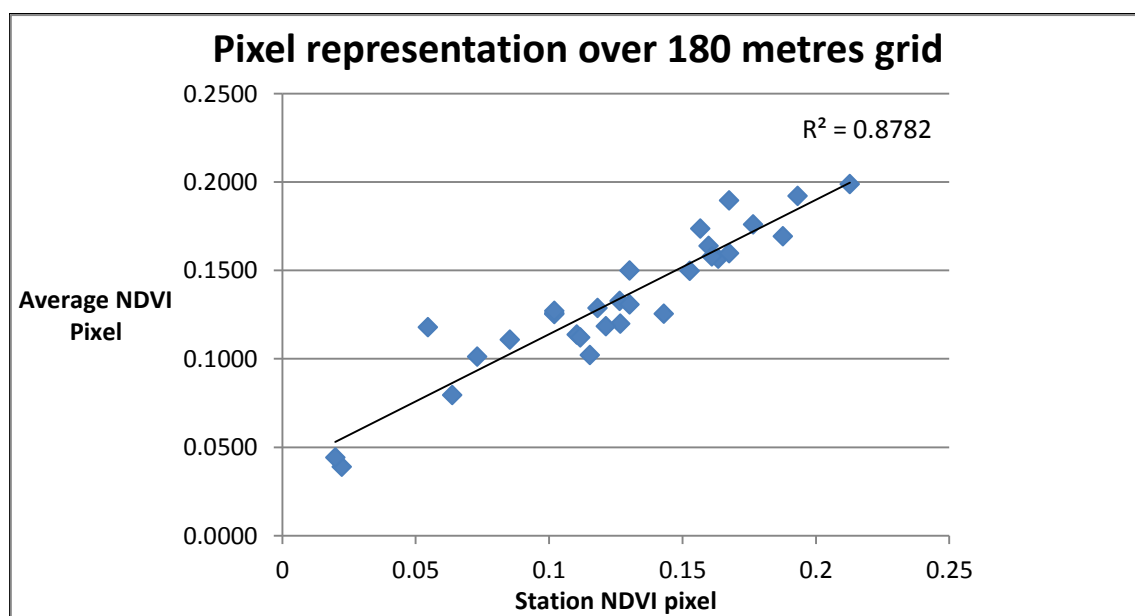


Figure 4-44: 180m NDVI pixel correlation

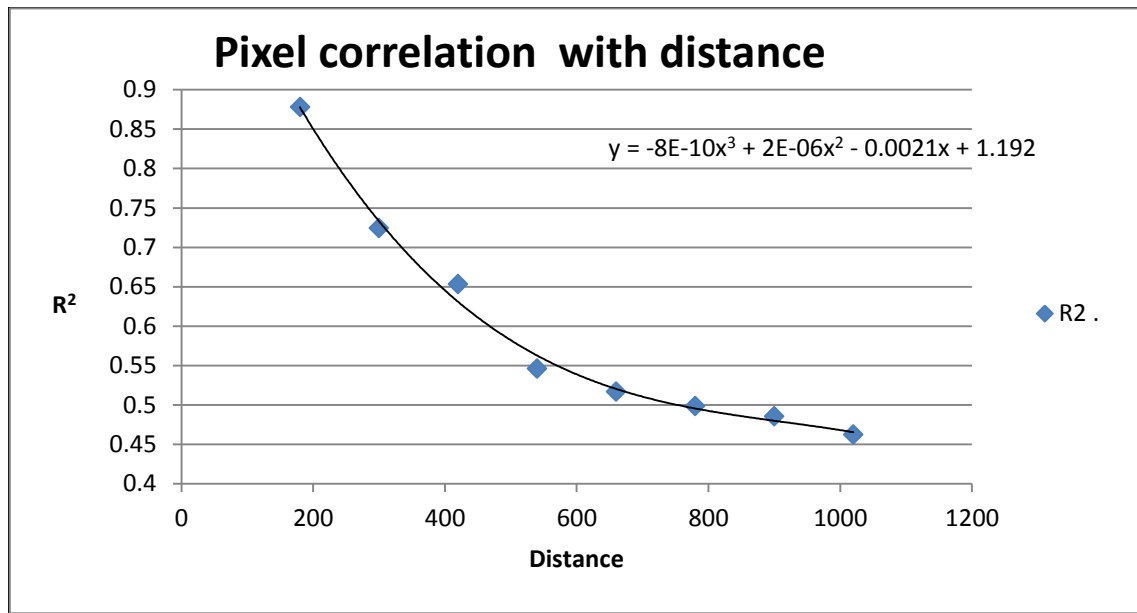


Figure 4-45: Pixel correlation with distance

Figure 4-45 shows that a higher correlation was found around pixels close to the rainfall station. As one moves further away from the station, the correlation decreases. A high $R^2 = 0.878$ was achieved on a 180m x 180m grid and the value of R^2 decreased as the grid increased. Depending on the level of accuracy that may be needed for decision making a choice for tolerable R^2 value can be made. This will allow for possible errors resulting from the scaling down of information.

4.5 TOPOGRAPHICAL ATTRIBUTES FROM MAPS AND GIS

Figure 4-46 shows the aspect map from which the aspect values shown on Table 4-1 were extracted. More stations are on the right side of the north–south azimuth line. Figure 4-47 shows variation in elevation for the rainfall stations in the area of study.

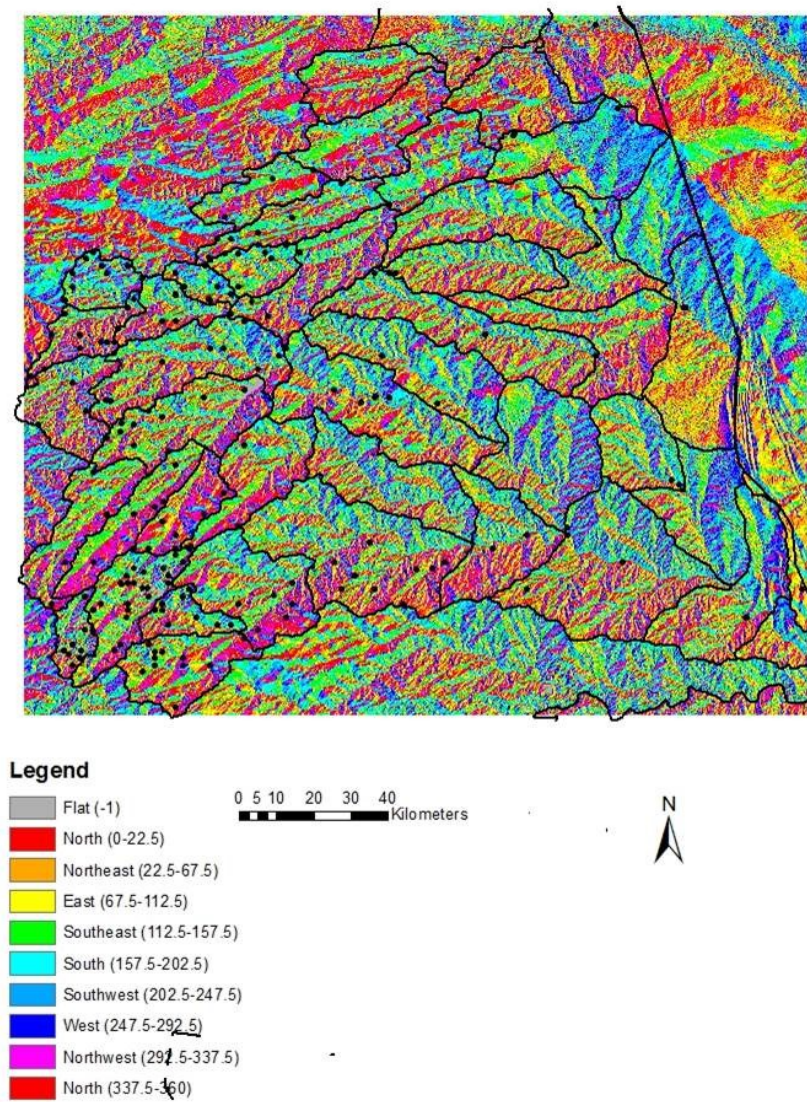


Figure 4-46: Aspect map of the Limpopo catchment

Table 4-1: Number of stations in area of study (per aspect)

Azimuth	Number of Stations
North	17
North East	19
East	14
South East	13
South	28
South West	15
West	12
North West	11

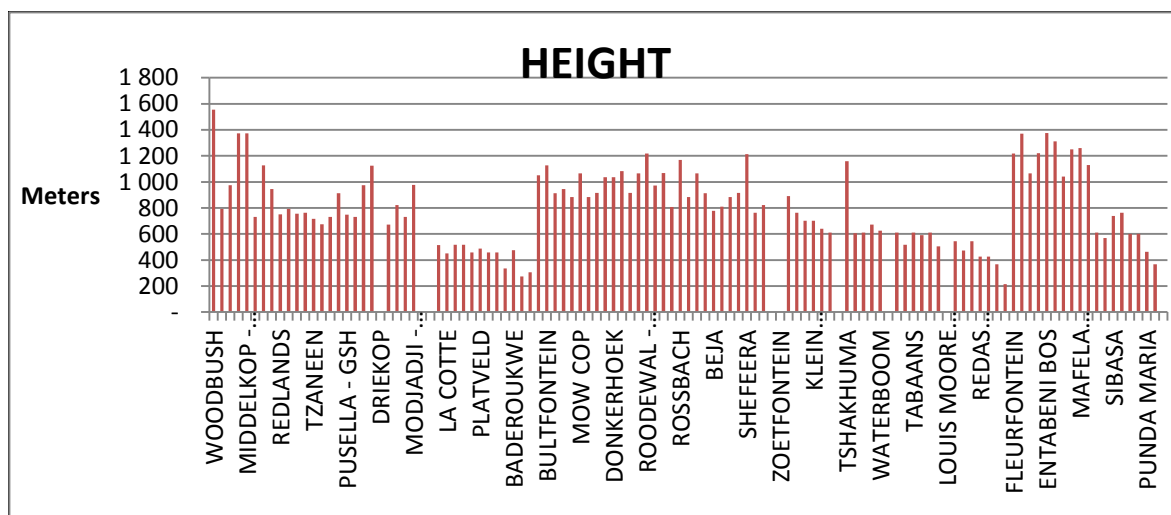


Figure 4-47: Station elevations

Table 4-1 presents the distribution of stations within the catchment. It is evident that there are more stations facing the North East, East, South East and South. The variation of altitude ranges from 500m above sea level to 1400m above sea level with most stations lying between 800m to 1100m above sea level.

4.6 MODELLING OF SPI USING VEGETATION INDICES AND TOPOGRAPHICAL ATTRIBUTES

After the model setup, running and validation, a set of results was obtained. Table 4-2 presents these results in the form of root mean square error (RMSE) and R^2 . The periods were divided into the wet and dry season. Equation 3.18 and 3.19 that was run for univariate analysis on the model yielded the relationships of SPI/NDVI and SPI/VCI. Equation 3.20 to 3.23 was set up for multi-variate analysis on the model to predict β_0 , β_1 , β_2 , β_3 and β_4 after bootstrapping to give improved coefficients. Figure 4-48 shows wet season performance per year while Figure 4-49 shows dry season performance per year. The variables fitted into linear regression to predict the SPI per season were then assessed to develop a robust model. This was achieved by analysing the R^2 and RMSE for each season per year. The years that yielded a better relationship between the variables and SPI were 1983, 1984 and 1991 (for the wet season) and 1984, 1991 and 1992 (for the dry season). The identified years were then used to develop a more robust model as shown in Figure 4-50. As stepwise multiple regression model was used, the model rejected elevation (DEM) as a significant parameter. This may be as a result of low altitude variation within the area of study. Alternatively, it may be that drought conditions are regional and affect areas independently of their attitude.

Year	Period	R ² (SPI Vs. NDVI)	Root Mean Square Error	R ² (SPI Vs. VCI)	Root Mean Square Error	R ² (NDVI vs. VCI)	Root Mean Square Error	R ² (SPI ~ NDVI + VCI)	Root Mean Square Error	R ² (SPI ~NDVI + VCI + ASPECT)	Root Mean Square Error	R ² (SPI Vs. VCI + ASPECT + DEM)	Root Mean Square Error	R ² (SPI Vs. NDVI + VCI + ASPECT + DEM)	Root Mean Square Error	β_1 (ndvi)	β_2 (vci)	β_3 (aspect)	β_0 (con stant)
WET SEASON																			
1983	Jan to March	0.4155	0.2897	0.4936	0.2697	0.2985	0.0473	0.5905	0.2436	0.5985	0.2441	0.5087	0.27	0.6051	0.2432	3.4126	0.0108	0.0007	-1.5426
1984	January to March	0.4561	0.2165	0.4623	0.2153	0.3527	0.1852	0.5763	0.1919	0.5744	0.195	0.5186	0.2074	0.5997	0.19	0.7144	0.0083	0.0005	-0.9366
1991	January to March	0.4057	0.2764	0.5138	0.25	0.8643	0.0906	0.5203	0.2494	0.5328	0.2492	0.5312	0.2496	0.5356	0.2495	0.2917	0.0199	0.0003	0.2575
1992	January to March	0.4515	0.2721	0.4776	0.2656	0.9328	0.0563	0.478	0.2666	0.4881	0.2717	0.5111	0.2656	0.5118	0.2666	1.0027	0.0195	0.0007	-1.6541
DRY SEASON																			
1983	June to August	0.4352	0.3254	0.4057	0.3353	0.301	0.0665	0.5435	0.2951	0.5303	0.2977	0.3927	0.3385	0.5303	0.2992	3.2684	0.0108	0.0002	0.3877
1984	June to August	0.3316	0.2898	0.4504	0.2628	0.2067	0.1771	0.5421	0.2408	0.5451	0.2266	0.4377	0.2519	0.5536	0.2254	0.8627	0.0125	0.0001	0.9722
1991	June to August	0.5587	0.1918	0.5783	0.1875	0.9249	0.0618	0.5818	0.1875	0.5879	0.1919	0.6606	0.1723	0.6615	0.1728	0.8513	0.0127	0.0003	-2.279
1992	June to August	0.5415	0.4242	0.5697	0.4109	0.9429	0.0558	0.5699	0.4125	0.5526	0.4207	0.5603	0.417	0.5607	0.4187	1.4785	0.0321	0.0005	-
Wet Season	January to March	0.4728	0.1461			0.3125	0.2652	0.5265	0.1819	0.5356	0.195			0.5497	0.213	1.3126	0.0154	-0.0003	-0.7359
Dry Season	June to August	0.5986	0.3424			0.1682	0.2161	0.689	0.3023	0.6949	0.2974			0.6963	0.2974	1.6529	0.0108	-0.0001	0.5188

Table 4-2: Results and performance of SPI modelling

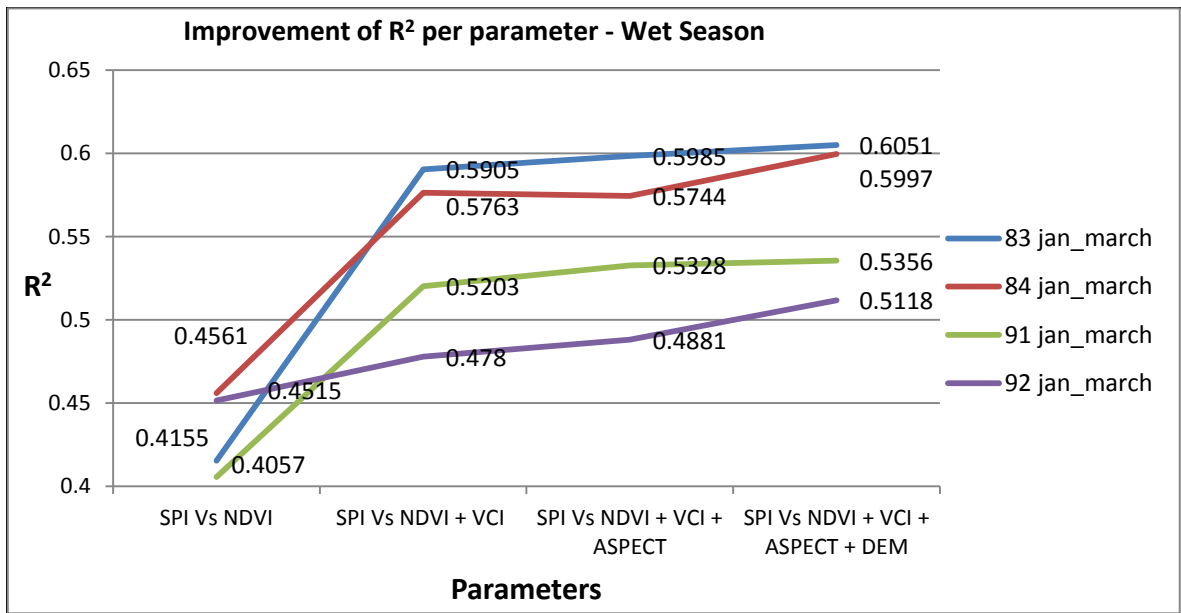


Figure 4-48: Performance of wet season SPI modelling

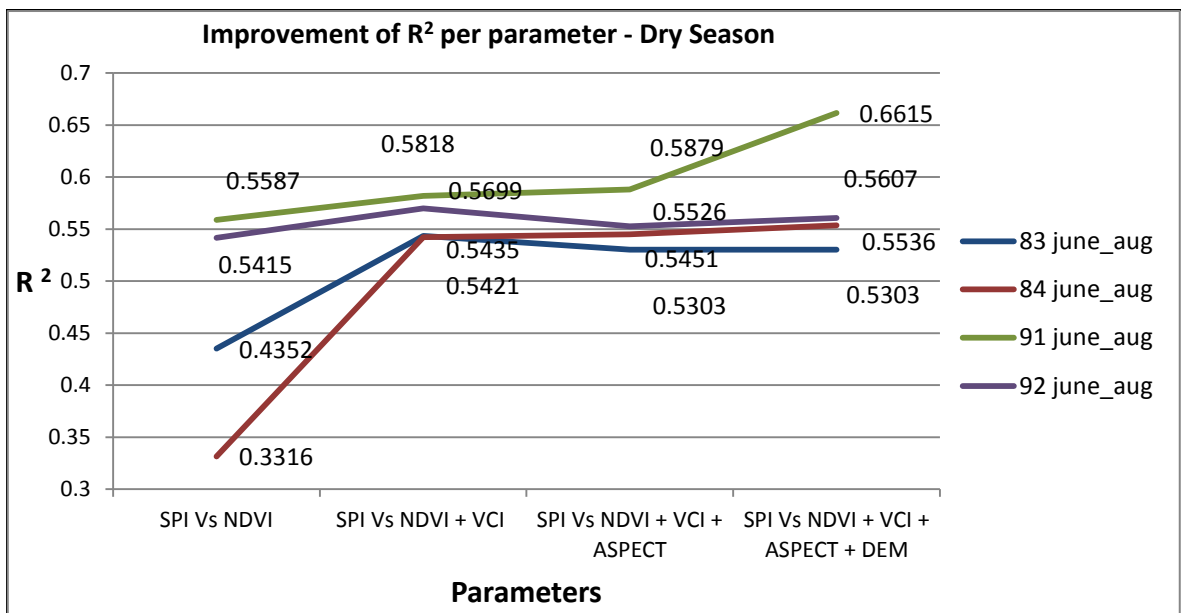


Figure 4-49: Performance of dry season SPI modelling

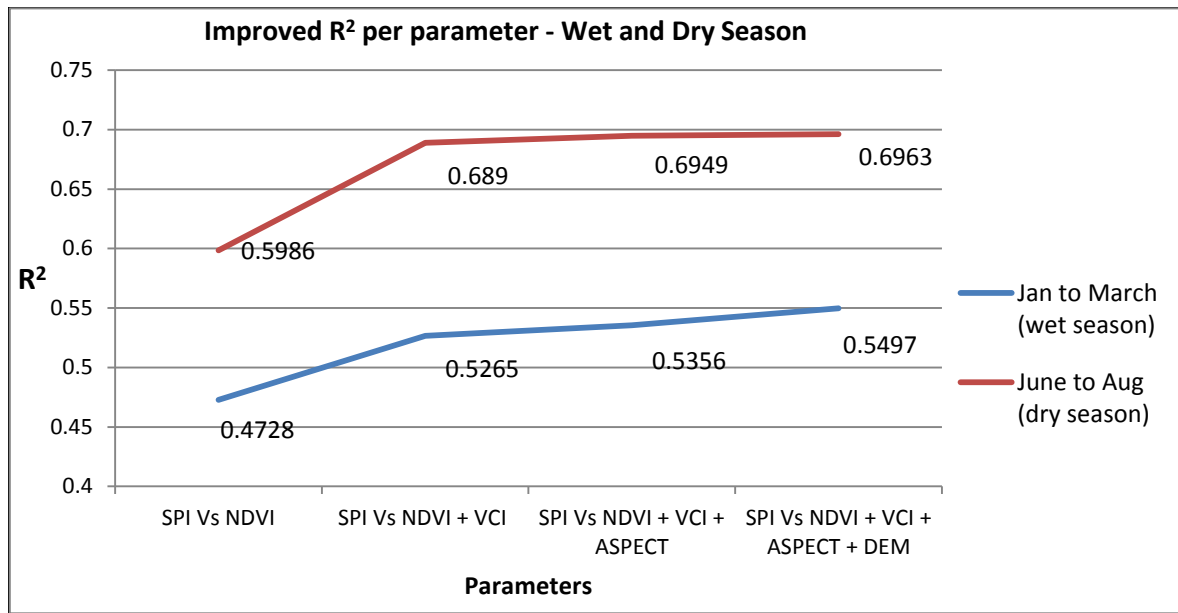


Figure 4-50: Performance of improved wet and dry season SPI modelling

Figure 4-48 shows that for the wet season in 1983, 1984 and 1991 there was better correlation ($R^2 = 0.605$, 0.600 and 0.536 , respectively) for the SPI and NDVI, VCI, Aspect and DEM except for 1992. For the dry season (Figure 4-49) better correlation was observed in 1984, 1991 and 1992 ($R^2 = 0.554$, 0.662 and 0.561 respectively). Improved results from the model were achieved when the wet season (January to March) and dry season (June to August) for the years selected were used to develop a single model for each season (Figure 4-50). This was done by using the years that performed better in the specific season.

A better correlation ($R^2 = 0.696$) was achieved for the dry season. For the wet season, $R^2 = 0.550$ was achieved. A significant agreement can be observed between the SPI, NDVI, VCI, Aspect and Elevation for the dry season. This may suggest the following:

- Different atmospheric forces influence drought at different seasons of the year.
- Vegetation is responsive over a three month period (indicating a brief time).
- The relationships between precipitation, vegetation indices and topographical attributes would provide a better insight into drought onset and severity.

As mentioned in the model development section, different models were run in the different order of adding variables. The results show a better correlation of the SPI with the VCI. Yet, as topographical attributes are added to the model, it becomes less significant. A strong relationship exists between the SPI and the NDVI. Furthermore, as topographical attributes are added, the results improve. On the other hand, the opposite was observed with the VCI.

Variations in vegetation indices can help to establish the effect of climatic factors on local vegetation. The variations will be of less practical value for large scale planning (e.g. SADC mitigation measures) but would help for local/community purposes since it would provide better insight into drought onset and severity. An SPI of -2.269 in 1992 recorded severe dry conditions, which were only last seen in 1969 and 1972 whilst in 1983 and 1984 the dry season was close to as normal as other years during the dry season. A wet season indicated -1.189 SPI value. Moderately dry conditions were identified in 1983. A SPI value of -1.606 was identified in 1992, which characterises a very dry condition (even though it is a wet season). These figures are in accord with the literature review and show that severe dry conditions were experienced during these years as confirmed by the SPI values.

Satellite based vegetation indices (NDVI) show 1991's wet season as the worst dry period. It also shows that the dry season was moderately dry. The 1992 images show severe dry conditions for the wet season. The 1983 wet season had a 0.6 NDVI value, which is average green for a wet season. (This is expected to have a closer to 1 NDVI value in order to show green). These images agree with the SPI values for the same periods, except for the years that show positive SPIs due to late rainfall (it was a drought year). In 1984 both seasons were drier as compared to the average of the same period. In the 1991 wet season, some areas received good rainfall and showed green. The dry season was however severely dry for the whole study area. The year 1992 was better than all the years as there were more green areas. Despite this, some areas still remained dry during the wet season.

The statistical relationship between the SPI, NDVI, VCI, Aspect and Elevation helps to clarify the vegetation response and time lag between the occurrences of precipitation at different meteorological stations. Lei Ji *et al.* (2003) studied the relationship between vegetation vigour and moisture availability, with satellite sensor data in the north and central Great Plains of the United States. Vicente-Serrano *et al.* (2006) conducted a study in Ebro valley, in the Mediterranean region, to determine spatial differences in the effects of drought on natural vegetation and agricultural crops. Dutta *et al.* (2012) also performed a study to predict agricultural drought through prediction of agricultural yield. In Dutta's study a model was used, based on NDVI-SPI. The above studies reveal the relationship of SPI and NDVI on different time lags. These studies nevertheless also depended on the availability of rainfall data to predict SPI. The challenge remained to find a possible solution to predict SPI following diminishing rainfall stations, which would result in non-availability of data.

This study reveals that seasonality has a very significant effect on the relationship between the SPI, NDVI, VCI, Aspect and Elevation. High correlations occurred during the dry season, but were much lower during wet season. Therefore, considering the whole area of study, the correlation between the SPI, NDVI, VCI, Aspect and Elevation is, in general, higher in areas with a low vegetation cover/activity (low average NDVI values). This could indicate that areas with a low vegetation cover/activity are more prone to the effects of drought than areas with a higher vegetation cover. The reason for this is that plants are more sensitive to water availability in their reproductive growth stage. The topographical attributes have an impact on the correlation between the parameters. For the dry season in 1991, elevation increased R^2 from 0.588 to 0.662. For the wet season in 1984, R^2 increased significantly from 0.574 to 0.600. For a robust model during the wet season, R^2 improved from 0.473 to 0.550, which was not too significant. For the dry period R^2 improved from 0.599 to 0.696. This showed a significant improvement on the value of R^2 as the attributes were added into the model. Aspect has more influence on the correlation than elevation. This could be attributed to the size of the catchment, which was used for this study as it does not have significant variation on altitude.

5. ASSESSING THE PERFORMANCE OF THE SPI MODEL

After the statistical regression analyses for the model development were achieved, the model needed to be verified using a period not used in the regression analysis. As indicated in Section 3.2.7, year 2012 was selected for this with field work conducted in the catchment area at Tzaneen, Mandlakazi, Ga-Modjaji, Thohoyandou and Giyani (Figure 5.1). The five communities were selected as they fall in different quaternaries and have different agricultural activities including significant commercial and subsistence farming. The field observation was done using meetings and visiting the fields with the farmers, the Water User Association, Water Managers from Tzaneen Dam, the Vhembe Municipality, Mopani Municipality and the Provincial Disaster Management Centre. The main field observations are presented later in this Chapter in Tables 5.1 and 5.2 together with the predictions from SAWS and the SPI regression model.

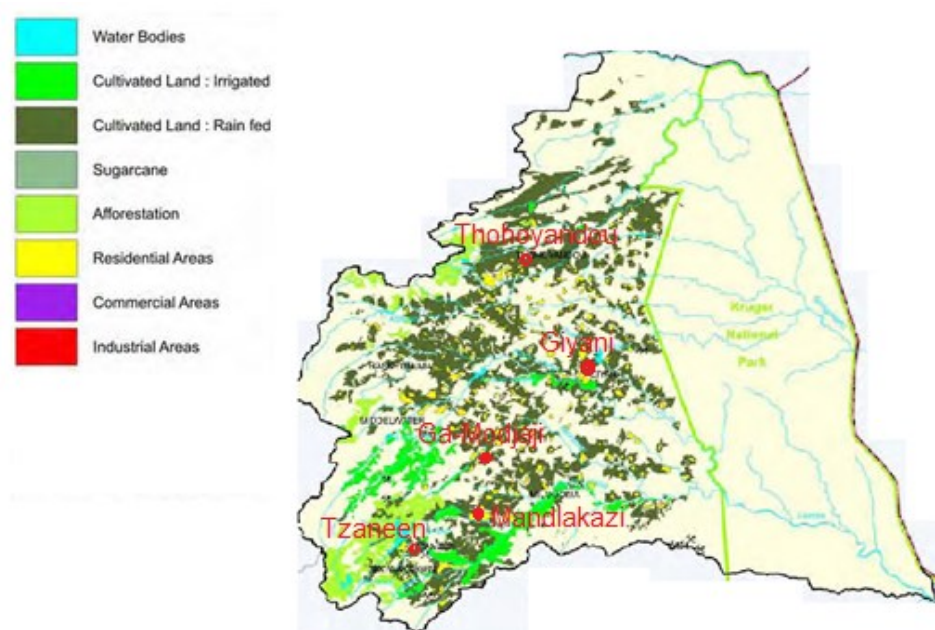


Figure 5-1: Land use map showing locations selected to verify SAWS and model-based SPI

Figure 5-2 and Figure 5-3 show the NDVI maps for the area of study for selected periods of year 2012. Figure 5-4 and Figure 5-5 show the VCI maps for the area of the study for the same periods.

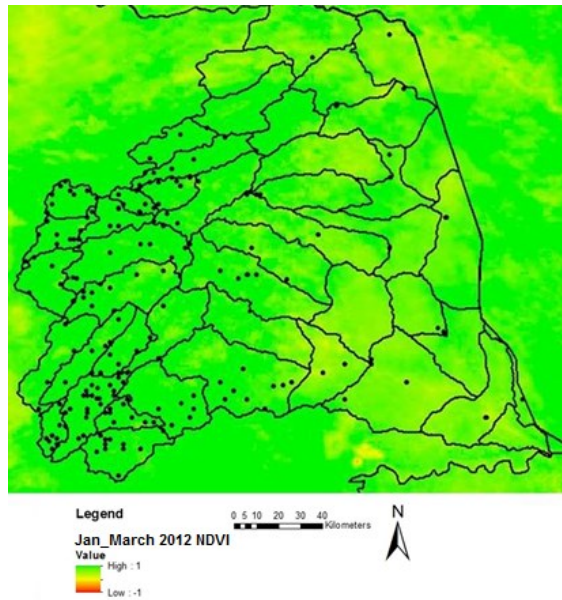


Figure 5-2: NDVI January to March 2012

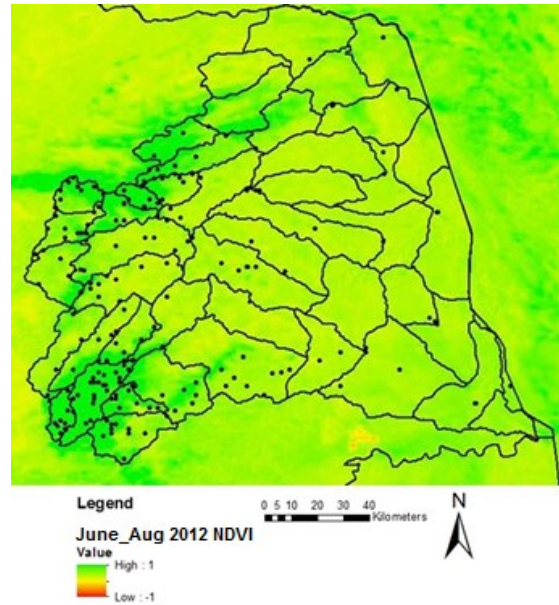


Figure 5-3: NDVI June to August 2012

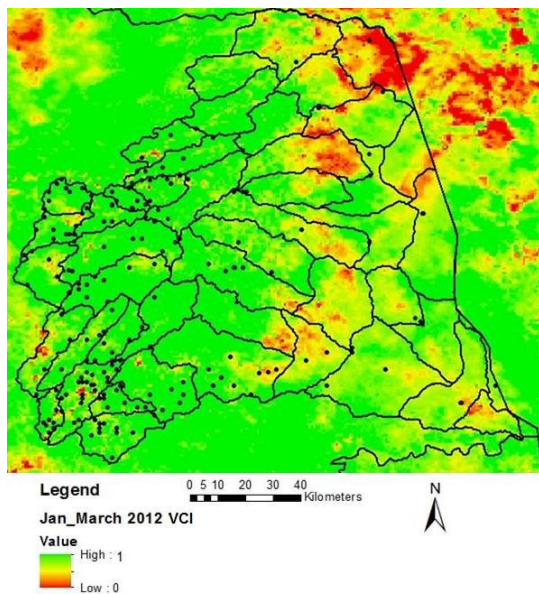


Figure 5-4: VCI January to March 2012

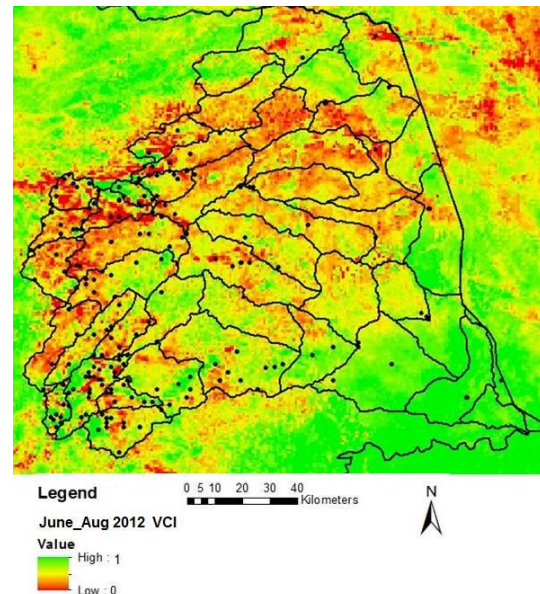


Figure 5-5: VCI June to August 2012

Using the NDVI and VCI images for 2012 and the SPI model developed in Chapter 4, model-based SPI maps for the wet season and dry season were obtained as shown on Figure 5-6 and Figure 5-7. The SPIs were then classified using the same classification used by SAWS to obtain Figure 5-8 and Figure 5-9

The classification is:

0.2 And below – extremely dry;

0.21 to 0.35 – severely dry;

0.36 to 0.4 – moderately dry;

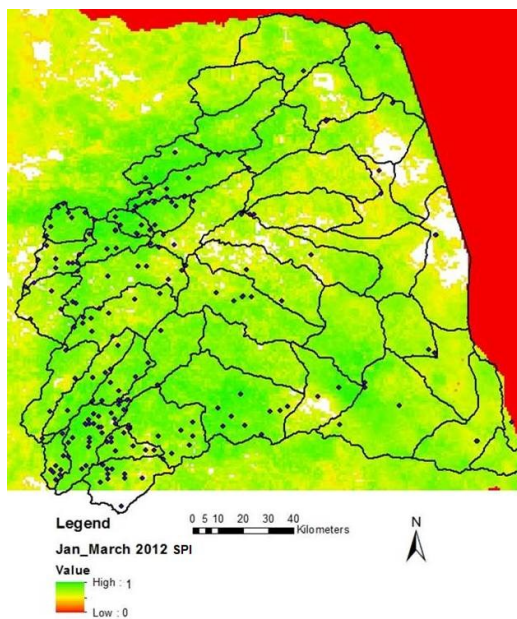
0.41 to 0.49 – somewhat dry;

0.5 to 0.65 – normal conditions;

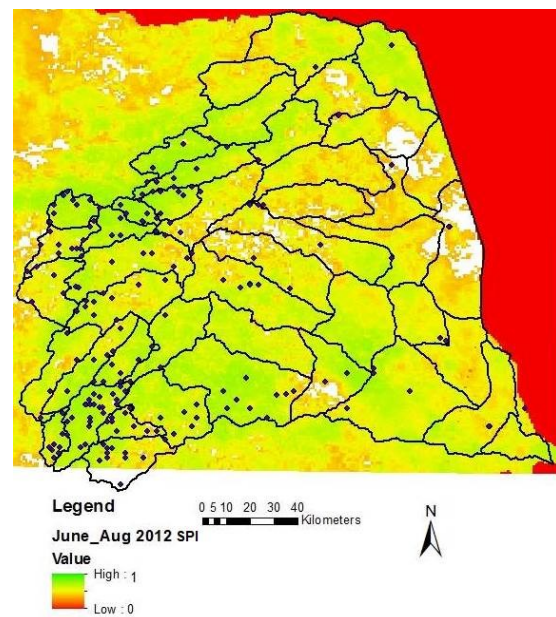
0.66 to 0.8 – wet conditions;

0.81 and above – extremely wet conditions.

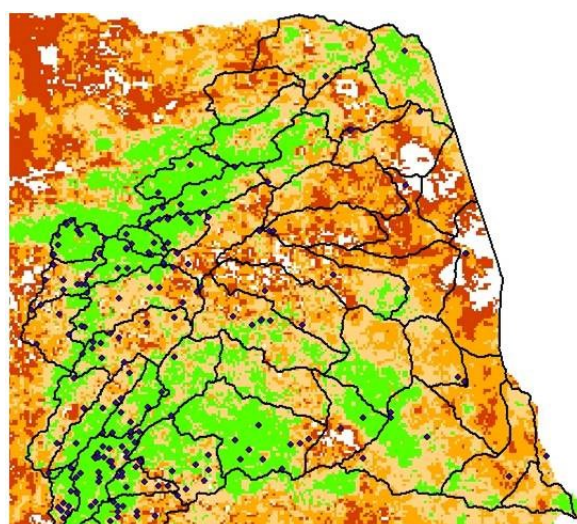
Areas with the same classification were mapped together based on a grid of 3 kilometres which is the estimated size of the smallest local community within the Limpopo. This obtained Figure 5-10 and Figure 5-12 which allowed reasonable comparison with the SAWS maps for the same periods.



**Figure 5-6: SPI January to March 2012
based on model**



**Figure 5-7: SPI June to August 2012
based on model**



Legend

SPI Spatial Jan_March 2012

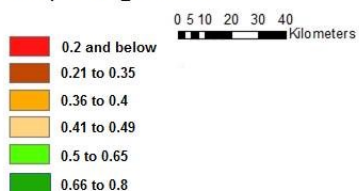
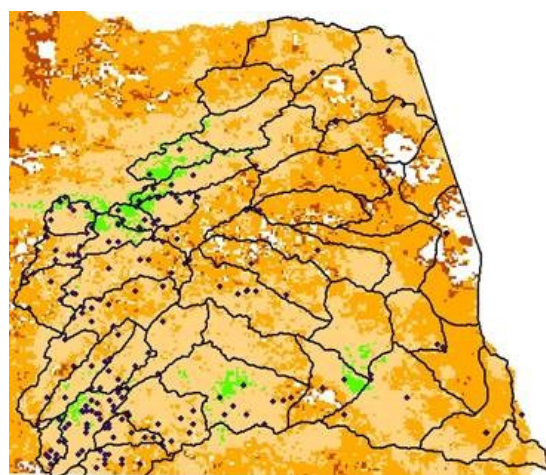


Figure 5-8: Classified SPI January to March 2012



Legend

SPI Spatial June_Aug 2012

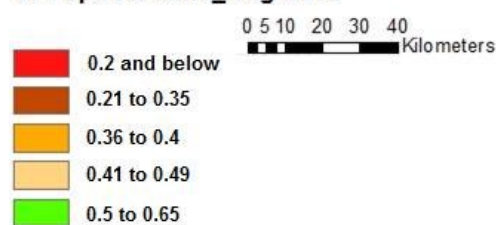
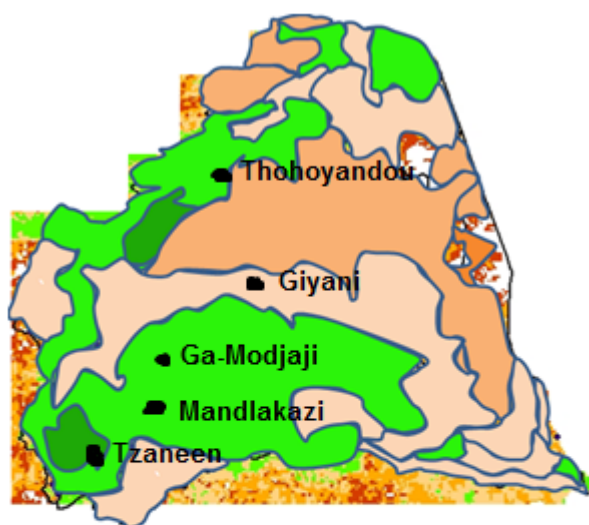


Figure 5-9: Classified SPI June to August 2012



Legend

SPI Spatial Jan_March 2012



Figure 5-10: Classified areas within 3 Km - SPI January to March 2012



Legend



Figure 5-11: SAWS SPI January to March 2012

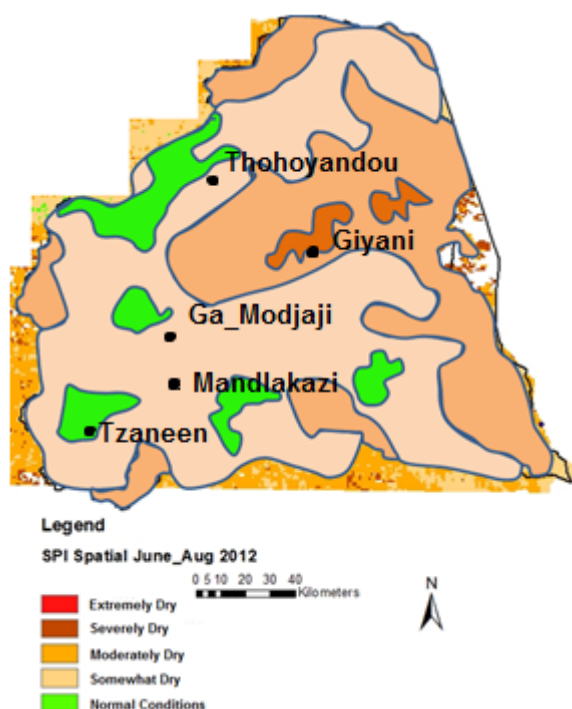


Figure 5-12: Classified areas within 3 Km - SPI June to August 2012

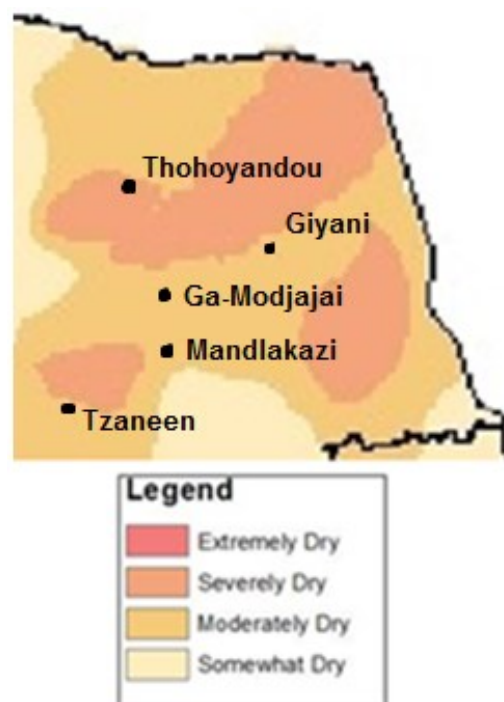


Figure 5-13: SAWS SPI June to August 2012

An assessment of how well the SPI regression model and the SAWS maps agree with the field observations of the drought conditions in the selected sites is carried out in Tables 5.1 and 5.2 respectively for the wet and the dry season of year 2012.

Table 5-1: SPI spatial comparison between SAWS and field observation – Wet Season

Community	SAWS interpretation	Model results	Field observation	Interpretation based on model results, field observation and the SAWS results
Tzaneen	Somewhat dry -1 to -1.4	Wet conditions 0.8 and above	Irrigation farmers are predominantly found in this area. The Letaba Water User Association/farmers confirmed the availability of adequate rainfall.	There is agreement between field observation and SPI model but not with the SAWS map
Mandlakazi	Somewhat dry -1 to -1.4	Normal conditions 0.5 to 0.65	The Catchment Management Agency identified normal conditions. Rainfed farmers are predominantly in this area. A normal harvest was achieved mainly for those who planted in good time.	Field observations are in agreement with the SPI model and not SAWS.
Ga-Modjaji	Somewhat dry -1 to -1.4	Normal conditions 0.5 to 0.65	The Mutale Farmers Association uses the riverbed as a water source and there was enough fruit to be sold. A combination of irrigation and rainfed farmers are found in this area. Normal rainy conditions were experienced in this area, with rivers running dry and water having to be sourced from a riverbed.	The SPI model is in agreement with the field observations unlike the SAWS map.
Thohoyandou	Somewhat dry -1 to -1.4	Normal conditions 0.5 to 0.65	There was adequate rain for livestock to be taken care of though it appears from the bulletin that rains came in late for rainfed farmers.	This could be taken to agree with both SAWS and the SPI model.
Giyani	Somewhat dry -1 to -1.4	Somewhat dry 0.36 to 0.4	The Merekome Water User Association and the Mopani Municipality confirmed the non-availability of water.	This was a dry period in summer for this area as predicted by both the SAWS and model results, hence s agrees with both the modelled and SAWS results.

Table 5-2: SPI spatial comparison between SAWS and field observation – Dry Season

Community	Saws interpretation	Model results	Field observation	Interpretation based on model results, field observation and SAWS results
Tzaneen	Moderately dry -1.5 to -2.9	Normal conditions 0.5 to 0.65	Agri-Letaba agricultural farmers in their meeting in August suggested that conditions experienced were as normal as other years. Normal conditions were experienced by farmers in this area as they had received enough rainfall and had enough water from the dam.	This agrees with the SPI model and not with the SAWS result.
Mandlakazi	Moderately dry -1.5 to -2.9	Somewhat dry 0.4 to 0.49	Normal harvest was experienced by rainfed farmers within the area (those who planted on time). Wrong planting timing resulted in some farmers experiencing moderately dry conditions.	Field results agree with both SAWS results and the SPI model depending on the planting time.
Ga-Modjaji	Moderately dry -1.5 to -2.9	Somewhat dry 0.4 to 0.49	Farmers with enough resources did not experience the worst of dry conditions as they could make use of water from the riverbed.	This agrees with SAWS results as this can be classified as moderately dry
Thohoyandou	Severely dry -3 to -3.9	Somewhat dry 0.4 to 0.49	The Department of Agriculture confirmed that in Madifha, east of Thohoyandou, some livestock owners resorted to harvesting grass and collecting tree leaves to feed their cattle. This may suggest the late arrival of rains for rainfed farmers. Nevertheless, irrigation farmers had survived.	This does not agree with the SAWS results. It also does not agree with the SPI model since the condition would be better classified as moderately dry.
Giyani	Moderately dry -1.5 to -2.9	Severely dry 0.2 to 0.35	Merekome Water User Association and the Mopani Municipality confirmed the non-availability of water. This area was the worst hit by drought in the area of study as there was no harvest for rainfed farmers.	The field observations agree with the modelled SPI and not with the prediction by SAWS

As Table 5-1 and Table 5-2 reveal, there is a significant difference between SAWS and SPI developed model. During the wet season, three areas agree with the model results and two areas agree with both model and SAWS results, for the dry season two areas agree with model results, one with SAWS results, one with model and SAWS results and one that does not agree with any of the results. This shows five areas agree with the model and field observation results, four areas that agree with both SAWS/model and field observation results and one that does not agree with any.

The wet season shows a somewhat dry condition for the entire study area from the SAWS SPI map (Figure 5-11). On the other hand, the model shows normal to wet conditions, and only the Giyani areas show somewhat dry conditions. According to the SAWS, moderately to severely dry conditions were experienced during the dry season in the area of study. When visited during the wet and dry seasons respectively in 2012, the Water User Associations pointed out that SAWS' long range forecast and drought maps, which are available online, were the only available information, which could be used for early drought warning. Makuleke village in Mopani experienced severe dry weather conditions and over 300 cattle died (SABC, 21/12/2012). This statement was confirmed by model results of severe drought in the area.

The seasonal pattern of rainfall and NDVI combined with the VCI, Aspect and Slope, suggest that the north-western and south-western part Luvuvhu/Letaba Water Management Area received higher rainfall than the rest of the catchment in the wet season of 2012. The South African Weather Services' results portray the same conditions throughout the catchment area which did not agree with field observations. This can be attributed to the smaller number of rainfall stations available in the western part of the catchment area.

6. CONCLUSIONS AND RECOMMENDATIONS

In this study, SPI was modelled using remote-sensed data with the aim of improving the spatial accuracy of drought monitoring. The drought-prone Luvuvhu/Letaba Water Management Area was selected for the study and data from 129 rainfall stations within the area were applied. The modelling was based on a linear regression with the rainfall-derived SPI from the rainfall stations as the dependent variable and satellite derived index NDVI, VCI and two topographical attributes (Aspect and Elevation) as the independent variables. The linear modelling was subjected to rigorous testing using the Akaike Information Criterion (AIC) and bootstrapping for robust determination of R^2 and RMSE. The AIC analysis eliminated elevation as a significant variable and two models; one for the dry and one for the wet season were finally obtained. These models were further subjected to verification using the observed drought conditions at 5 widely-spread communities in the study area for year 2012. For this, drought condition maps based on the modelled SPIs were obtained on a grid of 3x3 km in the study area. These matched the field observations reasonably well and were considerably better than the drought monitoring maps provided by the South African Weather Services (SAWS) which are based on data from sparsely located rainfall stations.

By using the SPI model, it is therefore possible to zoom into local/community scale and determine the severity of drought with more confidence. Improved and informed decision making can be achieved based on the results of this study. Data from remote sensing has been applied and this technique has evolved with time and can only improve in future.

Recommendations

The following aspects have been identified as candidates for further research:

- A larger catchment area with significant variation in altitude needs to be considered for future research as this will help to obtain a more comprehensive assessment of the method developed in this study.
- The development of a hybrid model that uses the spatially-precise modelled SPI and the sparsely determined rainfall-based SPI. This would combine the advantages of spatial precision offered by remote sensing and the ground truth of actual rainfall measurements.
- Development of Drought risk maps that show areas that face high risk using other variables such as soil, water availability and temperature conditions that are also indicators of drought conditions.

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www.nasa.com/.GES-DAAC/.PAL/.vegetation/.pal_ndvi.html#201	04 April 2012
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APPENDICES

OBSERVED RAINFALL DATA FORMAT FOR STATIONS

Month		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
Station Name	Year													
0679141 W	1960	67	248	96	109	12.5	27	0	8.5	29.5	17.5	238	497	1350
0679141 W	1961	77	244.8	240	155.5	11.5	24	36.5	45.8	29.5	31	66.6	81.4	1043.6
0679141 W	1962	132.1	0	40.6	93	14.5	0	0	0	1.2	5	219	401.8	907.2
0679141 W	1963	106.7	32.3	43.6	101.4	33	52.5	17.5	10	12	61.5	88.5	119.3	678.3
0679141 W	1964	94.5	161.2	37	50.4	16	0	0	4	14	148	109	530.3	1164.4
0679141 W	1965	306	94.5	51.3	70.3	11.7	8.4	4	20	50	23.5	117	116.5	873.2
0679141 W	1966	243	469.6	43.5	26.5	0	5	11.5	0	55.5	51	86.5	232.5	1224.6
0679141 W	1967	193	260	231.5	246.5	16	3	28	0	0	65	177	94.1	1314.1
0679141 W	1968	59.5	110.1	195	80.5	60	52	24.5	17.5	5	70.5	207	232.5	1114.1
0679141 W	1969	209	82	341	138	6.5	10	12	15	32	326.5	53	273.5	1498.5
0679141 W	1970	106	128.5	29.5	27	26.5	21	32.5	0	26.5	75.5	137.9	152.5	763.4
0679141 W	1971	366.5	131	36	211	91	11.4	0	0	18	183.5	204	149.1	1401.5
0679141 W	1972	668.5	385.5	412.5	106.5	53	6	4.5	5.3	7	160	188	33	2029.8
0679141 W	1973	149	126	125.5	134	25.7	0	30	12	178	159	168.5	377.2	1484.9
0679141 W	1974	346.5	447.5	222	81.5	98	5	0	12.5	110.5	32.5	249.3	236	1841.3
0679141 W	1975	321.5	323.4	246.5	78.6	43.5	15.5	3	10.2	7.5	57	96.6	442	1645.3
0679141 W	1976	339.5	276	370	101.9	115.5	15.5	0	7.5	21	78.5	150.3	105.3	1581
0679141 W	1977	475.5	226.5	365.3	91	19	0	0	52.5	138.2	53.5	117	252.9	1791.4
0679141 W	1978	999.9	222.3	161.5	79	15.7	0	13	5.8	28.6	57.1	277.7	176.1	2036.7
0679141 W	1979	223.6	143.7	185	58	56	0	14	89.5	41.5	157	185	299	1452.3
0679141 W	1980	232.5	364	140	38.5	9	0	5	39	97	127	349.5	214.5	1616
0679141 W	1981	494.5	386.5	240	51	19.5	0	4.5	55.7	49.5	216.5	206	169.1	1892.8
0679141 W	1982	143.2	88.7	78.1	50.9	88.8	0	7	2.5	36.5	74	171.6	153.4	894.7
0679141 W	1983	79	63.5	141	26	0	19	2	58	6.5	116.1	134.6	132.5	778.2
0679141 W	1984	77	130.5	204	73.5	0	8.5	135	21.5	36.5	111.4	261	33	1091.9
0679141 W	1985	192.9	296.1	170.1	18.7	91.5	42.1	1.6	0.9	54.2	135	71.5	123.8	1198.4

Month		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Ann
0679141 W	1986	130.7	136	107	448.1	30	11	0	16.5	19.7	145.5	207.5	113.2	1365.2
0679141 W	1987	76.5	292.2	93.1	43	22	28	0	26	135	80	98.7	347.5	1242
0679141 W	1988	138.7	387.5	359	45.5	0	68.2	23.5	36	71.5	141.1	61.5	128.5	1461
0679141 W	1989	121	251	47	48.5	15.5	43.5	3.1	18	8	89.5	229.5	260	1134.6
0679141 W	1990	329	188.6	161.7	100	0	0	11	8.7	12.5	83.5	152.5	257	1304.5
0679141 W	1991	331	234.6	328.2	3.2	28	29.5	0	1.1	23.3	11.6	108.5	66	1165
0679141 W	1992	61	60.8	83.8	25.5	0	26	0	0	6.7	31.4	78.6	180.6	554.4
0679141 W	1993	71.6	156.1	236.4	42.1	46.7	9	18.7	20.6	14	90.4	221.1	313.8	1240.5
0679141 W	1994	73.6	304	65.1	32.7	5.1	0.1	2.2	28.2	15	154.1	39.4	222.8	942.3
0679141 W	1995	191.5	214.6	199.6	93.9	30.8	1	5.5	28	6.3	76.2	366.6	340.2	1554.2
0679141 W	1996	458.5	743.4	113	57.4	154	29.5	69.9	53.4	2.7	77	181.5	158.5	2098.8
0679141 W	1997	498.5	251	371.6	53.7	25.2	0.2	21.6	3.2	103.8	90.4	204.6	148.1	1771.9
0679141 W	1998	495.9	69	39.1	33.5	0	3.2	64.9	9.6	68.2	174.5	194.8	413.8	1566.5
0679141 W	1999	427.3	307.1	301.7	139.1	66.2	13.8	0	13.9	21.2	62.5	222.8	198.8	1774.4
0679141 W	2000	481.7	999.9	581.8	237.1	27	124.6	4.9	0	0	0	0	0	2457

TYPICAL SPI, NDVI, VCI AND ELEVATION PER STATION

STATION NUMBER	STATION NAME	HEIGHT	NDVI 91 JUNE_AUG	SPI 91 JUN_AUG	ASPECT	VCI 91 JUN
0725756 3	SHINGWEDZI	215	0.17945258	-1.936220476	71.57	3
0681248 2	MAHLANGENE	274	0.22115120	-1.750661472	217.41	17
0681069 2	LETABA RANCH	335	0.20854488	-1.89042256	319.76	36
0725373 X	LETABA WOODLANDS	366	0.18297808	-1.742517692	198.43	6
0768382 0	SHINGWEDZI VLAKTEPLAAS	366	0.17916468	-1.692637738	251.57	23
0724590 9	REDAS APPROACH	425	0.22834864	-2.082785001	65.2	23
0724790 5	KRUGERWILDTUIN SHANGONI ARS	427	0.16747800	-1.846678485	26.57	14
0680133 1	LA COTTE	451	0.39492217	-1.527530014	338.20	23
0680280 0	HANS MERENSKY	457	0.30078745	-1.640077531	315.00	15
0680613 8	NONDWENI	457	0.19480492	-1.706294065	63.43	14
0680821 8	MAHALE	457	0.26041827	-1.639085189	306.87	25
0768011 3	PUNDA MARIA	462	0.20501259	-1.750993934	33.18	6
0724379 4	GIYANI	472	0.17382358	-1.668370685	205.35	10
0681077 6	BADEROUKWE	475	0.22409377	-1.687888211	12.99	14
0680439 7	PLATVELD	488	0.22409377	-1.596162917	71.57	3
0724301 9	MALAWMALELE	505	0.16747794	-1.983282902	290.56	3
0679859 2	BELLE OMBRE	515	0.23809740	-1.588996359	248.20	15
0680167 0	CHESTER	518	0.23135374	-1.443128606	10.01	15
0680225 6	BLACK HILLS	518	0.27637935	-1.34984404	112.38	11
0723705 2	CALEDON	518	0.24713328	-1.97136158	34.70	3
0724361 2	BOLTMAN	545	0.18153006	-1.898963603	65.64	1
0724391 4	NEW UNION GOLD FIELDS	545	0.24129243	-2.300910259	26.51	25
0679592 4	LEEUFONTEIN	549	0.22409377	-1.771297956	180.00	7

0679532 0	LETABA ESTATES	556	0.42097676	-1.917077602	165.96	11
0766779 6	PALMARYVILLE	570	0.34633794	-1.767293628	128.26	7
0723822 X	HA-DAVHANA	592	0.27686882	-1.993863806	126.67	23
0766898 7	THOHOYANDOU	600	0.29199484	-2.317012808	3.01	26
0767046 8	TSHANDAMA	600	0.15562958	-2.065104482	53.13	5
0723552 7	ONVERWACHT	605	0.34633794	-2.131551505	20.22	48
0679441 8	VALENCIA ESTATES	610	0.46423313	-1.970061415	257.01	25
0723485 6	LEVUBU	610	0.63005525	-2.069977344	29.05	20
0723577 0	VERSAMELING VAN WATERS	610	0.33080411	-2.086224068	174.09	22
0723656 2	BELLEVUE	610	0.22834864	-1.439274186	153.21	36
0723793 4	TABAANS	610	0.22163175	-1.781279315	177.27	36
0724138 7	BEND STORE	610	0.18469881	-1.505250937	11.31	7
0766748 2	BEUSTER	610	0.36666960	-2.379843458	140.19	25
0723638 1	WATERBOOM	625	0.28263524	-2.124520534	212.91	14
0723469 9	SCHAAPLAAGTE	640	0.15375610	-2.037562769	294.44	
0679378 4	BROEDERSTROOMDRIFT	671	0.48721784	-1.967091739	183.58	25
0723603 0	TSIANDA	671	0.23278953	-1.672739922	93.01	17
0679274 9	MOOKETSI - KOEDOESRIVIER	674	0.33080411	-1.803811128	358.03	18
0723359 3	JACHTSDRIFT	701	0.23263313	-2.003441527	125.13	3
0723363 X	KLEIN AUSTRALIE	702	0.45671713	-2.345662647	110.90	25
0679260 4	TZANEEN	716	0.49563241	-2.248143075	341.57	13
0679315 5	GRASKRAAL	731	0.60708463	-2.417756039	127.76	30
0679156 X	MOOKETSI - SAR	732	0.32507089	-1.471361284	302.91	6
0679277 4	MOOIHOEK	732	0.17748074	-1.879734385	315.00	19
0679407 X	BEAM ENDS	732	0.37669146	-2.102533897	192.99	25

0766837 1	SIBASA	739	0.39407009	-2.316660689	197.78	25
0679289 5	PUSELLA - GSH	749	0.44220740	-2.052625861	243.43	47
0679166 7	REDLANDS	750	0.57888603	-2.330334267	42.88	12
0679227 8	HANS MERENSKY HOëRSKOOL	755	0.30078745	-1.922448909	117.47	20
0679245 9	BOEKENHOUTBULT	762	0.19678235	-1.658095885	21.50	14
0679543 X	VYGEBOOMSPRUIT	762	0.23854484	-2.233125237	333.43	48
0723231 6	BONTFONTEIN	762	0.27953583	-1.645257003	34.08	18
0723334 X	NOOITGEDACHT	762	0.27755854	-2.196177612	214.70	5
0766863 6	GOOLDVILLE - HOSP	762	0.22547987	-2.446768547	135.00	14
0679290 6	TZANEEN - POL	777	0.39888623	-2.094587281	4.69	11
0723126 X	BEJA	779	0.34633794	-2.03095793	210.96	34
0679036 7	ALTYD MOOI	792	0.25348517	-1.815393711	281.82	23
0679221 7	DUIWELSKLOOF - MUN	792	0.37326756	-1.921277319	22.14	27
0723070 7	ELIM - HOSP	808	0.42878145	-2.045620313	12.99	17
0723155 X	GOEDEHOOP	811	0.27982470	-2.038090056	210.20	37
0679401 9	TRIANGLE	823	0.71970081	-2.225253801	127.79	2
0723278 8	GEVONDEN	823	0.60431993	-2.212475754		16
0722757 6	VYGEBOOMSPRUIT	884	0.17114335	-1.802034213	165.26	15
0722783 0	LONZUEVAL	884	0.34991902	-2.083113309	248.20	21
0722797 5	KOEDOESPOORT	884	0.22115120	-2.209265693	125.18	11
0723080 4	SETALI	884	0.22665927	-2.246582483	113.75	44
0723173 0	WILTONVALE	884	0.30529383	-2.183797531	172.75	29
0723331 4	TIMBADOLA BOS	890	0.49886313	-2.371352091	232.29	41
0678883 7	RAMATOELASKLOOF	914	0.27349961	-1.750085947	279.57	54
0679284 6	QUANTOCK	914	0.47212029	-2.388579253	84.21	3
0679456 4	RAVENSHILL	914	0.35702065	-1.779224903	350.45	23

0722675 9	VLIEGENPAN	914	0.20561238	-1.906375632	12.99	22
0723114 9	MYNGENOEGEN	914	0.45767358	-2.059986796	150.02	32
0722820 X	LOVEDALE PARK	915	0.25288486	-2.01508406	61.70	6
0723011 5	MODDERVLEI	915	0.41050604	-2.082733284	276.34	32
0723176 6	GROOTFONTEIN	915	0.28822923	-2.178299569	287.24	27
0679164 3	LETABA DISTRIC	945	0.54807413	-2.139230447	53.13	21
0722700 7	MAMPAKUIL	945	0.24129243	-1.462626186	178.15	23
0723041 7	SWEETWATERS	973	0.48904449	-2.173663627	337.11	21
0679135 3	BELVEDERE	975	0.58553499	-2.23279155	201.23	2
0679608 8	MODJADJI - NAT RES	977	0.46820593	-1.914944026	237.86	26
0722822 3	EAST LYNNE	1036	0.31699023	-2.186150972	79.38	17
0722861 0	DONKERHOEK	1036	0.24495350	-2.218853122	209.74	41
0766536 5	MANDALA	1040	0.51561749	-2.521727403	180.49	49
0722616 7	NATKRUIT	1052	0.19854544	-1.938835928	266.63	20
0722781 7	MOW COP	1065	0.40403989	-2.201155535	143.65	15
0723020 0	KLEINFONTEIN	1065	0.25667059	-2.12111793	300.96	48
0723113 7	VOORSPOED - BOS	1065	0.47977859	-1.892572444	3.65	32
0766030 3	ROODEWAL BOS ARS	1065	0.45938671	-2.20399455	175.78	24
0723055 1	DORINGBOOM	1067	0.33198628	-2.19605229	13.84	42
0722900 3	SPELONKEN - BOS	1082	0.48904449	-1.862804656	289.54	33
0679341 X	MODDERSPRUIT	1125	0.63174373	-2.284853994	56.11	29
0679161 8	CHRISTINASRUST	1128	0.66148657	-2.501554264	183.45	44
0722653 0	BULTFONTEIN	1128	0.16895697	-1.605960873	351.38	22
0766596 9	VONDO - BOS	1130	0.49993080	-2.338150801	133.47	9
0723513 X	TSHAKHUMA	1158	0.21699400	-2.165146972	254.74	15

0723073 2	ROSSBACH	1170	0.25572777	-1.950710581	152.02	47
0723182 6	SHEFEERA	1214	0.48548660	-2.468296505	178.78	12
0679019 8	TZANEEN DE HOEK	1219	0.57964033	-2.529831246	60.71	37
0723031 X	ROODEWAL - BOS	1219	0.42097676	-2.139597599	219.25	22
0765869 0	FLEURFONTEIN	1219	0.29023811	-2.164556286	186.71	55
0766150 6	PISANGHOEK	1220	0.47674203	-2.154688203	201.61	13
0766563 1	THATHE - BOS	1250	0.30078745	-2.478203565	215.84	29
0766568 0	MAFELA PLANTATION	1260	0.52773839	-2.6009229	120.12	39
0766509 9	MATIWA	1311	0.37469867	-2.721760393	330.95	21
0765898 0	STERKWATER	1370	0.53920162	-2.006885609	167.01	2
0679136 5	GRENSHOEK	1372	0.57275361	-2.302887694	171.73	56
0679139 0	MIDDELKOP - BOS	1372	0.64820230	-2.147880582	285.36	84
0766480 2	ENTABENI BOS	1376	0.52617824	-2.671960515	185.71	38
0678858 4	WOODBUSH	1555	0.37669137	-2.389380252	75.96	16

TYPICAL MODEL SCRIPT FOR A SEASON

```
data<-read.csv("NDVI_SPI_ASPECT Jan_March 91_92.csv")
attach(data)
names(data)
ls()
summary(data)
SPI_NDVI<-lm(SPI~NDVI)
summary(SPI_NDVI)
anova(SPI_NDVI)
NDVI_VCI<-lm(NDVI~VCI)
summary(NDVI_VCI)
anova(NDVI_VCI)
n=length(SPI)
RMSE<-sqrt(7.22/n)
```

relative root mean square error

```
RRMSE<-(RMSE/mean(SPI))*100
win.graph()
```

scatter

```
plot(SPI,NDVI)
hist(SPI)
qqnorm(SPI)
abline(lm(SPI~NDVI, data=data), col="red")
lines(lowess(SPI,NDVI), col="blue")
par(mfrow=c(2,2))
```

#Running multiple regression and stepwise regression

```
SPI_NDVI_VCI<-lm(SPI~NDVI+VCI)
summary(SPI_NDVI_VCI)
anova(SPI_NDVI_VCI)
```

```
SPI_NDVI_VCI_ASPECT<-lm(SPI~NDVI+VCI+ASPECT)
summary(SPI_NDVI_VCI_ASPECT)
anova(SPI_NDVI_VCI_ASPECT)
```

run a linear regression

```
SPI.lm<-lm(SPI~VCI+NDVI+as.numeric(DEM)+ASPECT)
summary(SPI.lm)
data<-is.numeric(data)
anova(SPI.lm)
```

#stepwise

```
SPI.lm.step<-step(SPI.lm)
```

re-run the regression (Without collinearity problems)

```
SPI.lm<-lm(SPI~NDVI+VCI+ASPECT)
summary(SPI.lm)
```

#bootstrapping for validation of the models

```
boot.res <- residuals(SPI.lm)
boot.num <- 1000
```

#number of bootstrap samples to take

```
B1 <- array(0, dim = c(boot.num, 4))
```

#array of zeros (number of rows = boot.num and number of columns = 5). The results from the bootstrapping will be stored in this array

```
for (i in 1:boot.num)
{Nstar <- fitted(SPI.lm) + sample(boot.res, replace = T)}
```

#sample residuals of lin reg and add them to the fitted values of lin reg

```
boot.model1 <- lm(SPI~NDVI+VCI+ASPECT) #regress Nstar on the original explanatory
variables
B1[i,] <- boot.model1$coefficients
```

#store the coefficients of boot.model1 to row i of B1

```
summary(boot.model1)
confint(boot.model1)
```

#confidence intervals of the variables of boot.model1

```
anova(boot.model1)
```

FIELD PHOTOS



Figure D 1: Presentation at the Stakeholder forum in Polokwane to water managers and SAWS



Figure D 2: Thapani dam visit in the around Tzaneen



Figure D 3: Presentation at stakeholder meeting with water managers



Figure D 4: Merekome farmers



Figure D 5: Small scale farming at Merekome



Figure D 6: Reservoir water storage used for irrigation



Figure D 7: Seedlings to be planted



Figure D 8: Presentation for Mutale Water Users Association



Figure D 9: Small scale farming for Mutale farmers



Figure D 10: Pumping station from the river



Figure D 11: Dry river bed in Mutale area



Figure D 12: Sump constructed for water pumping



Figure D 13: Mutale farmer operating from river bed source



Figure D 14: Tzaneen dam