THE EVALUATION AND QUANTIFICATION OF THE DROUGHT PROPAGATION PROCESS USING SATELLITE EARTH OBSERVATION PRODUCTS

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ABSTRACT

Droughts can be categorized in four types namely, meteorological, agricultural, hydrological and socio-economic drought. Droughts have the potential to occur either as an isolated event, mutually exclusive event or through the progression from one form to another. The use of drought indices were recognized as an approach capable evaluating and monitoring the characteristics of the different drought types. The aim of this study is to evaluate and quantify drought characteristics as it evolves and propagates form meteorological to agricultural drought, within two climatically different regions within South Africa, namely the uMngeni Catchment and the Breede-Overberg Catchment. These areas generally have insufficient networks of ground-based observations to provide continuous and long-term data. Therefore, Satellite Earth Observation (SEO) data and Google Earth Engine (GEE) were utilized. The Standardized Precipitation Index (SPI) was selected to quantify meteorological drought, whilst the Standardized Precipitation Evapotranspiration Index (SPEI) and Vegetation Health Index (VHI) was chosen to assess agricultural drought at both of the selected sites. The methodology undertaken firstly involved validating the SEO data against in-situ data. Thereafter, historical droughts were calculated by the SPI and SPEI indices at various timescales. Assessments were then conducted to determine the applicability of satellite based drought index VHI on quantifying agricultural drought conditions. The final assessment involved conducting propagation analysis between the drought indices. The findings of this study indicated that SEO have the potential to be utilized in the collection and monitoring of drought conditions. VHI was recognized to be scale dependent index, especially when considering averaging values. The findings of this study further suggested that the uMngeni region was more susceptible to the impacts associated with meteorological droughts characteristics whilst the Breede-Overberg region was more susceptible to the impacts associated with agricultural drought characteristics. Understanding the impacts and characteristics associated with the drought propagation process may further provide theoretical knowledge that can be used to facilitate more informed disaster, water and agricultural management and mitigation strategies to be implemented. If decision makers were to only consider drought using meteorological assessments for management decisions, the resulting strategies produced may be misleading as the impacts of an agricultural drought event may still be persistent.

DECLARATION PLAGIARISM

I, Trisha Sukhdeo declare that:

(a) The research reported in this dissertation, except where otherwise indicated, is my original work;

(b) This dissertation has not been submitted for any degree or examination at any other university;

(c) This dissertation does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons;

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Dr. S Gokool

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LIST OF ABBREVIATIONS

AMSRE	Advanced Microwave Scanning Radiometer on Earth Observing System
API	Application Programming Interfaces
ARC	Africa Rainfall Estimate Climatology
ARS	Automatic Rainfall Stations
AVHRR-CDR	Landsat Products, NOAA Climate Data Records of Advanced Very High Resolution Radiometer
AWS	Automatic Weather Stations
CDR	Climate Data Record
CHRS	Center for Hydrometeorology and Remote Sensing
CHIRPS	The Climate Hazards Group Infrared Precipitation with Station data
CMI	Crop Moisture Index
DWS	Department of Water and Sanitation
ECMWF	European Center for Medium-Range Weather Forecast
ENSO	El Nino Southern Oscillation
EROS	Earth Resource Observation and Science
EVI	Enhanced Vegetation Index
ETo	Reference Evapotranspiration
FEWS NET	Famine Early Warning Systems Network
GEE	Google Earth Engine
GLADS	Global Land Data Assimilation System
GRACE	Gravity Recovery and Climate Experiment
JAXA	Japanese Aerospace Exploration Agency
LST	Land Surface Temperature
LSTmax	Land Surface Temperature Absolute Maximum
LSTmin	Land Surface Temperature Absolute Minimum
MODIS	Moderate Resolution Image Spectradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index

NDVImax	Normalized Difference Vegetation Index Absolute Maximum
NDVImin	Normalized Difference Vegetation Index Absolute Minimum
NOAA	National Oceanic and Atmospheric Administration
PDSI	Palmer Drought Severity index
PERSIANN-CDR	Precipitation Estimation from Remotely Sensed Information Using Artificial Neutral Network - Climate Data Records
PET	Potential Evapotranspiration
PHDI	Palmer Hydrological Drought Index
PMB	Pietermaritzburg
SAWS	South African Weather Service
SEO	Satellite Earth Observation
SMAP	Soil Moisture Active Passive
SMDI	Soil Moisture Deficit Index
SMOS	Soil Moisture Ocean Salinity Satellite
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SRI	Standardized Runoff Index
SSFI	Standardized Streamflow Index
SST	Sea Surface Temperatures
SWSI	Surface Water Supply Index
TCI	Temperature Condition Index
Tmax	Maximum Air Temperature
Tmin	Minimum Air Temperature
TRMM	Tropical Rainfall Measuring
TTT	Tropical Temperate Troughs
USGS	United State Geological Survey
VCI	Vegetation Condition Index
VHI	Vegetation Health Index
WMO	World Meteorological Organizations

1. INTRODUCTION

Over the years, it has been recognized that environmental disasters such as droughts have gained increasing attention amongst various disciplines, including hydrology, meteorology, agricultural, and environmental science, particularly as the frequency and severity of these extreme climatic events has increased (Mishra and Singh, 2010; Bai *et al.,* 2020). Droughts are a common and significant form of natural disaster that affects the agricultural, socio-economic and environmental sectors, often occurring at various spatio-temporal scales (Van Loon and Laaha, 2015; Huang *et al.*, 2017; Shin *et al.*, 2018; Gevaert *et al.,* 2018; West *et al.,* 2019). Droughts are slowly developing events consisting of complex interrelationships between several meteorological and climatological indicators (Muthumanickam *et al.,* 2011; Bayissa *et al.,* 2017; Bai *et al.,* 2020).

There is no single universal definition of droughts, as this extreme event tends to vary depending on the type of hydrological variable (e.g., precipitation, soil moisture, streamflow) used to describe the drought (Sherval *et al.,* 2014). Despite this, drought can be defined broadly into either a conceptual or operational definition. The conceptual definition refers to the general descriptions of the physical processes (i.e. shortages of precipitation, soil moisture, evaporation, streamflow) and basic drought concepts whilst, the operational definition relates to identifying the onset, duration, intensity, severity, and termination of the drought (Mukherjee *et al.,* 2018).

However, in its simplest form, a drought event may be expressed as the deficit of water relative to average conditions over a prolonged period (Huang *et al.,* 2017; Shin *et al.,* 2018; Van Loon *et al.*, 2019; West *et al.,* 2019). Based on the aforementioned definition, droughts can be classified into the following categories: (a) Meteorological drought, which is associated with a deficit in precipitation below its average level and conditions; (b) Agricultural drought, which is related to periods of declining soil moisture supply falling below the level appropriate for the production of crops; (c) Hydrological drought, which results when there are conditions of persisting periods of inadequate water resource levels and storage supply at the surface and subsurface; and (d) Socio-economic drought, which is related with water resource systems failing to meet the demands of society, with the available supplies (Mishra and Singh, 2010; Sherval *et al.,* 2014).

Drought often manifests itself in different ways and can progress from one form to another over time. For example, a meteorological drought may lead to a decrease in soil moisture levels and may lead to the development of agricultural drought. This transition of drought event from one form to another is known as drought propagation (Van Loon, 2013; Shin *et al.*, 2018). The impacts of droughts are recognized to change as it evolves into its various types (Gevaert *et al.*, 2018). This may be owing to the complex mechanisms associated with the drought propagation process. This process is further characterized and influenced by several factors, such as catchment and climate conditions (Van Loon, 2013). It was also acknowledged that drought impacts may not always be proportional to the severity of the climatic event. For example, relatively mild drought events may have significantly large ecological and socio-economic effects, especially in areas with high levels of vulnerability and areas sensitivity to change (Vetter, 2009).

In South Africa, drought occurrence is relatively frequent, causing severe consequences to the country's economy, agriculture, ecology, and livelihood (Vetter, 2009, Meza *et al.*, 2021; Orimoloye *et al.*, 2022). According to Van Loon (2013), arid to semi-arid areas may be more susceptible to the impacts of drought events however, this being said, it does not indicate that drought in non-arid regions are less frequent (Cretat *et al.*, 2012). South Africa has many diverse climatic regions, which are typically affected by different types of drought, often varying in its characteristics, i.e. intensity, frequency, duration, and spatio-temporal extent (Rouault and Richard, 2005).

Historically, in South Africa, some of the most severe droughts experienced occur during the mature phase of El Nino. This phenomenon is often associated with drier conditions (dry spells), in the summer rainfall region (Baudoin *et al.*, 2017), and may also result in significant changes in precipitation patterns and modifications to the hydrological cycle (Fauchereau *et al.*, 2003; Bai *et al.*, 2020). Furthermore, the county's oceanic-atmospheric interactions, geographic location and spatio-temporal climate variability may account for the rise in the conditions of extreme weather and variability of the precipitation, thus contributing to the occurrence of drought (Fauchereau *et al.*, 2003). Therefore, there is a crucial need to understand these events in order to assist in the mitigation and management of these events to reduce their likely impacts (Mishra and Singh, 2010).

According to Shin *et al.* (2018), droughts are seen to have a more direct impact typically, with regards to the agricultural sector and hydrological systems. Recently, severe drought events in South Africa have resulted in impacts faced by the nation's agro-economic system. For example, over the past few years, South Africa has experienced high levels of decline in the yield and harvesting of agricultural products, increasing the country's vulnerability to food insecurity and causing numerous socio-economic problems (Baudoin *et al.,* 2017). South Africa's agricultural sector plays a crucial role in contributing to the country's economic wealth through the exporting of goods, creation of job opportunities, and sustaining the livelihood of communities (Baudin *et al.,* 2017). The pressures experienced in this area by changing climate characteristics and the rise in demand for water and agricultural resources may place additional stress on already limited water resources (Van Loon, 2013). These impacts are further likely to be exasperated by the occurrence of droughts (Ahmadalipour *et al.,* 2017).

The effect of droughts evolve as it progresses, therefore, its impact should be considered across several variables rather than trying to classify it into a single category. From a management perspective, if one was only to consider the effects of one form of drought and plan accordingly, this plan may not provide adequate relief as a significant part of the problem may still be prevalent. Therefore, it is essential to understand drought propagation. Furthermore, understanding droughts from numerous perspectives are critical due to the complex interactions and links found between the different types of drought (Zhang *et al.,* 2017). By gaining this holistic understanding, it will enable a comprehensive overview of the onset and offset times and characteristics of each drought to be assessed and observed in its respective stage, thus, providing valuable information that can be utilized in management, planning, and mitigation decisions.

Adequate monitoring and evaluating the drought propagation process may assist in informing management decisions. However, in order for this to take place there needs to be an approach that can provide reasonably accurate spatio-temporal information. The monitoring and understanding of droughts can be accomplished with the use of drought indices. According to Mukherjee *et al.* (2018), drought indices and indicators play a crucial role in tracking the hydrological cycle components, as they can be used to assess the effects of droughts and provide information on the different drought characteristics. Quantifying the times taken for a drought to propagate to its various stages, requires the use of drought indices to provide information that can then be utilized in drought management (Gevaert *et al.,* 2018). The use of drought indices, typically require records of detailed and continuous inputs for several hydrological and climatological variables (WMO, 2016). This information can be acquired from numerous sources such as in-situ observations, model simulations, data assimilation, and Satellite Earth Observations (SEO) (Wang *et al.*, 2016).

In order to obtain information on the characteristics of drought several hydrological and climatological variables, such as, precipitation, relative humidity, temperature etc., are required (West *et al.,* 2019). The gathering of this data can then be further used within the calculations of drought indices to provide an indication of the severity and occurrences of drought events. Drought monitoring has been accomplished historically with the use of in-situ based measurements (Ahmadalipour *et al.,* 2017; West *et al.,* 2019). However, many regions typically do not have adequate networks of in-situ data to obtain the required input data for the accurate assessment of drought (Ahmadalipour *et al.,* 2017). Areas such as South Africa are recognized to be a relatively data-poor region due to declining of operational observation stations over the past few decades (Lynch, 2003; Kroese *et al.*, 2006; Suleman *et al.,* 2020). However, in order to overcome these challenges, the technological advancements provided by SEO have the potential to provide information on the earth's processes and variables over various spatial and temporal scales. Thus, providing adequate information which can be utilized to explore drought assessments further.

It should be noted that often the process of collecting and analyzing of SEO information may contain large amounts of pre- and post-processing data, involve time consuming methods and may require technical expertise in its application. Cloud-based platforms such as Google Earth Engine (GEE), were acknowledged to be advantageous by providing a planetary-scale petabyte-data on a wide range of geospatial satellite information (Gorelick *et al.,* 2017). The application of the GEE platform facilitates large-scale environmental monitoring and analysis, without the need for large storage spaces, supercomputers or (Tamiminia *et al.*, 2020). Further advantages of this platform include its application of machine learning algorithms, Application Programming Interfaces (API) and it high-speed global parallel processing for the collection, visualization and analysis of geospatial data (Tamiminia *et al.,* 2020; Khan and Gilani, 2021).Therefore, GEE is a platform that has the potential to enhance the opportunities available for undertaking SEO studies, especially in developing countries and areas which are recognized to have limiting ground-based observation data available (Kumar and Mutanga, 2018).

Numerous studies have been undertaken worldwide on drought; however, most of these types look at individual components of drought. Over Southern Africa, it is recognized that there have been few assessments done on quantitatively analyzing the characteristics of drought and its propagation to the various types (e.g., from meteorological droughts to agricultural droughts). Therefore, this study seeks to contribute to the theoretical knowledge of drought by better understanding the impacts and characteristic of the drought propagation process. An understanding of this will thus, assist in contributing not only to drought management but also towards water and agricultural management decisions in South Africa. This study will, therefore, take a comprehensive approach in order to quantify the propagation of drought into some of its various stages, as well as highlight the influencing factors that contribute to the development and amplification of theses drought events.

1.1 Aim and Objectives

The aim of this study is to evaluate and demonstrate how the use of Satellite Earth Observations products and drought indices can be used to quantify and evaluate drought as it evolves and propagates to its different forms, which in turn can facilitate improved drought management in the future. For this purpose, there are several specific objectives that will be tackled in the study to achieve this aim, which is listed below:

- To conduct an in-depth review of literature on the various types of droughts and their associated propagation process.
- To identify and assess satellite-based products available to provide information on the input hydrological and climatological variables used in drought assessments.
- To validate and assess the applicability of satellite-derived drought variables against ground-based data.
- To determine the applicability of satellite derived drought indices in characterizing droughts

- To evaluate and quantify the spatial and temporal patterns and trends associated with the transition of drought from meteorological drought to agricultural drought using commonly applied drought indices.
- To evaluate the characteristics of the drought propagation process in two different climatic regions.

1.2 Research Questions

1. What are the most suitable satellite-based products, to provide adequate data for monitoring the transition between drought types?
2. Is the use of satellite-derived variables effective in calculating drought indices?
3. Do commonly applied drought indices aid in quantifying drought at multiple spatial and temporal scales?
4. Can the use of satellite drought indices provide adequate information on the characteristics of drought?
5. What are the common trends that occur as droughts evolve from meteorological drought to agricultural drought to another?
6. Which climatic region experiences more severe droughts and why?

1.3 Organization of Dissertation

This dissertation is broken down into five Chapters. Whereby, Chapter One provides an introductory overview on the research project undertaken for this dissertation. This chapter will also highlight the aims, objectives and research questions set out for this research study. Following this section Chapter Two provides a literature review analysis on the concept of drought and its associated propagation process, several case studies are also reviewed within this section in order to develop a comprehensive understanding of drought characteristics and how they are quantified. Further literature evaluations were conducted in this chapter on the application of drought indices and Satellite Earth Observations. At the end of the Chapter Two, a synthesis of literature is presented. This synthesis forms a critical component of the dissertation as it highlights the current gaps in knowledge and areas that require further attention. It also will serve to sets the scene for the investigations that are to be undertaken and justify why certain techniques will be used in the methodology.

Chapter Three of the dissertation describes the selected study sites of two climatically different regions and details the methodology undertaken for the validation of the Satellite Earth Observation data against ground-based observations. The methodology undertaken to quantify the droughts characteristics using selected simple drought indices is also discussed within this Chapter. The results of the spatio-temporal drought characteristics and propagation analysis at two climatically different regions are then presented in Chapter Four. Thereafter, a detailed discussions on the results acquired was conducted and highlighted in Chapter Five. The concluding remarks, limitations and recommendations of the findings from this research study are discussed in the final chapter of this dissertation

2. LITERATURE REVIEW

This chapter provides a review of literature on drought and its associated propagation process. Firstly, this chapter highlights the factors contributing to the development and impacts of droughts. Information is then provided on the properties and characteristics associated with the various types of droughts. Following this, the drought propagation process is highlighted. The next part of this chapter looks at the different methods available to monitor droughts, including the use of satellite-based products and drought. Finally, a review of the Standardized Precipitation Index (SPI) Standardized Precipitation Evapotranspiration Index (SPEI) and Vegetation Health Index (VHI) is undertaken.

2.1 Factors Influencing Droughts

Modifications to the hydrological cycle and its processes, as a result of changing climate characteristics, catchment characteristics and anthropogenic interventions may ultimately affect the development and impacts of droughts (Van Loon *et al.,* 2016). This may further lead to changes in hydrological responses and feedbacks and cause a rise in the risks and vulnerabilities of society, the environment, economy and agricultural sectors (Mishra and Singh, 2010; Ahmadalipour *et al.*, 2017; Nkhonjera, 2017; Mukherjee *et al.,* 2018).

One of the primary factors that play a crucial role in influencing the hydrological cycle and the characteristics of drought is the alterations in climate conditions (e.g. changes in rainfall patterns). Climate change is entering an unprecedented period, which may result in changes to weather patterns and the occurrence of more frequent extreme events such as droughts (Vetter, 2009; Mishra and Singh, 2010). Since droughts are typically regional with regards to their spatial extent, it is also important to note that each region has different and specific climate characteristics (WMO, 2016). Areas that experience high levels of climate variability are often susceptible to conditions of extreme dryness and wetness (Umiati *et al.,* 2019). According to Mishra and Singh (2010), some of the climatic factors that play a significant role in the occurrence and development of drought are prolonged periods of decreased rainfall or increased temperature, low relative humidity levels and high wind speeds. Therefore, it can be deduced that by modifying the hydrological cycle (e.g., through climate change), drought events are likely to become more frequent, especially under the conditions of a continuously changing environment (Bai *et al.,* 2020; Huang *et al.,* 2017). In South Africa, it has been observed that there were significant rises in inter-annual fluctuations of hydro-climatic processes and associated droughts events (Cretat *et al.,* 2012). This can be attributed to weather systems and phenomena such as anticyclones, El Nino Southern Oscillation (ENSO), Tropical Temperate Troughs (TTT) and Sea Surface Temperatures (SST) which are commonly associated with influencing droughts in this region (Dube and Jury, 2000; Cretat *et al.,* 2012; Nicholson *et al.,* 2018; Mukherjee *et al.,* 2018). These phenomena may be further exacerbated by the influence of climate change.

According to Mukherjee *et al.,* (2018) there are multiple interrelated characteristics that significantly influence the impacts of drought events, especially in different regions. Therefore, a secondary factor that has the potential to influence drought characteristics and impacts are catchment characteristics (e.g., topography, geology, altitude, vegetation cover, soil properties and land-use activities). Catchment characteristics are typically heterogeneous in nature and variable across different regions (West *et al.,* 2019). South Africa is a country that has a diverse range of climatic regions and ecosystems. These catchment characteristics may form guiding factors which influence the movement of water in the hydrological system (e.g., evapotranspiration, soil moisture recharge rate, surface and groundwater discharge), affect the response of drought propagation characteristics (i.e. duration, frequency, severity) and influencing catchment response times (i.e. onset time, lagging response, attenuation and pooling) of the drought (Van Loon, 2013).

Besides climate variability, the mismanagement of human activities also have the potential to control the onset, propagation and impacts of droughts (Mukherjee *et al.,* 2018). Van Loon *et al.,* (2016) stated that in human dominated environments the occurrence of drought may not be solely perceived as a natural hazard. The Anthropocene is considered to be a human-modified era, which typically results in the direct or indirect impacts on the hydrological system and the occurrence of droughts (Van Loon *et al.,* 2019). Whereby, indirect impacts may be recognized as the role that humans play regarding their contribution towards accelerated climate change, e.g. rapid urbanization, contributing to the increased emissions greenhouse gasses (Bai *et al*, 2020). Whilst, the direct effect humans may have on droughts, can be seen with the impacts from activities and intervention methods put in place for the provision and use of water resources for example, the construction of dams, land-use activities or the abstraction of surface and groundwater supply which may cause changes to the hydrological patterns of the surrounding landscapes (Van Loon, 2013; Van Loon *et al.*, 2016; Wang *et al.*, 2016).

It is important to note that the continued mismanagement of human activities on land (e.g. poor agricultural practices, deforestation etc.,) and the impacts of prolonged drought events may further lead to conditions of degradation occurring and thus the occurrence of desertification. Furthermore, as a result of the increasing demands for water resources and the pressures presented by global change issues such as population growth, it is becoming highly important to study the different type of droughts in terms of ensuring that there is adequate management and mitigation methods being put into place, especially for the water and agricultural sectors (Motlagh *et al.*, 2017).

2.2 Types of Drought

Droughts are classified into four categories, this may be identified as meteorological, agricultural, hydrological and socio-economic droughts. It is noted that even though droughts are classified into separate categories, in most cases these types different drought types overlap and their impacts maybe felt concurrently. This section briefly describes and highlights the features and mechanisms associated with each of the different drought types.

2.2.1 Meteorological Drought

A meteorological drought can be defined based on the duration of dry period and degree of dryness that occurs due to a lack of precipitation, of which is greater than that of the normal precipitation experienced over a region (Mishra and Singh, 2010; Bayissa *et al.*, 2017; Shin *et al*, 2018). It is a type of drought that generally occurs over relatively short time-scales and will likely have few direct impacts, however, despite this it is often an early indicator to more impactful and significant dry events (West *et al.*, 2019). Precipitation deficiency may therefore, be considered as the originator of all types of droughts and potentially be the starting point for the development of agricultural and hydrological drought, especially in areas that are more dependent on precipitation than that of catchment/river flow (Van Loon, 2013; Shin *et al*, 2018).

Meteorological droughts may further play a role in providing an early indication of drought events before it affects the components of agriculture and hydrological water systems (Bayissa *et al.*, 2017). It should also be noted that other climatic conditions such as higher temperatures, increased wind speed, or lower humidity, in conjunction with precipitation may play a role in influencing the occurrence and impacts associated with drought events. However, Itsukushima, (2019), suggested that a lack of precipitation may not be the only contributing factor towards the development of meteorological droughts, for example, in a mountainous region the catchment characteristic such as topography may play a role in influencing the distribution and amount of rainfall received in an area, and thus influence the meteorological drought persisting in this region.

2.2.2 Agricultural Drought

Agricultural drought occurs when the moisture supply of a region experiences a consistent reduction below the climatically appropriate moisture level for the production of crops (Sherval *et al.,* 2014). This type of drought typically occurs over a medium- to long-term scale, causing impacts such as reductions in crop yields, thus eventually resulting in imbalances between the demand and supply of food resources (West *et al.,* 2019). In rainfall driven regions, there is greater potential for agricultural droughts to be driven by deficits in precipitation (West *et al.,* 2019), as the sustained presence of meteorological drought over a region, impacts the local hydrology. According to Ahmadalipour *et al* (2017), there is a significant relationship found between rainfall, vegetation health and yield abundance. It is recognized that the transition of drought from meteorological to agricultural is greatly dependent on seasonal conditions experienced in an area (Kwon *et al.,* 2019). These can thus, be identified as important factors that should be taken into account when conducting agricultural drought assessments.

. It is also recognized that the impacts and effects drought pose on the agricultural sector may also be seen through the hindering and impeding of crop growth and reductions in crop yield (Yao *et al.,* 2020). According to Keyantasha and Dracup (2002), cultivated agriculture typically require continuous supplies of water in order to optimize their growth and yields of production, therefore the occurrence of agricultural drought may lead to further impacts and vulnerabilities faced on the agro-economic sector of a region. However this being said it should also be noted that natural vegetation may also be equally affected by the impacts of agricultural drought events. Further impacts faced in conjunction with the occurrence of agricultural drought, is imbalances in food demand and supply, this is especially the case of areas that rely on rain-dependent agriculture (Gidey *et al.,* 2018).

2.2.3 Hydrological Drought

A hydrological drought refers to a period of insufficient surface and subsurface water resources (Mishra and Singh, 2010). Groundwater may therefore, be identified as a sub-component of hydrological droughts (Van Loon, 2013). Typically hydrological droughts are related principally to the response of the catchment to meteorological droughts, of which may further be depends on factors such as the catchment water storage properties, influencing rainfall patterns, conditions associated with the water partitioning process in catchments or be dependent on the soil and rock water storage properties of a region.

Hydrological droughts may be identified as a natural phenomenon, however, it is also an event that can be significantly affected by the direct and indirect interventions of anthropocentric activities such as, land use change, over abstraction, irrigation and engineering projects (Sherval *et al.,* 2014; Mukherjee *et al.,* 2018). For example, poor land management practices, increased abstraction of water resources (which far exceeds rates of recharge) or overexploitation of resources may result in changes to the characteristics of soil and cause reductions in the through flow and percolation of water to recharge the groundwater and streamflow (Han *et al.,* 2019; West *et al.,* 2019).

Hydrological droughts can be considered to be one of the major drought forms that impact the economy and society, however it may be the slowest to develop (Keyantasha and Dracup, 2002). Furthermore, the occurrence of hydrological drought tends to have a later onset period than meteorological drought, with the corresponding propagation time being dependent on local landscape and climate conditions (Huang *et al.,* 2017). Therefore, the monitoring of this type of drought plays a vital role in managing of the availability or water usage of water resource management systems.

2.2.4 Socio-Economic Drought

A socio-economic drought develops when the demands for economic goods exceeds the available supply due to shortfalls in water supply, as a result of weather-related events (Shin *et al*, 2018; Mishra and Singh, 2010). This is a type of drought also tends to focus on the impacts associated with the availability of commodities (e.g. food and water resources) and their relationship with meteorological, hydrological, and agricultural drought (Shin *et al*, 2018). Socio-economic drought is not a propagation type that is based on hydrological variables alone, due to this type of drought occurring when water availability is lower than the demand (Gevaert *et al.*, 2018).

When looking at a socio-economic context of drought Dube and Jury (2000), states that the increasing rate of the growing population of southern Africa play a significant role in contributing to the drought problem experienced in this area, as this rise has led to increasing pressures and stress placed on the regions already limited water resources (i.e. water for domestic and agricultural use). Furthermore, Botai *et al* (2016), suggests that there are links that which connect droughts to other global epidemics such as famine, diseases, and increased vulnerabilities. This type of drought tends to pay particular interest in the social aspects and its related impacts. For example, typically the wealthy communities may be capable of coping with the impacts and occurrence associated with drought events better the poorer communities. Therefore by having a better understanding this type of drought we are able to make more informed decisions with regards to managing our resources and designing mitigation strategies to lessen the burden of the impacts faced by drought events.

2.3 Drought Process and its Impacts

2.3.1 Drought Propagation Process

The occurrence of drought events is a complex process with varying characteristics experienced among different regions (Sherval *et al.*, 2014), as it is an event that involves both atmospheric and hydrological processes (Mishra and Singh, 2010). According to Shin *et al.* (2018), drought propagation can be described as the evolution of the type of drought over time, with each type of drought being characterized by unique spatial and temporal characteristics (Wang *et al.*, 2016). Since drought occurrences may have significant implications on other hydrological components it is possible that droughts can transition from one form to another especially under conditions of prolonged occurrences (Tirivarombo *et al.*, 2018). For example a drought may start off occurring through a deficit in precipitation over a prolonged period of time, this a can then potentially result in the water deficit propagating to the surface and sub-surface parts of the hydrological cycle bringing rise for the development of the other types of drought classes. Whereby the persisting low conditions of precipitation might cause soil moisture and evapotranspiration deficits, leading to the development of agricultural droughts occurring. Subsequently this deficit, if prolonged may subsequently result in surface water resources (streamflow) and groundwater recharge being reduces and thus the occurrence of a hydrological drought may occur.

According to Wang *et al.* (2016), in order to reduce the vulnerabilities experienced by drought there is an important need to distinguish between the different drought types and understand how droughts propagate from one type to another. Furthermore, understanding the process of drought propagation necessitates improving the way in which communities and vulnerable areas are able to prepare for future drought through the adoption of strategies to mitigate and plan for the likelihood of future drought events, especially at regional and national scales (Yao *et al.*, 2020).

The degree to which drought propagation occurs, may vary, depending of factors such as the climatic conditions (i.e. temperature and precipitation anomalies), catchment characteristics, as well as the vulnerability, stability and coping capabilities of the system to change (Gevaert *et al.*, 2018; Van Loon and Laaha, 2015). According to Gevaert *et al* (2018), there is a significant relationship acknowledged between the different climate regions and the occurrence of the drought propagation process. For example, drier continental climate experience a relatively slower propagation development of droughts and tropical climate areas may experience a relatively faster onset of drought propagation.

It is acknowledged that there is a highly non-linear pattern observed in the physical processes and mechanisms involved in the propagation of droughts (Shi *et al.*, 2022). This may be accounted for by the feedbacks experienced and the unequal development of impacts through multiple levels of society and the environment (Mukherjee *et al.*, 2018). Figure 2.1, depicts a general understanding of these mechanisms and feedbacks associated with the drought propagation process.

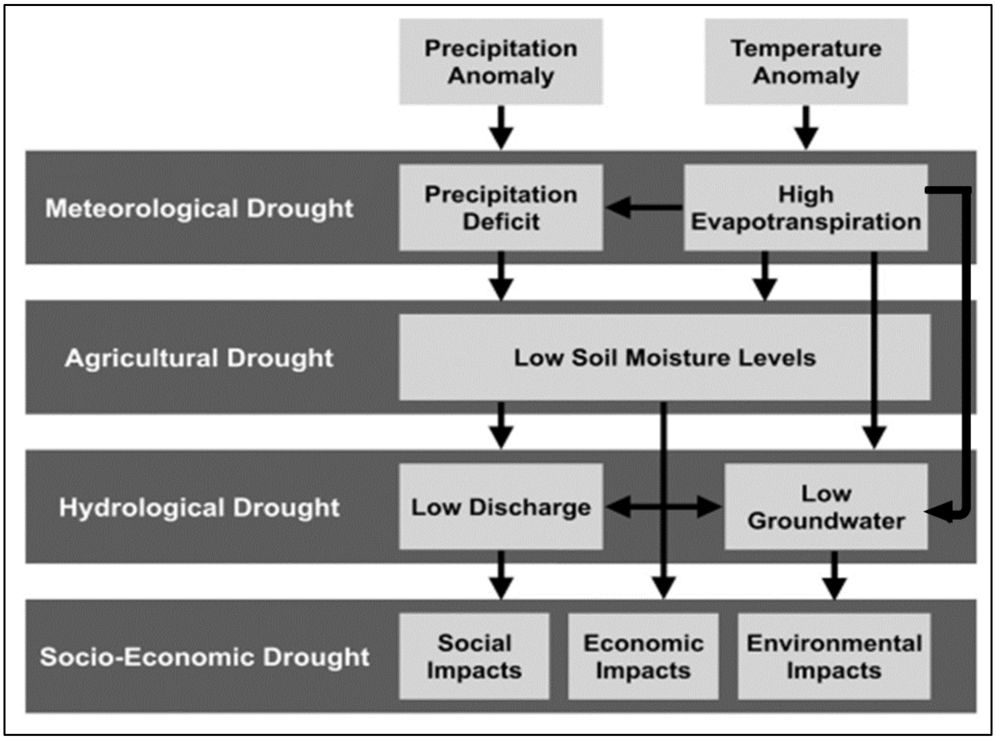

Figure 2.1: A conceptual representation of drought propagation, its associated impacts and interactions (Van Loon 2015; West *et al.*, 2019).

Rainfall may be considered to be the major driver of variability especially in the water balance and plays a crucial role in drought propagation, as the amount and distribution of rainfall typically influences other features such as soil moisture levels and vegetation growth (Muthumanickam *et al.*, 2011). Large scale atmospheric circulation systems such as ENSO are also recognized to have the ability to impact on the propagation times of drought events, as these are phenomena that influence evaporation and rainfall patterns (Huang *et al.*, 2017; Han *et al.*, 2019). Modifications to the hydrological cycle may further contribute to the response times of the onsets, lagging, attenuation and the occurrence drought event between the different propagation stages (Gevaert *et al.*, 2018). With regards to temperature anomalies, this is recognized as a variable that plays significant role in hydrological cycle, as is may be seen as a controlling factor affecting processes such as the formation of clouds, evaporation and transpiration.

However, it was also acknowledged that not all droughts are induced by climatic events, but possibly through human induced activities (Dube and Jury 2000). Van Loon *et al* (2016), acknowledged that people tend to not only have a passive role at the end of the drought propagation process, but also an active role in influencing the process of propagation. For example, anthropogenic influence and global change issues such as population density are seen to play a significant role in impacting and propagating drought events (Mukherjee *et al.*, 2018). It is apparent that without significant modifications to the water cycle by human interventions and activities, agricultural and hydrological droughts may be caused by meteorological anomalies and modified by the properties of the catchment such as, soils, geology, and land cover (Van Loon *et al.,* 2016).

According to Li *et al.*, (2022), it was acknowledged that there is a threshold for propagation to occur between two types of drought. This threshold period refers to the cumulative time required for the triggering of the of a drought event (i.e. the propagation time). For example a small-scale or light meteorological drought event may not trigger the occurrence of an agricultural or hydrological drought event as there may still be soil moisture or streamflow discharge present from the events earlier stage. However, a transition of drought may develop from a meteorological drought to agricultural or hydrological drought, if the drought event maintains its intensity (e.g. severe drought conditions) and persist for a long enough duration to trigger the onset of another drought type (Van Loon and Laaha, 2015; Hao et al, 2018; Li *et al.*, 2022; Shi *et al.,* 2022)

The close interconnected processes and mechanisms between the atmosphere, surface and subsurface within the hydrological cycle indicates that there is thus a relationship between meteorological, agricultural, and hydrological droughts (Shin *et al.,* 2018). The continuation of the drought propagation process from meteorological to agricultural to hydrological drought is dependent on numerous processes including the occurrence, development, persistence and lag times of the drought event (Yao *et al.,* 2020). However, it is important to note that the different drought forms may occur as a mutually exclusive events, for example an agricultural drought may occur whilst a meteorological drought is still persistent. However, some drought events may also occur as an isolated event, for example, a hydrological drought may occur earlier than the onset of a meteorological drought. Whereby, rather than a deficit in precipitation, over-abstraction of water resources or poor land management practices by humans cause changes to soil profiles and water holding capacity thus, influencing a deficit in water storage levels (Van Loon and Laaha, 2015; Van Loon *et al.,* 2016).

2.3.2 Drought Impacts a South African Perspective

Drought is a complex phenomenon, which often has a rippling effect of impacts faced across all sectors of the environment, economy and society (Meza *et al.,* 2021; Meque and Abiodun, 2015). South Africa is a region, which has a high water reliance for its agro-economic sector, and may therefore be highly susceptible to the impacts associated with droughts (Meza *et al.*, 2021). It was noted that the severe droughts in South Africa, particularly in the early 1980s, 1990s and the period of 2014-2016, have resulted in significant impacts on many different regions across south Africa, and places extra stress on the country's agro-economic and water supply systems (Meza et al., 2021) for example there has been significant declines in the harvesing of agricultural products, especially over recent drought years (Baudoin et al., 2017).

Typically, rain-dependent crops at both a subsistence and commercial scale are likely to be affected by the projected increase of drought events. Rain-dependent Subsistence farming is likely to more susceptible to the impacts of drought, as they are highly dependent of climate resources for their growth (Meque and Abiodun, 2015). However this being said it should also be noted that for areas like South Africa commercial farming underpins the country's food security for majority of the population and can be significantly affected by the projected rise in drought conditions (Meza *et al.*, 2021).

In South Africa the agricultural sector plays a large contribution to the GDP, and plays a significant role in ensuring food security, it facilitates job creation for low skilled people economic growth and development and provides raw materials for secondary sector activities (such as manufacturing and retail) which may in turn reduce a countries dependency on international exporting (Sifiso *et al.*, 2017; Meza *et al.*, 2021). Over the past years several areas in South Africa have had a significant decline in agricultural production, this decline in yields were likely to further lead to ecological as well as economic vulnerabilities faced, for example the country may need to invest more money in importing agricultural products, which may lead to increased food prices and may also potentially contribute to food insecurity in affected regions (Mdungela *et al.*, 2017). The uncertain and erratic nature of droughts is known to have an uneven distribution of impacts, whereby, it is noted that the most vulnerable people to the shocks of drought (from a farming perspective), are those who engage in subsistence and small scale farming (Mdungela *et al.*, 2017).

During the 2015/2016 drought period several provinces within south Africa were declared as disaster areas, due to the suffering of not only a lack of water resources but also severe declines on the agricultural sector (production and yields of agricultural products), and a resultant effect on the GDP of the country (Sifiso *et al.*, 2017). It was noted by Bureau for Food and Agricultural Policy that due to the frequent reoccurrences of drought in recent years, there will likely be medium to long-term adverse effects faced on the perennial crops in several regions of the country (such as in the Western Cape Province) (Pienaar and Boonzaaier, 2018). Some of these effects may be especially impactful to agricultural businesses. Whereby in many cases across the country farmers have abandoned engaging in vegetable production or have decided to preserve their long-term crops by not harvesting during certain seasons.

It can be noted from an agricultural perspective that even though the impacts of rainfall shortages may result in reductions to crop yield production, the scope of its impacts may be further. The way in which a region is able to cope with these impacts may be further dependent of a host of other factors such as the degree of exposure and vulnerability that a socio-ecological system of an area would have, the ability of a system to cope with change, the level of development in an area, the socio-economic status of an area, etc., in the same way it is acknowledged that some regions may me prone to higher risks associated with total crop production loss due to droughts (Kamali *et al.*, 2018; Meza *et al.*, 2021).

In South Africa there is a constant evolution in legislature with regards to how the country manages disaster risks, this is increasingly important, especially with regards to the increasing frequency of disasters like droughts occurring, with drought governance providing the framework to provide relief and emergency support. However the root of the problem may lie in the implementation of proactive measures. The provision of information from past experiences and impacts provide learning opportunities on the way in which mitigation and adaption methods would be most effective with regards to reducing the impacts of future drought events (Baudoin *et al.*, 2021). Therefore, a comprehensive understanding of the evolution from meteorological drought to agricultural drought may pave the way forward in improving the way in which we manage and mitigate our agricultural systems to reduce the impacts of drought, It is therefore acknowledged that the government should considered prioritizing the implementation of appropriate drought management measures to respond to areas of particular vulnerabilities, and areas less resilient to the impacts of droughts (Mdungela *et al.*, 2017). One of the ways forward is to understand the impacts of droughts in an integrated manner and not the use of just one type of drought. Droughts types typically tend to overlap each other, thus understanding a single drought type alone may not provide adequate data to effectively understand the characteristics of drought (frequency, duration, severity) of a system, thus leading to misjudgments on the extent of how to cope with the drought.

2.4 Drought Monitoring Methods

In order to conduct a drought assessment, measurements or estimates of key hydrological variables (e.g. precipitation, soil moisture, streamflow) need to be acquired to characterize and quantify the different drought types and their intensity (Bai *et al*, 2020; Misha and Singh, 2010; Ahmadalipour *et al.,* 2017). Historically, the use of ground-based observation networks and in-situ instrumentation have been used to acquire measurements on the various hydro-climatic variables required for drought assessments (Ahmadalipour *et al.,* 2017; West *et al.,* 2019). Ground-based observations provide invaluable information on the various hydrological processes and facilitate a robust means of better understanding the mechanisms behind their processes and their impacts. The use of these instruments are advantageous, with regards to providing relatively accurate estimations and measurements of hydrological processes as they occur on the earth's surface. However, a limitation that may be experienced with the ground-based observations are that in numerous regions majority of the information provided by in-situ instrumentation are point-measurements, making it difficult to obtain a representation of accurate spatio-temporal patterns of the variable's distribution over large geographic extents (Lynch, 2003; Ahmadalipour *et al.,* 2017; Vather *et al.,* 2018).

The traditional methods used for drought assessments and monitoring typically relied on the use of in-situ data. However, one of the main challenges experienced, especially in developing countries such as South Africa, is the poor availability of dense networks of ground-based instrumentation (Muthumanickam *et al.,* 2011; Bayissa *et al.,* 2017; Abdulrazzaq *et al.,* 2019). Owing to the sparse and unevenly distributed nature of most of these ground-based networks, it is often difficult to estimate variables in a continuous and adequate manner, especially in areas prone to having few or no in-situ instruments available. If this information is utilized in drought assessments it may further result in the insufficient capturing of spatial variability of drought events over larger areas (Bai *et al*, 2020, Muthumanickam *et al.,* 2011).

Satellite Earth Observations (SEO) are widely recognized as a way to enable the collection of information on the various processes and variables on the Earth's surface, without being in direct contact with the object of interest or area (Jong *et al.,* 2004). It assists in facilitating a greater understanding of the different earth systems and processes (Jong *et al.*, 2004; Ahmadalipour *et al.,* 2017). SEO products may also further complement the information gathered by traditional methods that rely on ground-based meteorological and climatological observations through the use of data assimilating products (Gidey *et al.,* 2018). Therefore, the use of SEO is viewed as a suitable alternative source able to overcome many of limitations associated with in-situ observations (Bayissa *et al.,* 2017; Ahmadlipour *et al.,* 2017).

For drought assessments continuous long-term data are required in order to have statistically sound results, SEO enable the effective collection of information in a continuous, cost-effective manner over various spatial and temporal resolutions (Bai *et al.,* 2020; Muthumanickam *et al.,* 2011). Due to the complex heterogeneous nature of droughts as well as their various influencing factors, the use of SEO has been proved to be a widely used application utilized in the retrieval of climatological, atmospheric and surface variables and opens avenues towards monitoring drought, for example the development and application of satellite-derived drought indices (AghaKouchak *et al.,* 2015; Bento *et al.,* 2018; West *et al.,* 2019). The development of satellite-derived drought indices have become promising tools available for effectively monitor drought characteristics and assist in the development of early warning systems (Gidey *et al.,* 2018) (Ahmadalipour *et al.,* 2017). It is a technique that can be utilized to provide valuable information and represent almost all aspects of the different types of drought, thus enhancing our understanding of this phenomena (West *et al.,* 2019).

However, despite the advantages that are associated with SEO products, one of the most commonly presented shortfall found in several satellite-based products is that the presence of clouds, which influences the spatio-temporal results making it difficult to achieve global cloud-free data (Fensholt *et al.,* 2011). This is especially problematic in areas prone to the presence of tropical clouds. Cloud cover may influence the forward scattering observations, thus introducing bias in measurements and poor capturing of events (e.g. droughts and floods) in a timely manner (Fensholt *et al.*, 2011). It is further acknowledged that the influence of atmospheric drag, orbital debris and the Earths gravitational field may result in slight movement or changes to the satellites inclination of orbit and may influence the accuracy of the data acquired (Riebeek, 2009).

There are numerous satellite products available to provide information on hydrological and climatological drought-related variables, each ranging with different spatial and temporal scales and resolution, some examples of these SEO products and their specifications are presented in Table 2.1. However it, should be noted that often the process of collecting and analyzing satellite information may contain large amounts of pre- and post-processing data and may require technical expertise. Therefore, the use of cloud-based platforms such as Google Earth Engine which are capable of providing planetary-scale geospatial information from a variety of available satellite products have become quite popular in recent times (Gorelick *et al.,* 2017). GEE was established in 2010 and hosts a wide range of satellite products and information on numerous earth processes with over 40 years' worth of data records. GEE facilitates the acquisition, analysis and assessment of SEO data, from a freely accessible portal. The information provided by this platform may be especially useful to monitoring and assessing earth processes in developing countries and areas which are recognized to be data-poor (Kumar and Mutanga, 2018). Therefore, the use of SEO and Google Earth Engine provides an effective means of collecting, assessing and monitoring of drought-related variables (AghaKouchak *et al.,* 2015).

Table 2.1: A select few examples of the various Satellite Earth Observation Products with their associated features and specifications available in GEE that are commonly used for drought monitoring applications

SATELITE PRODUCT	VARIABLE	SPATIAL RESOLUTION	TEMPORAL RESOLUTION	RECORD LENGTH
CHIRPS	Precipitation	0.05°	Daily	1981 to Present
TRMM	Precipitation	0.25°	3-Hourly, Monthly	1998 to 2019
PERSIANN - CDR	Precipitation	0.25°	Hourly, Daily	1983 to Present
FEWS NET Land Data Assimilation	ET, base flow, Rainfall, soil moisture, heat fluxes,	0.1°	Monthly	1982 to present
MODIS Terra Net Evapotranspiration	ET, Latent Heat flux	500 m	8 – Days	2000 - Present
MODIS Terra Vegetation Indices	Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI)	500 m , 250 m	16 –Day	2000 to Present
MODIS Terra Land Surface Temperature and Emissivity	Land Surface Temperature (LST)	1 km	Daily, 8-Day	2000 to Present
ERA5	Air temperature, wind speed, surface pressure, precipitation	28 km	Daily	1979 to 2020

GLADS	ET, evaporation, base flow, groundwater, soil moisture, soil temperature, air temperature, precipitation	0.25°	3-Hourly	2000 to Present
AMSR-E	Precipitation, Soil Moisture, Ocean Water Vapor, Near-Surface Wind Speed	25 km	Daily	2002 to 2011
SMOS	Soil Moisture, Temperature, Vegetation Surfaces	35 km - 50 km	2 - 3 Days	2009 to Present
SMAP	Soil Moisture, Plant water stress	3 km , 9 km, 36 km	2 - 3 Days	2015 to Present
Landsat	Temperature, surface Reflectance, Atmosphere Reflectance, NDVI	30 m	Once every 2 weeks, 8 –Days	1972 to Present
NOAA Climate Data Records (CDR) of AVHRR NDVI	Normalized Difference Vegetation Index	0.05°	Daily	1981 to Present
GRACE	Surface Water Storage, Groundwater Storage, Soil Moisture, Runoff	~330 km	Monthly	20022017

2.5. Drought Monitoring using Drought indices

Drought indices play an essential role in formulating efficient drought monitoring and prediction systems (Mendicino *et al.,* 2008). They are able to account quantitatively for the aspects of drought characteristics (i.e. severity, duration, frequency and spatial extent) in a consistent manner (Keyantasha and Dracup, 2002; Bloomfield and Marchant, 2013). Several indices have been derived over the recent decades and have become a useful tool in providing a framework to evaluate the different types of drought types over various spatio-temporal scales (Mishra and Singh, 2010).

It is important to distinguish between drought indicators and drought indices, whereby, drought indicators are identified in a broader sense, as parameters such as precipitation, evaporation, temperature streamflow, etc. which are aggregated (WMO, 2016). Whilst, drought indices are considered to be quantitative measures used to characterize drought levels, this can be accomplished through the assimilation of data into a single numerical value from the use of one or more hydro-climatic variables or indicators (Mukherjee *et al.*, 2018). For drought monitoring, the indicator/s are typically converted into or utilized within drought indices to determine drought characteristics (Tirivarombo *et al.,* 2018).

The selection of indices is often made based on factors such as local conditions experienced, the nature of the indicator, and the availability of data in the selected area and the validity of the data (Botai *et al.,* 2016). It should be noted that typically the various types of drought indices are likely to experience different degrees of sensitivity when applied in different climatic zones (Mishra and Singh, 2010; Mukherjee *et al.,* 2018). Drought indices have become recognized as a primary tool for communicating drought levels and simplifying complex relationships, through quantifying drought characteristics (WMO, 2016). Owing to these properties of indices it thus, allows and enables informed decisions to be made on water management, agricultural management and early warning detection of drought events (Zargar *et al.,* 2011)

Most indices derived typically require information on meteorological variables either singularly or through a combination of several indicators (Mukherjee, *et al.,* 2018). The use of satellite-derived products and drought indices have facilitated the possibility of using long-term data series in the monitoring of drought-derived indicators and drought events over larger areas (Mendicino *et al.,* 2008). Satellite-derived drought indices have been recognized to be a method which has revolutionized the way in which drought can be monitored and assessed as they are diverse in nature and new indices are frequently being proposed (Zargar *et al.,* 2011). Due to improvements and technological advancements, there are constantly new techniques, sensors and algorithms being developed or improved to characterize drought (Zargar *et al.,* 2011).

There are numerous drought indicators and indices developed around the world that assist in monitoring, quantifying and predicting drought characteristics. These indices can range from simple to complex, from common standardized-based to remote sensing based or from single-variable use to multi-variable use. Some examples of the most extensively used meteorological agricultural and hydrological drought indices as well as their advantages and limitations are shown in Table 2.2.

Table 2.2: Examples on some of the different drought indices available with their associated advantages and disadvantages

DROUGHT INDEX	DROUGHT TYPE	ADVANTAGES	DISADVANTAGES/ LIMITATIONS	REFERENCE
China Z Index	Meteorological	It enables for the monitoring of both wet and dry events over multiple time steps. Calculations involves are relatively simple. This type of index allows for missing data.	Shorter timescales tend to be less well represented as compared to methods such as SPI.	WMO, 2016; Bayissa et al, 2017
Precipitation deciles	Meteorological	This index is flexible with regard to timescales. The methodology is relatively simple for numerous situations. It is applicable in both wet and dry regions.	Due to it only requiring precipitation as an input, the impacts of other variables such as temperature are not considered in the drought assessment.	Zargar *et al.*, 2011
Palmer Drought Severity index (PDSI)	Meteorological	Input variables are monthly temperature and precipitation. It is a satellite-based drought index. It accounts for temperatures and soil characteristics of different climatic zones. It is applicable worldwide.	It is sensitive to seasonal changes. It is based on the simplification of the soil moisture component. It is associated with fixed timescales, poor spatial comparability and weak portability.	Keyantash and Dracup, 2002; Botai *et al.*, 2016; Bai *et al.*, 2020
Standardized Precipitation Index (SPI)	Meteorological	Low-cost calculations, widely available on multiple timescales. It is able to facilitate comparisons of extreme conditions in different locations. It is a time-scale versatile index that allows for the monitoring of short- and long-term water supply.	It requires long-term continuous records of data for periods no less than 30 years. Requires knowledge of the local climatology.	Ahmadalipour *et al.*, 2017; Gevaert *et al.*, 2018; Botai *et al.*, 2016; Zargar *et al.*, 2011
Standardized Precipitation Evapotranspira tion Index (SPEI)	Meteorological, Agricultural	Requires monthly/weekly precipitation and temperature records. It is able to detect droughts at various timescales. It was developed as a modification to the SPI index to address water supply-demand issues.	The input data needs to be continuous and complete, with no missing months. Due to its monthly application rapid developing droughts may not be quickly identified.	Botai *et al.*, 2016; WMO, 2016

Crop Moisture Index (CMI)	Agricultural	It involves the computation of a simple water budget. It consists of relatively simple calculations. It provides information on soil moisture estimates at a short-term weekly basis.	This index is seen to be unable to provide long-term information in drought monitoring. This index may be sensitive to an increase in potential evapotranspiration.	WMO, 2016; Mishra and Singh, 2010
Soil Moisture Deficit Index (SMDI)	Agricultural	It allows for the detection of soil moisture deficit irrespective of the type of climatic conditions of an area. It takes into account the whole soil profile at different depths. It is adaptable to the different crop types.	This is a complex index regarding calculations and input variable. Concerns of this index regarding the auto-correlation with the soil depths used.	WMO, 2016; Mishra and Singh, 2010
Enhanced Vegetation Index (EVI)	Agricultural	This is a satellite based index. It is used to detect and indicate vegetation healthy, green biomass, patterns of plant productivity and density. It provides good spatial coverage at high resolution over all types of terrains.	The period of available records is relatively short. It is not able to distinguish if the stress experienced by plant canopies are caused by impacts other than drought.	Ahmadalipour *et al.*, 2017; Muthumanickam *et al.*, 2011; Zargar *et al.*, 2011
Temperature Condition Index (TCI)	Agricultural	This index is a satellite based index. It is determined with the use of Land surface temperature. It provides good spatial and temporal resolution and coverage.	It is a relatively new index and has a relatively short record length. This product is also susceptible to potential cloud contamination.	WMO, 2016
Vegetation Condition Index (VCI)	Agricultural	This is a satellite-based drought index. It was developed as an indicator for vegetation cover status. It indicates the deterioration or acceleration of a vegetation under changing weather conditions.	Due to this index being based mainly on detecting vegetation it is primarily useful during the growing seasons of vegetation. It has a relatively short period of record length. There is potential for errors due to clouds.	Mishra and Singh, 2010; West *et al.*, 2019

Vegetation Health Index (VHI)	Agricultural	This is a satellite-based index. It covers the whole globe at a high resolution. It is calculated by coupling the data from Vegetation Condition Index and Temperature Condition Index. It is able to detect drought in any season.	A limitation is the record length for this satellite data is relatively short. The limitations of VCI and TCI are also applicable with this index.	Ahmadalipour *et al.*, 2017; WMO, 2016
Palmer Hydrological Drought Index (PHDI)	Hydrological, Groundwater	Modified version of the PDSI to account for long-term droughts affecting streamflow, stored water and groundwater. Able to calculate the ending of a drought based on the precipitation needed with the use of soil moisture ratios. It's based on the water balance approach.	Requires a series of complete monthly records of input parameters. The impact of human activities and influences are not considered in the calculations. Calculations involved are relatively complex.	WMO, 2016; Botai *et al.*, 2016
Surface Water Supply Index (SWSI)	Hydrological	It is used to detect anomalies that may be found in surface water supply resources. This can allow for all seasons to be represented. Input data used is streamflow and precipitation. This index is suitable for use in mountainous regions.	This index may be limited due to the variability of the spatial and temporal scale represented by the different hydro-climatic variables. The computation process may be seen as relatively difficult.	Mishra and Singh, 2010; Botai *et al.*, 2016; Keyantash and Dracup, 2002
Standardized Streamflow Index (SSFI)	Hydrological	Input parameter is monthly or daily streamflow data. Relatively easy to calculate. Can be used with the SPI program. Allows for missing data due to single variable input.	May be limited due to the use of only streamflow data being required. It is a relatively new index.	WMO, 2016
Standardized Runoff Index (SRI)	Hydrological	This index determines the loss in streamflow seasonally as a result of climate. It incorporates various hydrological processes that influence the reduction in streamflow. It has a calculation procedure similar to that of SPI.	The length of data record is seen to influence the SRI values. It requires complete recodes of data. It is also seen to have limitations when it comes to the fitting of probability distributions in its calculation.	Van Loon, 2013; Mishra and Singh, 2010

2.5.1 Case Studies: Drought propagation monitoring using various drought indices

A study by Zhang *et al* (2017), assessed the various stages of drought propagation, in India with use of indices such as the SPI, SRI, SSMI, and VCI. The methodology undertaken used both remotely sensed and in-situ data. It was noted from linear regressions between the drought indices that when comparing the indices for a propagation analysis the lag time of transformation was identified (using a cross-correlation analysis of linear regressions) to be approximately one month between the meteorological, agricultural and hydrological drought. However some cases were reported where all three types of droughts typically simultaneously. This further indicates that in this region there is a rapid transition of drought types, especially when precipitation deficits are continuous. Findings from this study also depicted that soil moisture and hydrological conditions exhibited lower variability as compared to the relative precipitation experienced in the area

Huang *et al.*, (2015), assessed the response of meteorological to agricultural droughts in the Wei River Basin (WRB), China. The drought indices utilized were the PDSI and SPI index. The results from this study indicated that there was a seasonal scale influencing the lagging period of agricultural droughts in this area. Whereby, the lag period for this study was determined using correlation relationships between the selected indices. There was a faster response time found during summer (approximately 3 months) and a slower response time found in the autumn months in this region. During the summer months the shorter lag time was assumed to be due to the high-frequency of rainfall experienced. It was also acknowledged that a potential reasoning behind the slower response in lag time was due to the buffering effect the soil and/or variations of Arctic Oscillations in this region.

A study by Gou *et al.*, (2017), analyzed meteorological drought in the Lower Mekong Basin with the use of satellite products. The ground-based observational networks in this region are limited, thus CHIRPS satellite products were utilized in this study along with the drought index SPI. Results from this study indicated that CHIRPS was able to provide data that properly captured the drought characteristics at various timescales with the best performance achieved by the 3-month SPI time scale. This study also assessed the impacts of meteorological drought on vegetation with the use of the Vegetation Health Index (VHI). Results from this study suggests that CHIRPS performed well with regards to determining SPI, there was also a good consistency in intensity and frequency with the gauge derived SPI. However, SPI derived from CHIRPS tended to overestimate the severity of both flood and drought periods. However at the 6- and 12-month scale there was an underestimation of drought severity. Through correlation analysis's it was deduced that VHI and SPI3 have a relatively agreeable evolution, whereby, the variations of VHI generally correspond well to the wet and dry period of drought conditions. It further indicated that meteorological droughts have significant impact on vegetation health (Gou *et al.,* 2017).

Li *et al.,* (2022), assessed the propagation from meteorological droughts to agricultural drought at a high resolution and over several spatio-temporal scales. This assessment was conducted in the Loess Plateau, China. Precipitation data was acquired from the satellite GLADS product and the indices utilized in this study was the SPI and SSMI drought index. The propagation time for this assessment was identified using a copular function and conditional probability. Results indicated that the propagation time taken for an agricultural drought to develop is relatively short during the summer and longer in the winter, this indicating that there is a seasonal scale occurring in the propagation of droughts in this area. It was further noted that the study area is in a region prone to temperate continental monsoon climatic conditions. The conditions associated with this phenomena (e.g. rainfall and temperature variability and potential evapotranspiration) was considered to be the main driving factors for the most of the propagation from meteorological to agricultural drought in this area.

Gevaert *et al.,* (2018), looked at assessing the effects of climate conditions on drought propagation timescales. Assessments were done by cross-correlating standardized indices (SSMI, SRI and SSFI) from global hydrological models and SPI. The results from this study indicated that there was longer accumulation periods detected during the winter drought events as compared to the summer drought events. Land surface and global hydrological models were cross-correlated in order to evaluate the drought propagation times. The results from this evaluation, indicated that for the transition of meteorological drought to agricultural drought the land surface models showed a slower propagation time than the global hydrological model. However the land surface models tended to have faster propagation times when there is a transition to a hydrological drought. Results further indicated that from this study, there was a close relationship found between climate type and drought propagation times. Whereby it was identified that in dry and continental climates the propagation times were slower than in tropical climates.

A drought propagation study was conducted by Ding *et al.*, (2021), assessing three drought types in different climatic regions in China. The drought index assessed was SPEI, SRI and PDSI. In order to analyze the relationship between the different drought types, Pearson correlation coefficients were used. The seasons significantly sensitive to the drought propagation process was also assessed in this study. Results indicated that at an annual scale the propagation from meteorological drought to agricultural drought was the most prominent in many of the selected regions. It was recognized from this study that in the arid to semi-arid regions there was a stronger propagation relationship between agricultural to hydrological drought especially during the summer months rather than the winter months. Overall the conclusions further indicated that for hydrological drought propagation in different climatic regions there were several driving factors experienced (e.g. soil moisture content, evapotranspiration and irrigation levels).

2.6 Selected Drought Indices for assessment

From the review of drought indices and propagation study, it is apparent that there are numerous different indices available to quantify the various types of droughts and their associated characteristics. However, for the purpose of this research study the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI) and the Vegetation Health Index were selected for further evaluation to determine and quantify meteorological droughts and agricultural droughts. The selection of these indices were based on factors such as (1) The ease of the index's implementation and application, (2) The type and availability of input data required by the index, (3) The scope of area the index is applicable in, (4) The sensitivity of the index to changing climate conditions and (5) The timescales available by the index's application for the monitoring of drought characteristics. This section of Chapter Two provides insight on the features of the selected indices and their application

2.6.1 Standardized Precipitation Index (SPI)

Standardized Precipitation Index (SPI) proposed by McKee *et al.*, (1993), is recognized as one of the most used index for monitoring, quantifying and characterizing meteorological drought

(WMO, 2012; Ahmadlipour *et al.,* 2017; Cruz-Roa *et al.,* 2017; Gou *et al.,* 2017; Gevaert *et al.,* 2018; Zhong *et al.*, 2019; Umiati *et al.*, 2019; Bouaziz *et al.*, 2021). SPI is an index established to detect and track drought events with the use of monthly rainfall data records over a given area for investigation (Bouaziz *et al.*, 2021). This is a drought index that is a based on the standardization of precipitation anomalies (Zhong *et al.,* 2019). It is further able to determine drought characteristics such as duration and intensity at a variety of time steps (WMO, 2012; Bouaziz *et al.,* 2021). The World Meteorological Organization (WMO) has adopted and recommended that SPI should be referenced as the standard meteorological drought monitoring technique used around the world (WMO, 2016; Abdulrazzaq *et al.,* 2019; Gou *et al.*, 2017).

SPI is a statistical approach based on a probability distribution method to analyze droughts (Botai *et al.,* 2016; Gou *et al.,* 2017; Zhong *et al.,* 2019; Bouaziz *et al.,* 2021). This index is able to provide relatively good statistical consistency and predictability on the effects of drought at short- and long-term scales (Umiati *et al.,* 2019). The calculations involved in quantifying meteorological drought characteristics are seen as a simplistic and effective approach (Keyantash and Dracup, 2002; Zagar et al, 2011). It is a versatile index capable of quantifying drought characteristics at numerous timescales (e.g. from 1 month to 48-month timescales) and allows for the monitoring of water supply availability (Mishra and Singh, 2010; WMO, 2016; Cruz-Roa *et al.,* 2017; Gou *et al.,* 2017; Abdulrazzaq *et al.,* 2019; Tirivarombo *et al.,* 2018). It is considered as a method that is spatially invariant, thus, allowing for droughts to be assessed and monitored in a number of different regions (Gevaert *et al.*, 2018; Tirivarombo *et al.,* 2018).

Due to SPI being a normalized index, it is able to represent wet and dry condition, allowing not only drought events but also wet periods to be monitored (WMO, 2012; Ahmadalipour *et al.,* 2017; Gevaert *et al.,* 2018). The probability-based nature of SPI makes this index well suited to providing information for risk management and decision making (WMO, 2012). SPI has a wide range of applications including drought and flood monitoring, drought forecasting, frequency analysis, spatial-temporal drought analysis and characterization (Gou *et al.,* 2017). These calculated timescales are typically estimated through the accumulation of precipitation records before the standardized procedure in order to represent the short- and long-term drought events experienced over an area (Zhong *et al.,* 2019).

The method used to calculate SPI uses only continuous, long-term historical monthly precipitation records as its input variable to assess droughts (Keyantash and Dracup, 2002; Mishra and Singh, 2010; Abdulrazzaq *et al.*, 2019). Ideally for statistically sound results of SPI there needs to be long-term records of at least 30 years' worth of precipitation data (WMO, 2016; Gou *et al.*, 2017; Tirivarombo *et al.*, 2018). Despite all the advantages proposed for this index, there are also associated disadvantages with SPI e.g., due to its univariate variable as an input parameter this index may not provide an integrated view of the different drought types (Kwon *et al.*, 2019). Furthermore, since SPI only uses a single input in its calculations it may only able to quantify precipitation deficit, and thus, may not be representative of the overall water balance and surface conditions (Gevaert *et al.*, 2018; WMO, 2012).

The Standardized Precipitation Index is calculated by determining the amount of standard deviation whereby, the value assigned by a given precipitation event is either more or less than that of the historical mean (Equation 2.1) (Tirivarombo *et al.*, 2018; Bouaziz *et al.*, 2021). Generally for SPI, the precipitation series utilized has a monthly resolution, whereby, the fitting of the probability distribution is calculated for each month separately (Gevaert *et al.*, 2018). Owing to the standardized procedure undertaken to calculate SPI, it is recognized that this index is able to facilitate comparisons of precipitation with its multi-year average (Zagar et al, 2011).

$$SPI = \frac{Xi - x}{\sigma} \tag{2.1}$$

Whereby X*i* is the annual rainfall at a given time *i*, *x* is the mean annual rainfall and σ is the standard deviation

The classification system developed by McKee *et al.*, (1993), was established to define the resulting intensities and criteria for drought events at any given timescale from SPI. The SPI values are classified into 7 conditions of drought (Table 2.4), of which every month in the designated record length is assigned a SPI value based on their average conditions of wetness or dryness (Gou *et al.*, 2017; Umiati *et al.*, 2019).

Table 2.3: Classification for the Standardized Precipitation Index values (McKee *et al.*, 1993)

SPI VALUE	DROUGHT CATEGORY
≥ 2	Extreme Wet
1.5 to 1.99	Severe Wet
1 .0 to 1.45	Moderate Wet
-0.99 to 0.99	Normal
-1.0 to 1.49	Moderate Drought
-1.5 to -1.99	Severe Drought
≤ -2	Extreme Drought

Even though SPI is a form of meteorological drought index it has the potential to be configured to correspond to varying impacts, different timescales and reflect the drought conditions of other drought types for example at a longer timescale SPI is able to reflect certain characteristics of agricultural and hydrological droughts (Zagar et al, 2011; WMO, 2016; Gou *et al.,* 2017). It is also important to note that typically SPI relates the amount of precipitation in a certain month to the average climatic or seasonal conditions experienced at the selected location (Gevaert *et al.,* 2018). For example, in drier climates limited water conditions may be considered as the norm, whilst in wetter climates until severe drought thresholds are reached the water stress may not be seen as relevant (Gevaert *et al.,* 2018).

2.6.2 Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) was developed by Vicento-Serrano *et al.,* (2010). This index has the potential to characterize drought events whilst incorporating the effects climate change has relative to droughts (Ogunrinde *et al.,* 2020). SPEI is recognized to be a relatively new drought index capable of analyzing drought variability and impacts (WMO, 2016; Begueria *et al.,* 2014). The application of the SPEI drought index facilitates a comprehensive quantification approach of measuring water availability, as it is able to take into account atmospheric conditions (e.g. temperature, wind speed and humidity) which affect the severity of drought events (Stagge *et al.,* 2015; Nejadrekabi *et al.,* 2022).

SPEI is an index which is relatively simple in its calculation and is applicable for use at a global scale (Begueria *et al.,* 2014). One of the main advantage of this index is that it is capable of detecting change of global warming and its effect on temperature and evapotranspiration (Vicente-

Serrano *et al.* 2010; Pei *et al.,* 2020; Nejadrekabi *et al.,* 2022). This is a flexible and versatile index whereby, its calculations can be computed across multi-temporal scales e.g., from 1-month to 48-months (WMO, 2016). Since SPEI' computation method is based on similar principles as the SPI index it was established, that their classification system of drought (Table 2.4), would also be based on similar drought categories (Vicento-Serrano *et al.,* 2010; Tirivarombo *et al.,* 2018).

Table 2.4: Classification for the Standardized Precipitation Evapotranspiration Index (SPEI) values (Vicento-Serrano *et al.,* 2010)

SPEI VALUE	DROUGHT CATEGORY
≥ 2	Extreme Wet
1.5 to 1.99	Severe Wet
1 .0 to 1.45	Moderate Wet
-0.99 to 0.99	Normal
-1.0 to 1.49	Moderate Drought
-1.5 to -1.99	Severe Drought
≤ -2	Extreme Drought

With regards to the computation of the SPEI index it is noted that the procedures undertaken for its calculation is similar to that of the SPI (Ogunrinde *et al.,* 2020). For example, the SPEI drought index requires complete and continuous input data for no less than 30 years (Ogunrinde *et al.,* 2020). It is noted however, that the SPEI's calculation makes use of an added temperature component and takes into account the water balance (WMO, 2016). Typically, the calculation of SPEI is based on the use of monthly rainfall, air temperature and Potential Evapotranspiration (PET)/ Reference Evapotranspiration (ETo) data (Ogunrinde *et al.,* 2020; Nejadrekabi *et al.,* 2022). Reference Evapotranspiration estimations can be acquired through the application of several models/equations such as, Penman-Monteith (Equation 2.2), Hargreaves (Equations 2.3a and 2.3b) whilst Potential Evapotranspiration can be estimated using the Thornthwaite Equation (Equations 2.4) below:

$$ETo = \frac{0.408\Delta\,(Rn-G)+\gamma\frac{900}{T+273}u_2(e_s-e_a)}{\Delta+\gamma(1+0.34u_2)} \qquad (2.2)$$

Where, ETo is the Reference Evapotranspiration, Rn is the Net radiation flux (MJ/m2day), G is the Sensible heat flux in soil (MJ/m2day), γ is a psychometric constant, (kPa/°C), e_s is the Mean saturation vapor pressure (kPa), e_a is the Mean ambient vapor pressure (kPa), Δ is the Slope of saturation vapor pressure curve, T is the Mean temperature (°C) and U_2 is the Wind Speed at 2 m height (m/s-1)

$$ETo = 0.0023(Ra)(Tm + 17.8)(Tmax - Tmin)^{0.5} \tag{2.3a}$$

$$Ra = \frac{\frac{24(60)}{\pi} G_{sc} d_r [(w_s sin_\varphi sin_\delta) + (cos_\varphi cos_\delta sin_{w_s})]}{2.45} \tag{2.3b}$$

Whereby, ETo is the Reference Evapotranspiration, Ra is the Extraterrestrial Radiation, (MJ/m^{2}day), Tm is the Mean temperature (°C), T_{max} is the Maximum temperature (°C), T_{min} is the Minimum temperature (°C), G_{sc} is the Solar constant (0.0820 MJ/m^2), d_r is the Inverse relative distance of the Earth and the Sun, w_s is the Sunset hour angle (radius) and φ is the Latitude, δ is the Solar declination.

$$PET = 1.6 \left[\frac{10Tai}{I}\right]^{a} \qquad I = \sum_{i=1}^{12} \left[\frac{T_{ai}}{5}\right]^{1.5} \tag{2.4}$$

Whereby, PET is the Potential Evapotranspiration, Ta*i* is the Mean monthly air temperature (°C) for month *i*, I is the annual heat index and α is a calculated constant value $(0.49 + 0.0179I - (7.711x10^{-5})I^2 + (6.751x10^{-7})I^3)$

The calculations used to derive this index is based on the probability of non-exceedance of the climatic water balance (Tirivarombo *et al.,* 2018). The climatic water balance facilitates the comparison of available water with the atmospheric evaporative demand (Begueria *et al.,* 2014). Therefore, the climatic water balance of this index is expresses though the difference between the precipitation and PET/ETo data (Stagge *et al.,* 2015; Pei *et al.,* 2020). Following the calculation of the climatic water balance procedures can be undertaken to transform the original values into standardized unit. This is accomplished by fitting the climatic water balance values to a log-logistic probability distribution (Begueria *et al.,* 2014). After this transformation the probabilities are then converted into a standard normal distribution in order to acquire the final SPEI values (Stagge *et al.,* 2015).

It is highly acknowledged that the process of evapotranspiration plays a role to some degree in determining soil moisture variability and subsequently vegetation water content, which is known to directly affect agricultural droughts (Vincent-Serrano, *et al.*, 2010). According to Moorhead et al., (2015), it was further noted that two of the major components of the water balance is precipitation and evapotranspiration, whereby evapotranspiration can be representative of loss of water through soil evaporation and plant transpiration, whilst precipitation is representative of water being added to a system. Therefore it can be deduced that there is potential for SPEI, which incorporates both precipitation and evapotranspiration in its calculation to monitor agricultural drought conditions.

It was also noted by Vincent-Serrano *et al.*, 2010, that drought indices which consider only evapotranspiration data have the potential to monitor agricultural drought conditions, it was further noted by this study that SPEI tends to perform better than that SPI and PDSI, with regards to identifying drought impacts on agriculture. This is further supported by the study conducted by Tian *et al.*, (2018), which looked at evaluating several different indices for the monitoring of agricultural droughts. These indices included PDSI, Palmer Z-index, SPI and SPEI. The aim of his study was to determine which index would be most appropriate for monitoring droughts. The results indicated that SPEI demonstrated the best potential from all indices, with regards to capturing the impact of agricultural droughts.

Studies by Vincent-Serrano, *et al.*, 2010; Wang *et al*, 2015; Ahmadalipour *et al.*, 2017, Kamali *et al.*, 2018; Potopova *et al.*, 2014; Labudova *et al.*, 2017 and Gou *et al.*, 2019, have further indicated that SPEI is an index capable of potentially monitoring the characteristics of agricultural drought. It is understood that in its entirety SPEI is more often considered to be a meteorological drought, however within this study SPEI is taken in the context of evaluating agricultural drought conditions owing to its relation to vegetation and water use. SPEI's limitations however are recognized and considered.

2.6.3 Case Studies: Application of SPI and SPEI

Tirivarombo *et al.*, (2018), assessed SPEI and SPI in the Kafue basin within northern Zambia. From this case study it was identified that under the extreme category of drought SPI performed better with regards to identifying more droughts than SPEI. Comparative assessment were conducted in order to establish and analyses whether potential evapotranspiration has an effect on the drought index. However, SPEI was able to identify more drought in the moderate to severe category. Both of these indices were able to pick up temporal variations of drought. The results from this study also suggested that a factor that provided a significant role in characterizing droughts was temperature variability. From a correlation analysis between the two indices it was found that the precipitation was the major driver of drought, with a positive relationship ($R > 0.5$).

Potopova *et al.,* (2015), assessed the performance of SPEI and Standard Yield Residuals on the influence of drought on crop productivity at various lags. The results from this study indicated that there was a relatively strong relationship found between the crop yields residuals and SPEI, especially during the critical growth stages of the crops. It was also apparent from this study that over the past 12 years in the months of April to June, there was a significant increase in the drought risk and yield variability. It was further noted from the assessment that winter crops in this area are more likely to cope with drought conditions than spring crops. It was also acknowledged that during the germination and early stages of the crop production there was a lagging period of SPEI (at a 1-, 3- and 6-month timescale).

A study by Abdulrazzaq *et al.,* (2019), evaluated and spatially mapped meteorological drought at 11 stations in Iraq for selected years between the periods of 2000 to 2017. The rainfall data was obtained from TRMM in order to calculate SPI. Further analysis such as the use of the ordinary Kriging geostatistical interpolation technique in ArcMap was conducted. The results from this study indicated that the integration of satellite data from TRMM and SPI calculations was an effective tool to conduct drought assessments and map the spatial distribution of droughts.

A comparative assessment of SPI and SPEI's applicability for drought impact on crop production was undertaken by Labudova *et al.,* (2017) in the East Slovakian Lowland. 1-, 2- and 3-month timescale was utilized for both SPI and SPEI. A correlation relationship was determined using the Standardized Yield Residual Series, which is a method that determines agricultural drought risk. The results from temporal evolution of drought in this study, indicated that most crops depicted a greater correlation with SPEI rather than SPI. Results further indicated that the spring and winter crop yields had significantly declined when drought conditions persisted over these seasons. It was concluded by this study that the use of SPI and SPEI had a significant relationship with the yield of crops, and can be considered a suitable method for drought impact assessments. However, a recommendation made was that for future drought studies other topographic and climatic conditions should be considered.

A study by Umiati *et al.,* (2019), aimed to assess precipitation based drought indices in East Java. Evaluations and assessments were conducted at a provincial scale and was based on the SPI method with rainfall data acquired from the TRMM satellite. 25 districts were assessed in this areas study site, from further analysis it was determined that there are 13 districts with a low drought hazard index. The areas that experienced moderate drought hazard index had its greatest value being 0.523 and lowest being 0.33 (Umiati *et al.,* 2019).

2.6.4 Vegetation Health Index (VHI)

Typically, the characteristics of agricultural droughts are variable across space and time (Bhuiyan *et al.,* 2017). The Vegetation Health Index (VHI) is identified as a suitable index capable of identifying and facilitating good representation of the impacts and characteristics of agricultural drought, as it provides information on the vegetative stress, health and the influence of temperature conditions on drought (Ekundayo *et al.,* 2020).

VHI is a widely recognized and used agricultural drought index developed by Kogan (1995), it is based on the use of remote sensing information and takes into account surrounding ecosystem features (Bento *et al.*, 2018; Masitoh and Rusydi, 2019). VHI was recognized to be one of the first attempts to identify and monitor drought related agricultural impacts through the use of remotely sensed data (WMO, 2016). According to the World Meteorological Organization 2016, this index may be preferred by potential users due to its ease of application. (Ahmadalipour *et al.,* 2017).

VHI is an index derived using a linear arithmetic and weighted average, of two sub-components, namely the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI) (Kogan, 2000; Bento *et al.,* 2018; Masitoh and Rusydi, 2019; Ekundayo *et al.,* 2020). Both the VCI and TCI are based on satellite data which is able to reflect both vegetation cover and temperature anomalies respectively (Gou *et al.,* 2017). These two components are further able to facilitate for the delineating of seasonal and/or inter-annual drought events (Gidey *et al.,* 2018).

However, it should also be noted that due to this being a satellite-based approach for monitoring droughts the data utilized in its calculation may potentially be susceptible to cloud contamination affecting the results (WMO, 2016).

The VCI component is typically calculated using the satellite-derived Normalized Difference Vegetation Index (NDVI) values. By incorporating NDVI information, the VCI component is able to account for vegetation state, stress, cover and the spatial-temporal estimations of weather impacts on vegetation (Bento *et al.,* 2018). This component incorporates information from the near infrared (NIR) and visible (VIS) portions of the electromagnetic spectrum (Bhuiyan *et al.*, 2017). VCI is able to determine and quantify the advancement and deterioration of a vegetation in response to weather conditions and thus, portray the dynamic features of precipitation as compared to NDVI (Gidey *et al.,* 2018). It is further capable of detecting and identifying vegetation canopy stress experienced over an area (Masitoh and Rusydi, 2019). Typically with regards to VCI, a low values indicates that there is presence of unhealthy vegetation cover and typically portrays conditions of barren, rocky, and sandy land cover. Whilst a high VCI value depicts a healthy vegetation cover with dense vegetation (Patil *et al.*, 2021).

The TCI component of VHI is capable of quantifying the vegetation health under thermal conditions, this is typically based on the top-of-atmosphere brightness temperature or based on Land Surface Temperature (LST) (Bento *et al.,* 2018). TCI acquires its LST information from the thermal infrared (TIR) portion of the electromagnetic spectrum (Bhuiyan *et al.,* 2017; Bento *et al.,* 2018; Gidey *et al.,* 2018). Understanding LST can provide vital information for drought assessments as it provides insight on the impacts of heat-related stress experienced by vegetation and crops (Masitoh and Rusydi, 2019). This is a crucial component that needs to be considered when accounting for agricultural drought as it gives an indication of plant stress due to conditions of high temperature and low humidity.

VHI is considered to be a robust agricultural drought index with various applications including drought prediction, and providing efficient methods to monitor the spatial extent on characteristics of agricultural drought (i.e. magnitude, duration and severity) (Gidey *et al.,* 2018). It is an index dependent on vegetation, weather, environmental factors and ecological conditions experienced over an area of interest (Patil *et al.,* 2021). Furthermore, the vegetation health of an area, is an important feature to be assessed as this provides an indication on the vegetation stress experienced over an area (Gidey *et al.,* 2018).

According to Bento *et al.,* (2018), there are two assumptions that form the rationale behind the VHI formula, (1) VHI is derived such that the lower the NDVI and Higher the LST is the poorer the Vegetation health experienced, (2) The VHI is commonly computed through the averaging of VCI and TCI, this is so due to there being no prior knowledge of temperature and vegetation contributions to vegetation health (Bento *et al.,* 2018).

VHI datasets have been widely applied for the monitoring of crop yield and production, excessive wetness, early drought warnings and for assessments of irrigated areas (Gou *et al.,* 2017). It is important to note that the contribution of VCI and TCI to VHI is significantly dependent on different factors such as location condition (e.g. latitudes, land cover, topography) and temporal conditions (e.g. seasonality, day/night) (Masitoh and Rusydi, 2019). According to Gidey *et al.,* (2018), in order for an effective evaluation of agricultural drought, there needs to be at least 10 years' worth of SEO data and the use of an effective drought index such as the VHI.

According to Kogan (1995), VHI can be categorized into five threshold scales to classify the drought severity, this can be seen in Table 2.6. VHI, VCI and TCI estimate the cumulative vegetation health, humidity and temperature conditions respectively and can be characterized from a scale of 0 to 100, whereby, zero (0) expresses extreme stress and 100 expresses favorable conditions. If VHI results in a low value it is an indicator of unhealthy vegetation as well as signify a drought event as these conditions may result from low levels of available water resource supply and/or nutrient in the soil that promote plant growth (Ekundayo *et al.,* 2020).

Table 2.5: Classification System for Vegetation Condition Index, Temperature Condition Index and the Vegetation Health Index (Kogan, 1995)

Vegetation Condition Index/ Temperature Condition Index/ Vegetation Health Index Classification	
Value	**Category**
> 40	No Drought
30 - 40	Light Drought
20 – 30	Moderate Drought
10 – 20	Severe Drought

0 – 10	Extreme Drought

The impacts of drought on vegetation stress is noted to vary in areas under irrigation and non-irrigated areas. Ambika and Mishra (2019) indicated that there is usually a reduction in vegetation stress in areas that are irrigated than in rain-fed regions. This may be due to irrigation playing a role in increasing soil moisture availability of an area, which in turn may lead to an increase in the growth, density, yield and productivity of vegetation and crop growth. VHI is recognized as an index which produces efficient empirical probability of the occurrences for agricultural drought (Bhuiyan *et al.*, 2017). Furthermore, VHI has the potential to predicting crop yields and assist in making informed agricultural decisions (Patil *et al.*, 2021). Furthermore, VHI provides the potential for the monitoring of vegetation health and land surface temperature at resolution's that can assist in identifying the roll irrigation may play on vegetation growth during drought events, and can further provide information that can be used to facilitate the adequate monitoring and management of crops in both rain-fed regions and irrigated regions

2.6.5 Case Studies: Application of VHI

A study undertaken by Ma'rufah *et al.,* (2017), analyzed the relationship between meteorological drought and agricultural droughts over Indonesia. This was achieved by using monthly data from satellite-based products such as CHIRPS and MODIS to better understand the characteristic of these droughts especially during El Nino years. Correlation analysis was conducted between SPI (at multiple timescales) and VHI to spatially determine the time lag between the two drought types in this region. It is recognized that both meteorological and agricultural drought tend to be variable in its characteristics. Both of these drought types are seen to experience greater severity and a wider extent of drought experienced in this region, during a strong El Nino as compared to a weaker one. Results showed that the correlation relationship between VHI and SPI-3 were significant. They also indicated that the propagation time of agricultural droughts tends to be lagged about 3 months behind the occurrence of meteorological drought in this area. Therefore, this implies that during three months may have significant impacts on the development of agricultural droughts.

A study by Bento *et al.,* (2018), was conducted in order to do a climatological assessment of drought impacts with the use of VHI, in the Mediterranean. The aim of this study was to assess the contribution NDVI and LST have with regards to characterizing VHI. Assessments are done by estimating VCI, TCI and VHI, thereafter the results were correlated with the standardized approach of SPEI. Results indicate that VHI is highly influenced by vegetation cover. The correlation analysis showed that in semi-arid climatic conditions VCI had a greater effect of contributing to the drought. Whilst TCI had a greater influence effecting drought in moister climate classes. It was concluded by this study that in different climate regions it is possible to evaluate the roles of VCI and TCI to VHI by maximizing the correlations found between VHI and SPEI.

A study by Ekundayo *et al.,* (2020), assessed drought events over Nigeria for the period of 2003 to 2010. Assessments were done with the use of VHI and SPI-12. Results indicated that both the indices were able to detect the occurrence of mild, moderate and severe drought. It was also indicated VHI provided better consistent and wider spatial extent values of drought characteristics than compared to SPI-12. It was also acknowledged that there was a pattern of mild drought development followed by moderate and then severe droughts across the area. It was also noted that in this area, the moderate drought were the most dominant drought event experienced an area coverage ranged by 10% to 56%.

A study by Masitoh and Rusydi (2019), analyzed drought in an East Java watershed with the use of the remote sensing index VHI. This study conducted assessments in the dry season in order to determine the influence of NDVI and LST to VHI. Further analysis was conducted with methods of correlation and regression analysis. Results indicated that there was a negative correlation between NDVI and LST. However the correlation analyzed determined that relationship between LST and VHI was 0.35, whilst the relationship between NDVI and VHI was 0.63. These results indicated that VHI in this area was more likely influenced by internal vegetation conditions as compared to land surface temperatures.

A study by Gidey et al (2018), assessed the long-term agricultural droughts characteristics at Raya using VHI. Assessments were conducted to assess how agricultural drought responds to variable rainfall in this area with the use of a linear regression model. The results indicated that average cover of NDVI in the rainy seasons experienced a decrease of about 3% to 4%, whilst the coverage of LST was seen to have gained a significant increase by approximately 0.52 to 1.08 ^{0}C. When analyzing the relationship between rainfall seasonality and agricultural drought that there was a positive relationship of $R^2 = 0.357$ to $R^2 = 0.651$, this further indicated that in the rainy seasons the potential for the occurrence of agricultural drought is diminished in this area. Conclusions were drawn from this study that agricultural drought can be better monitored with the use of remote sensing and GIS-based drought indices such as VHI.

A study by Bhuiyan *et al.,* (2017), analyzed thermal stress impacts on vegetation health and agricultural drought in India. This area is prone to heat waves during the monsoon periods which may result in thermal stress and a degradation of vegetation health being. This study was GIS-based with the use of VCI, TCI and VHI being assessed. Results indicated that there was a strong correlation between TCI, LST and VHI and that thermal stress has a significant contribution to influencing vegetation health and crop yield productivity. In this study normal SPI algorithm months could not be used as a monsoon period in this area has a 4-month duration, therefore the procedure undertaken to calculate SPI was normalized with a MathWave Technology software to reflect precipitation anomalies for the monsoon seasons only. Results indicated that there was a very poor correlation between SPI and VHI, possibly due to SPI not taking into account the impact of temperature,

2.7 Synthesis of Literature

Typically droughts are considered to have significant effects on all sectors of society, the economy and the environment. It was acknowledged from the literature that the impacts and characteristics of droughts tend to evolve and change as drought transitions from one type to another. Therefore, there is a need to understand the mechanisms and characteristics of these drought types in a holistic and integrated manner, in order to facilitate effective management and mitigation strategies.

Drought characteristics have a wide and variable spatio-temporal scale, which may be difficult to adequately represent based on point measurements from traditional methods of acquiring hydro-climatic variables (i.e. from Ground-based observation networks). Further limitations acknowledged about in-situ data especially in developing countries like South Africa, is the lack of density in ground-based networks.

Most drought indices require serially complete records of long-term data in order to facilitate a better understanding of the conditions associated with the various types of drought. This is often difficult with the use of traditional methods of ground-based observations. The information acquired from this source of data may be patchy with long records of missing data (e.g., from instrument malfunction). This may further lead to uncertainty in results if these records are adopted in drought studies. The use of Satellite Earth Observation data was seen as a viable option to explore for conducting drought assessments as it is generally able to provide long-term records of data over large spatial and temporal scales.

However it was also identified that the collecting of SEO information from the satellite product source may be a gap in itself. As some of these sources are not freely available to the public directly, they require large amounts of storage space for the collection of the necessary raster outputs, and the pre- and post-processing methods involved may be complex. Therefore as a way forward to bridge the gaps associated with collecting satellite data the use of a cloud-based platform, known as Google Earth Ending was utilized to acquire the necessary satellite-derived data from several sources of satellite products. This platform is capable of providing geospatial data which can assist in monitoring and analyzing large-scale environmental and Earth conditions.

South Africa is an area recognized to be prone to be affected by the occurrence of drought, especially with regards to its agro-economic sector. It is an area with has a high dependency on agriculture at both a subsistence and commercial level. Majority of South Africa's agricultural sector is rain-dependent and plays a crucial role with regards to providing economic value to the country. Agricultural production yield is typically dependent on weather conditions and rainfall availability. Due to the rapid changes in climate and catchment conditions (e.g. land-use change) agricultural drought risks may be further aggravated (Ahmadalipour *et al.*, 2017).

It is apparent that the agricultural sector plays a vital role in ensuring food security, employment opportunities and the sustenance of economic development for the country. Droughts and their impacts pose a threat to the agro-economic sector of the country. Therefore understanding droughts through and agriculture perspective will provide further insight on how we can manage out systems better. However, it is apparent that there tends to be overlapping of the drought types. Owing to this drought management decisions need to take into account the integrated and transitioning effect of drought types in order to gain a better perspective ensuring coping and mitigation measures can be put in place

It is acknowledged from literature that there is an interconnected relationship found between the different drought types. Since rainfall deficit may be seen as a precursor to the deficit of other hydrological variables (e.g., soil moisture). It is important to understand the mechanisms and patters associated when drought events transform from one type to another. Owing to the importance of the agricultural sector in South Africa, the propagation of meteorological droughts to agricultural drought were considered for this research project. Understanding droughts in an integrated and holistic manner can provide valuable information that can be beneficial to facilitate the development and improvement of policies and strategies regarding managing and responding to drought hazards.

Numerous drought indices available to quantify the characteristics of drought. However, it was determined that there were three drought indices which would be appropriate for further investigation in this research project. The first index is the Standardized Precipitation Index (SPI), which is recommended by the World Meteorological Organizations (WMO) as the standard method to calculate meteorological drought index. The second drought index selected was the Standardized Precipitation Evapotranspiration Index (SPEI), this is an index capable of depicting condition of both meteorological and agricultural drought. A further advantage for the selection of SPI and SPEI are the indices ability to facilitate the quantification of droughts for both long-term and short-term timescales. The final drought index for assessment was the Vegetation Health Index (VHI), which utilizes satellite-based imagery to estimate and provide an adequate means of spatially and temporally representing agricultural drought. VHI is also capable of detecting drought in any season, it is also able to cover a relatively long duration of data and is applicable at a worldwide scale. Furthermore, the information from the SPEI has the potential to assess the applicability of the satellite-based drought index VHI.

Generally if from a management decisions were made based solely on the assessment of one type of drought or drought index, the impacts associated with the entire drought event may not be fully understood, and these decisions made may be highly misleading. For example, if a rainfall event occurs following a drought period, it may indicate the recovery of a meteorological drought. However, just because a meteorological drought recovered does not mean that the entire drought event has ended. It could potentially indicate that the meteorological drought may have manifested itself into another type such as agricultural drought, whereby, the soil moisture levels may still be too low to potentially recharge enough to support the growth of crops. By evaluating droughts with both the a meteorological and agricultural drought perspective, the conditions associated with both drought types over the same period may provide information that can potentially assist in the development of better management, mitigation and adaptation strategies associated with drought events.

From the evaluation of literature it was apparent that there were several gaps identified. This research project looked to address the issues associated with these shortfalls. Some on these research gaps included the following:

a) There have been few studies that utilized the use of Google Earth Engine to facilitate the collection and analyzing of Satellite Earth Observation data both spatially and temporarily in a comprehensive.
b) With the changing climate projections over recent year there have been more significant impacts faced, especially in developing countries. Therefore there is a greater need to better understand the mechanisms and patterns behind these events in order so that better and more informed disaster, water and agricultural management decisions can be made.
c) Majority of the drought assessments done especially in South Africa analyzes droughts through its single drought type or drought index, and does not take into consideration quantifying the drought propagation process. From a management perspective, if there is a propagation of meteorological to agricultural drought occurring and management decision only took in to account one type of drought type, the strategies undertaken to cope with the effect of the propagated event may not be as effective.
d) Different regions are likely to be impacted differently by drought events and characteristics. Therefore, the management decisions undertaken would need be suited for the particulate climatic region. There has been a lack of research done with regards to comparing the impacts and conditions associated drought propagation at different regions within South Africa.

3. METHODOLOGY

Following the review of literature in the previous chapter, it is apparent that there are numerous drought indices and Satellite Earth Observation products that can be utilized to quantify the different drought characteristics. In order to address the aims and objectives set out by this project, this chapter will consist of a general methodology, a detail description for the project's study sites, and highlight the procedures that were undertaken for the acquisition, calculations and analysis of the selected drought monitoring techniques and drought indices utilized, namely the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI) and the Vegetation Health Index (VHI)

3.1 General Methodology

The methodology undertaken in this research project, was guided from approaches evaluated within Chapter Two. The methodology adopted intended to further achieve the objectives set out in Chapter One, which include the following:

- To validate and assess the applicability of satellite-derived drought variables against ground-based data.
- To determine the applicability of satellite derived drought indices in characterizing droughts
- To evaluate and quantify the spatial and temporal patterns and trends associated with the transition of drought from meteorological drought to agricultural drought using commonly applied drought indices.
- To evaluate the characteristics of the drought propagation process in two different climatic regions.

The methodology undertaken utilized four steps, whereby the first step involved the collection, sorting and analysis of several hydro-climatological variables (e.g., rainfall, air temperature, NDVI, and LST data), through the use of both ground-based observations and Satellite Earth observations (SEO). The ground-based observation data (i.e. rainfall and temperature) was acquired from several Automatic Weather Stations (AWS) and Automatic Rainfall Stations (ARS). Whilst the SEO data was acquired from various available satellite products each with their own features. In order to process the large amounts of data needed the planetary-web-based platform of Google Earth Engine (GEE) and JavaScript writing was utilized as a major method in collecting analyzing and displaying the satellite information.

The second step involved conducting a validation study between the SEO information and ground-based in-situ data. This step was applied in order to assess the applicability of the SEO information. Two sites were assessed for the validation study, whereby these sites were selected based on factors such as the availability, record lengths of data and the density of in-situ ground-based rainfall and temperature stations. Each of the selected sites assesses a different hydro-climatic variable i.e. rainfall and air temperature data

Following the validation study, the third step adopted involved monitoring, identifying and quantifying the characteristics (e.g. duration, extent, severity) and impacts of historical meteorological and agricultural droughts. This assessment was conducted at two different climatic regions within South Africa. The procedure of this step, involved utilizing the appropriate SEO long-term data in calculating the SPI and SPEI. The calculation of these standardized drought indices was achieved through the use of RStudio packages and python script writing. In order to determine the satellite-derived drought index VHI, Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) imagery and data were acquired through the use of GEE script writing. The information acquired was then applied into ArcGIS for the calculation of the components of VHI, namely, Temperature Condition Index (TCI) and Vegetation Condition Index (VCI).

The final step undertaken, involved assessing and evaluating the drought propagation process within the two climatically different regions. Drought propagation refers to the transition of drought from one form to the other. Therefore, in order to assess this, the information acquired by calculating SPI, SPEI and VHI, were further compared in an integrated manner. The results from this comparison would further be used to identify patterns and trends on the propagation from meteorological drought to agricultural drought. The information gathered from this study would then be evaluated in order to facilitate added knowledge for better management and mitigation decisions in the agricultural and water resource sectors.

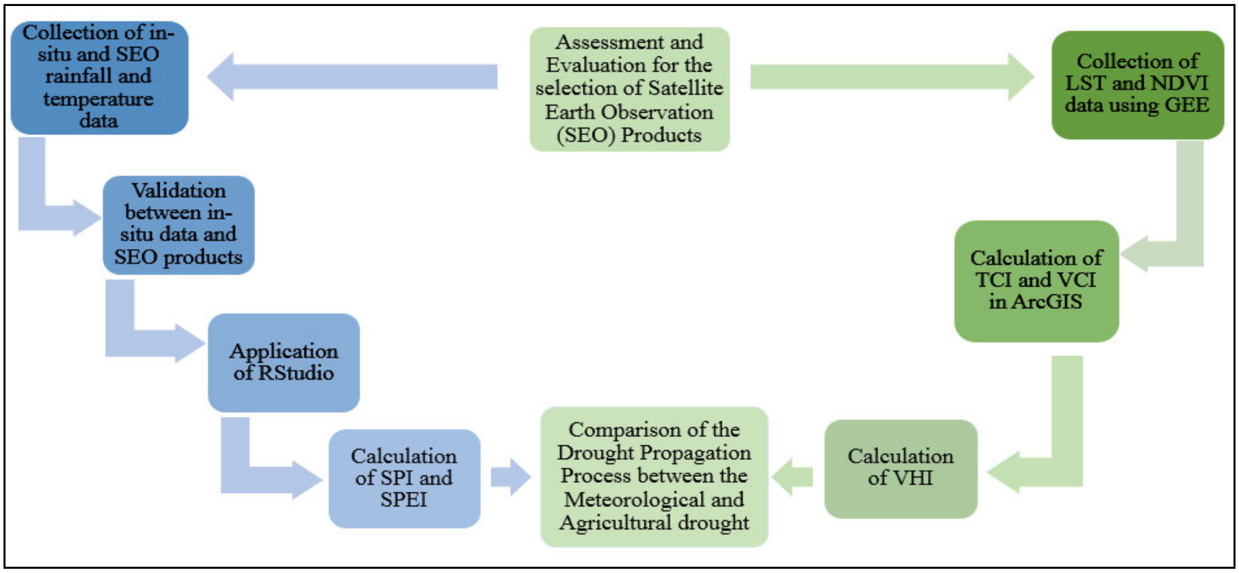

Figure 3.1: Generalized procedure undertaken to evaluate and quantify the drought propagation process using selected drought indices

3.2 Study Site Description

South Africa is geographically located at -29,046° N, 25,063° E, between the tropics and mid-latitudes. It is an area characterized with arid to semi-arid conditions and seasonal variability of hydrological and climatological variables, such as rainfall and temperature (Nkhonjera, 2017). South Africa typically has an average annual rainfall of ~500 mm (Cretat *et al.*, 2012). The variability in rainfall may be accounted for by regional processes and dynamic atmospheric-ocean features such as, El Nino Southern Oscillation (ENSO) and sea surface temperature. South Africa is a country with a range of diverse climate types and land regimes.

For the purpose of this research project, two climatically diverse regions will be assessed to better understand the impacts, effects and characteristics of the drought propagation process. The first area for assessment includes the uMngeni catchment, located in the KwaZulu-Natal Province. Whilst the second study site is the Breede-Overberg catchments located in the Western Cape Province. Both these areas are heterogeneous in their own right with different climatic conditions, land use activities and anthropogenic influence. This section of the methodology chapter highlights in detail the study sites evaluated and assessed for this research project.

3.2.1 uMngeni Catchment

The province of KwaZulu-Natal is situated on the south-eastern part of South Africa bordering the South Indian Ocean and is characterized with sub-tropical climate conditions, summer rainfall and cold dry winters (Ndlovu and Demlie, 2020; Mengistu *et al.*, 2021). Generally, the eastern most part of the province is recognized to experience wetter conditions. The rainfall patterns experienced in this area may be accounted for by the presence of the warm Mozambique current, ocean-atmospheric interaction, the province's topography and physiographic features.

Within KwaZulu-Natal, the area chosen for further assessment was the uMngeni Catchment (Figure 3.2). The mean annual precipitation received in this catchment is highly variable occurring mainly in the summer months (October to March) ranging between approximately 600 and 1500 mm per annum. On average temperature ranges between 14 and 22°C (Hughes *et al.*, 2018). The uMngeni catchment is recognized to have a surface area of approximately 4349 km^2. Furthermore, it is noted that the Department of Water and Sanitation (DWS) sub-divided the uMngeni Catchment at secondary, tertiary and quaternary catchments. For the purpose of this study, assessments will be done at the fourth catchment level scale. Therefore, 12 quaternary catchments within the uMngeni catchment were considered for further the drought assessment (Namugize *et al.*, 2018).

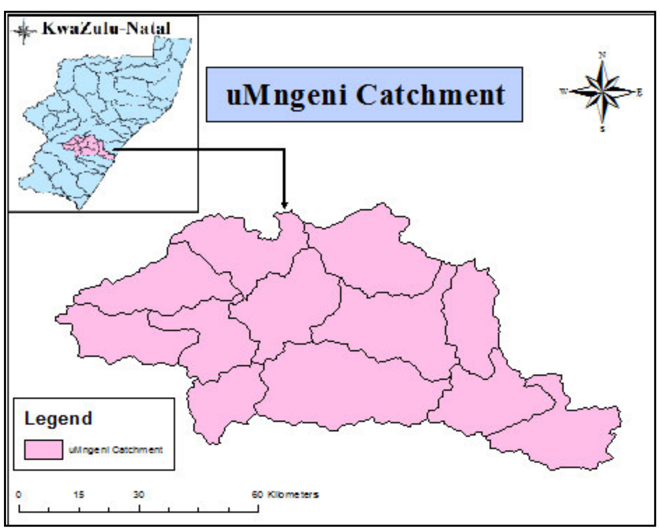

Figure 3.2: The uMngeni Catchment study site located within the KwaZulu-Natal Province

The uMngeni catchment is a highly important socio-economic area, as it consists of at least half of KwaZulu-Natal's population (Namugize *et al.*, 2018). The natural vegetation found in the uMngeni catchment, is highly heterogeneous due to land use activities and land cover (Figure 3.4), for example forestry, agriculture, mining and urbanization catchment accounts for the major water supply for industrial water use, agricultural water use and domestic water use for both Pietermaritzburg and Durban, as well as surrounding informal settlements within the catchment (Namugize *et al.*, 2018).

3.2.2 Breede-Overberg Catchments

The Western Cape Province is located within the south-western part of South Africa bordering the Atlantic and Indian Ocean. The climate conditions experienced over this region are Mediterranean and Temperate with warm dry summers and majority of the rainfall occurring during the winter months (June to August) (Naik and Abiodum, 2020). According to Omar and Abiodun (2020), this area experiences different types of rainfall regimes due to their locations, topography, altitude and the atmospheric-land-ocean interactions (i.e. El Nina, mid-latitude and tropical systems). Furthermore, it is an area influenced by two currents namely, the cold Benguella Ocean current to the west of the province and the warm Agulhus Ocean current to the south of the province.

Located in the Western Cape Province, the Breede-Overberg catchments will be considered as the second study site to be assessed in this research project (Figure 3.3). This selected area consists of the entire Breede catchment and the lower Berg sub-catchment known as the Overberg region. This study site has an area of approximately 19 786 km^2 and comprises of important water resource systems (e.g. Breede River, large estuaries, coastal rivers and tributaries) that supply water for domestic, agricultural and ecological use (Gcanga *et al.*, 2018; Naik and Abiodum, 2019). Typically, due to the mountainous terrain and climatic conditions found in this region the average annual rainfall can range from as high as 1000 mm/year to as low as 250 mm/year (DEAP, 2011).

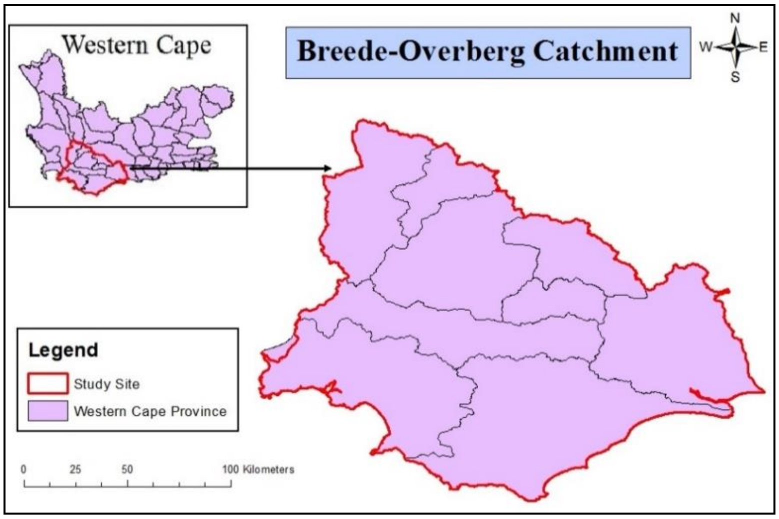

Figure 3.3: The Breede-Overberg Catchment study site area within the Western Cape Province

The Breede-Overberg catchment is characterized with a range of land use activities from commercial and subsistence agriculture, and urban to peri-urban land-use (Figure 3.4) (Cullis *et al.,* 2018). Within the Breede-Overberg catchment numerous agricultural activities occur from irrigated agriculture, production of high-value crops, the growth of other fruits and vegetables, and dry land agriculture such as, wheat cultivation (Rensburg *et al.,* 2011). Agriculture is identified as one of the largest water-use sectors and economic driver in these catchments with it accounting for approximately 87% of the annual water demand (DEAF, 2018; Cullis *et al.,* 2018).

The population growth in this area has resulted in a significant rise in demands for the already declining supply of available water (Cullis *et al.,* 2018). The Breede River and its surrounding estuaries provide a major contribution of water supply to the local agriculture and supports the local economy (Gcanga *et al.,* 2018). Another issue that typically plagues this area is the chronic water shortages that occurs due to its climatic rainfall patterns especially in summer (Rensburg *et al.,* 2011). The water supply in this region may be further stressed due to the occurrence and impacts of drought events.

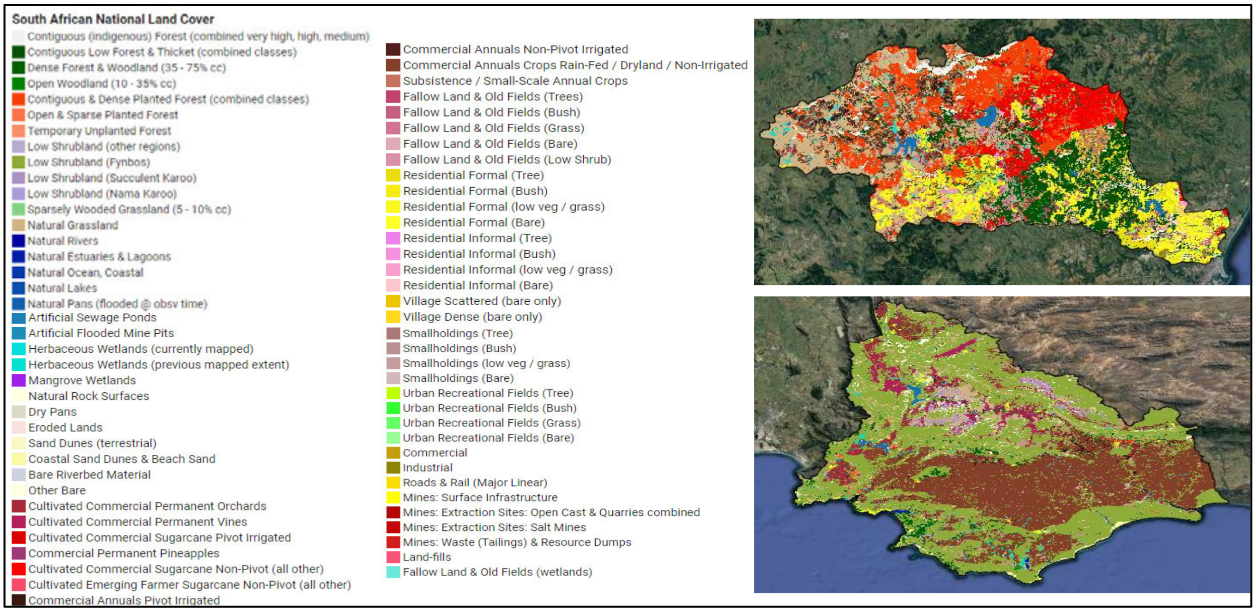

Figure 3.4: Land cover and land-use within the uMngeni Catchment and the Breede-Overberg Catchment (South African National Land Cover, 2018)

3.2.3 Validation Study Sites

A validation study was adopted in this research project to assess the applicability of the selected Satellite Earth Observation products as compared to ground-based observations. It is noted that the selection of the validation sites were based on factors such as the density of in-situ observation stations, location of the in-situ stations, type of data available at the stations and the record lengths of data at these stations. From the criteria set out two potential validation sites were considered for further assessment, namely the U20J sub-catchment and the Lower Overberg (G40-G50) sub-catchments. Whereby, each of the selected validation sites were chosen to assess different hydro-climatic variables.

U20J sub-catchment within the uMngeni Catchment (Figure 3.5), was selected as the first validation site, and facilitated the collection and assessment of rainfall data. It is an area with an approximate area of 0.063 km^2 and is characterized with an elevation of approximately 600 m to 890 m above sea level and variable rainfall patterns (Strydom *et al.*, 2020). The land cover and land use activities for this validation site varies from built-up and urban land use to forestry plantations, cultivated commercial and subsistence agriculture.

The second validation site was identified as lower Overberg (i.e. G40 and G50 sub-catchments), found within the Breede-Overberg Catchment (Figure 3.5). This site was considered to facilitate the collection and assessment of air temperature data (minimum and maximum). The G40 and G50 sub-catchments are identified to have an approximate area of 0.71 km^2. The topography of this area is significantly mountainous even along the costal planes. According to the Overberg District Municipality Climate Change Report (2018), it was stated that the mean temperatures were expected to increase, thus resulting in changes to the water balance, crop productions yields and impacts faced on the food security in the area.

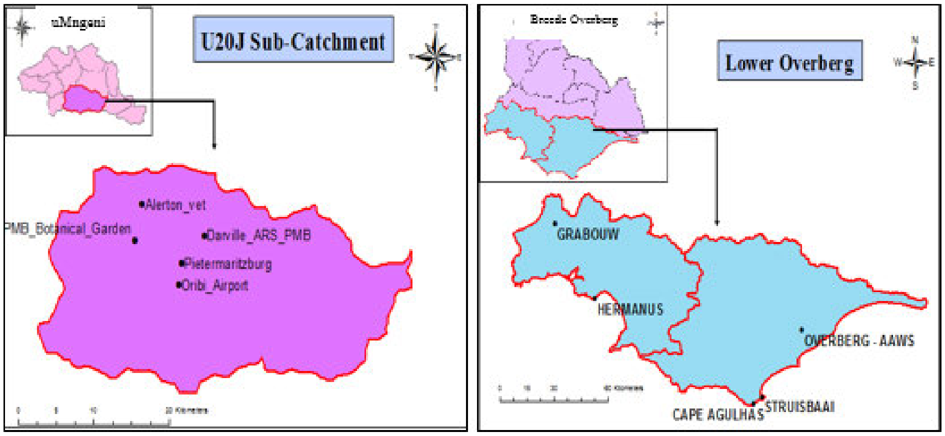

Figure 3.5: Two selected validation study sites i.e. the U20J sub-catchment within the uMngeni catchment and the lower Overberg (G40 and G50 sub-catchment) located within the Breede Overberg catchment

3.3 Data Acquisition

In order for assessments to be made on drought propagation, information on several hydro-climatological variables need to be acquired. It is recognized that these variables are typically heterogeneous in nature, space and time. The acquisition of this information can be done through a variety of sources. For the purpose of this research study, the sources used to collect the necessary information are Ground-Based Observations and Satellite Earth Observations. This section will highlight the different types of data collected and utilized in the research project and its associated features.

3.3.1 Ground-Based Observation Data

Ground-based observation networks provide valuable real-time information on the various hydrological and climate parameters (e.g. rainfall, air temperature), and an indications as to what is happening on the earth's surface. Therefore, the ground-based observations acquired were utilized in the validation assessment of this research project. The rainfall, minimum air temperature (Tmin) and maximum air temperature (Tmax) data were acquired from several in-situ Automatic Rainfall Stations (ARS) and/or Automatic Weather Station (AWS) networks (Table 3.1), within the two selected validation study sites.

Table 3.1: List of selected rainfall and temperature in-situ stations

Variable	Station Name	Longitude	Latitude	Station Type
Rainfall (U20J Sub-Catchment)	Allerton	30.3558	-29.5736	ARS
	Botanical Garden	30.3472	-29.607	ARS
	Oribi Airport	30.3995	-29.6478	AWS
	Pietermaritzburg	30.4029	-29.6278	AWS
	Darville	30.4299	-29.6024	ARS
Temperature (G40 and G50 Sub-Catchments)	Grabouw	19.0298	-34.1525	AWS
	Hermanus	19.2246	-34.4324	AWS
	Overberg	20.2521	-34.5516	AWS
	Struisbaai	20.0569	-34.8002	AWS
	Cape Agulhas	20.0131	-34.8262	AWS

The in-situ rainfall and air temperature (Tmin and Tmax) data was acquired from the South African Weather Service (SAWS). The procedure for obtaining this data involved firstly logging into the SAWS website (https://www.weathersa.co.za/home/aboutclimateatsaws). From this website a list of available weather and rainfall stations were downloaded in a KMZ format and the stations were viewed using Google Earth Pro. Thereafter, selected AWS and ARS were identified based on the availability, station density, station type and record lengths of the rainfall and temperature data. It should be noted that the choosing of these stations (AWS and ARS) further guided the selection of validation study sites. The final step undertaken involved submitting requests to collect the necessary variable information.

With regards to the collection of in-situ rainfall information, daily data from five rainfall stations within the U20J sub-catchment were collected for the period of 1996 to 2020. Whilst for the collection of air temperature information, the daily Tmax and Tmin at five selected stations within the G40 and G50 sub-catchments were collected for a period of 2000 to 2020. It should be noted that the ground-based in-situ data acquired contained numerous patches and large amounts of missing data over the collected record period. Therefore before the collected information could be utilized in the validation study, the data from the in-situ networks underwent procedures to be appropriately sorted and infilled to acquire a period of most complete records, for the hydro-climatic data across all the selected stations.

3.3.2 Satellite Earth Observation (SEO) Data

The Satellite Earth Observation (SEO) products assessed and utilized in this research project were recognized to have datasets with open access and available in various formats for download. Google Earth Engine (GEE) platform was utilized as the main approach to acquire, visualize and download the necessary data of drought-related variables, from different SEO products for the selected study sites.

GEE is a planetary scale platform capable of providing and analyzing satellite imagery and geospatial Earth science data. In order to use this platform firstly an account needed to be created to access GEE, this was done using the following site https://signup.earthengine.google.com. Once registered, access to the platform and all the available SEO information and datasets are freely available for assessing, collecting and evaluating by logging on the GEE website https://earthengine.google.com. Within this platform information on the availability, specification, tools, documentation and features of the datasets from various satellite products are available through an assessable dataset catalog. Also available on this site are tutorials on the Java scripting language utilized by the platform to perform functions that analyze, visualize and download the required satellite imagery and dataset information. Procedures were conducted to familiarize and better understand the script writing language before utilizing the GEE platform. For the purpose of this project, the code editor tool (https://code.earthengine.google.com), along with java script writing within GEE platform facilitated the accessing, configuring, acquiring and analyzing hydrological and climatological geospatial data from various satellite products. The SEO products that were utilized for this research project include:

The Climate Hazards Group Infrared Precipitation with Station data (CHIRPS) dataset, which is able to provide daily rainfall values at a quasi-global spatial extent (50° S- 50° S) over a spatial resolution of 0.05°. CHIRPS was selected as a potential product for further assessment as it provides relatively accurate long term data (available from 1981 to present). Studies done by Bayissa *et al* (2017), Zhong *et al.*, (2019), Bijaber *et al.*, (2018) have indicated that the use of the SEO product CHIRPS has the potential to be further applied in drought assessments.

The Precipitation Estimation from Remotely Sensed Information Using Artificial Neutral Network Climate Data Records (PERSIANN-CDR) which provides long-term records of gridded precipitation at a spatial resolution of 0.25°. Furthermore, it is recognized to have long record lengths from 1983 to present. It has a global spatial coverage of 60° S to 60° N. The precipitation data from this satellite is generated from Gridsat-B1 infrared data through the PERSIANN-CDR algorithm (Zhong *et al.*, 2019). Due to its long record of over 30 years this product has the potential to be used in further drought assessments.

ERA5 Daily Aggregates product, which is considered as the fifth generation and latest global climate reanalysis product which consists of a combination of modelled and observation data. The ERA5 product capable of providing information of several variables including air temperature, sea level pressure, wind, etc., further information on its available parameters may be found at https://cds.climate.copernicus.eu/. This product has a spatial resolution of approximately 27830m. For the purpose of this research study, the variables utilized by the ERA5 product was the minimum and maximum 2m air temperature bands. Furthermore, the availability of long-term records from this dataset (for a period of 1979 to 2020), makes it a potential product that can be utilized in drought index calculation.

The Moderate Resolution Image Spectradiometer (MODIS) Terra Vegetation Indices (MOD13A1.006) product, provided information on two vegetative layers, namely satellite derived Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI). For the purpose of this research project global 16-day smoothed values of NDVI were utilized to calculate the VCI component of the Vegetation Health Index. This SEO product has a spatial resolution of 500 m and a record length from 2000 to present with corrected atmospheric surface reflectance that have been masked for the presence of clouds, aerosols and water.

The MODIS Terra Land Surface Temperature (LST) and Emissivity product (MOD11A1) was also utilized in calculating the agricultural drought component of TCI. This product provides information on daily LST and emissivity values at a global spatial extent, with a resolution of gridded 1 km and a record length from 2000 to present. The MODIS product is recognized to have an up-to-date algorithm, quality flag, zenith satellite view and higher quality of spatial-temporal variations (Gidey *et al.*, 2018). The LST values from this product are represented by the MODIS bands 31 and 32 for both day-time and night-time respectively.

3.4 Data Analysis

Following the collection of the necessary drought related-variables this section of Chapter Three, will highlight the procedures undertaken to validate the SEO data. This section will also discuss the techniques and methods utilized to calculate, and analyze the selected meteorological and agricultural drought index (i.e. The Standardized Precipitation Index, The Standardized Precipitation Evapotranspiration Index and the Vegetation Health Index).

3.4.1 Validation Study

The validation study was undertaken at two sites namely, the U20J sub-catchment and the Lower Overberg sub-catchment (G40 and G50). This study was conducted in order to assess the applicability of the data from satellite products as compared to ground-based in-situ data. Typically, the data obtained from ground-based observation stations provide point measurements of the rainfall and air temperature, and thus may not be as representative over the conditions of larger spatial scales. However the information provided gives an indication of real-time estimations of several variables. For the purpose of this research study rainfall data was assessed within the U20J sub-catchment and air temperature (Tmin and Tmax) data was assessed within the Lower Overberg sub-catchments.

During the data collection process of ground-based observations, it was acknowledged that there were numerous patches of missing data amongst the in-situ data records obtained for both rainfall and air temperature. Owing to the amount of missing data present, procedures were firstly conducted to infill (using the nearest neighbor regression method) and determine a period of most completed records for each type of variable (i.e. rainfall and air temperature). Following this procedure it was acknowledged that the period of most completed rainfall records was an eight-year period from 2001 to 2009. Whilst the most complete record length of in-situ Tmin and Tmax data, was identified as a six year period from 2014 to 2020.

The second step of the validation assessment involved the collection of Satellite Earth Observation data. This data was acquired through Google Earth Engine and Java Script writing. Whereby CHIRPS and PERSIAAN-CDR were the products used to acquire the rainfall data and the ERA5 Reanalysis satellite product was used to obtained Tmin and Tmax records. For the validation assessment the SEO data was acquired for the same point location and record length as the selected ground-based data.

The final procedure for this assessment looked at comparing and validating the SEO data to the ground-based in-situ data (rainfall, Tmin and Tmax). This assessment included the use of several regression and statistical evaluations (Table 3.2) such as, determining the Mean (μ), Standard Deviations (SD), Pearson correlation (r), Coefficient of Determination (R^2), Root Mean Square Error (RMSE), Standard Error (SE) and Paired T-test. Furthermore time series graphs were also created in order to evaluate, compare and validate the rainfall, Tmin and Tmax. With regard to the evaluation of the results from the rainfall products, the best performing SEO rainfall product will be further used as input variables within the selected drought indices at both the study sites.

Table 3.2: List of statistical and regression formulas utilized in the validation study

Name	Formula	Symbols
Mean	$\mu = \frac{\sum x}{N}$	μ = Mean $\sum x$ = Sum of all data values N = number of *x* values

Standard Deviation	$SD = \sqrt{\frac{\sum_{i=1}^{N}(xi - \mu)^2}{N}}$	SD = Standard Deviation N = Number of observations xi = Observed values of a sample μ = Mean value of the observation
Pearson Correlation	$r = \frac{\sum(xi - \mu x)(yi - \mu y)}{\sqrt{\sum(xi - \mu x)^2 \sum(yi - \mu y)^2}}$	r = Pearson correlation xi = Value of x-variable in the sample μx = Mean of the x-variables yi = Value of y-variable in the sample μy = Mean of the y-variables
Coefficient of Determination	$R^2 = 1 - \frac{RSS}{TSS}$	TSS = Total sum of squares RSS = Sum of squares of residuals
Root Mean Square Error	$RMSE = \sqrt{\frac{\sum(Pi - Oi)^2}{n}}$	Pi = Predicted value of the *i*th observation in the dataset Oi = Observed value of the *i*th observation in the dataset n = Sample size
Standard Error	$SE = \frac{SD}{\sqrt{n}}$	SD = Standard Deviation of the sample n = Number of samples

3.4.2 Application of RStudio to Calculate SPI and SPEI

One of the main requirements needed in order to calculate SPI (McKee *et al.*, 1993) and SPEI (Vicente-Serrano *et al.*, 2010) are historical monthly records of data as its input variables. However, this monthly input data needs to contain completely continuous long-term records for a period of at least 30 years. Satellite Earth Observation produces were determined as an adequate source of providing this continuous long-term data. It was noted that the rainfall input data used would be acquired from best performing SEO product (CHIRPS and PERSIANN-CDR) from the validation study.

Typically, SPI only requires monthly rainfall data. However, since SPEI considers the water balance in its determination, the input variables required for SPEI's calculation are monthly rainfall, minimum air temperature (Tmin), maximum air temperature (Tmax) and the latitude of the selected study sites. It should be noted that for the SPEI calculation the latitude of the uMngeni catchment was set at a value of -29.6 degrees, whilst the latitude for the Breede-Overberg catchment was set at -34.1 degrees. The input rainfall, Tmin and Tmax data were collected as catchment averages for a 31 year period from 1988 to 2020, from SEO products (i.e. CHIRPS, PERSIANN-CDR, ERA5 Reanalysis Product), for both of the selected study sites (i.e. uMngeni catchment and Breede-Overberg Catchment).

As mentioned, in the literature review several studies have indicated that SPEI is an index capable of potentially monitoring the characteristics of agricultural drought. It is understood that in its entirety SPEI is more often considered to be a meteorological drought, however within this study SPEI is taken in the context of evaluating agricultural drought conditions owing to its relation to vegetation and water use. SPEI's limitations however are recognized and considered.

For the purpose of this research project SPI and SPEI will be derived using RStudio Programming. The RStudio software package is a highly recognized software environment for analyzing data, statistical computing and displaying statistical graphics. This was identified as a platform capable of calculating the drought indices SPI and SPEI. The first step undertaken involved the downloading of the software program from the following website (https://cran.r-project.org/bin/windows/base/). Thereafter, procedures were undertaken to better understand the coding language utilized within RStudio. Further information on the CRAN-library repository, software, documentation and programming packages available on the RStudio platform can be found at https://cran.r-project.org. For the purpose of this project the SPEI-Package (Version 7.1) was selected to calculate and graph both SPI and SPEI at several different time scales (3- month and 6-months). This SPEI-Package was acquired from the freely available CRAN-repository, whereby, further information on the specifics of this package may be found at https://cran.r-project.org/package=SPEI.

Literature by Vicente-Serrano et al (2010), (2012a), (2012b), (2014), (2015), as well as Begueria et al (2010) and (2014), detail the calculations of SPI and SPEI and the implementation of the

SPEI-package in the R-computing envionments (e.g. RStudio). From the initiation of this index's package it is noted that the SPEI-Program package has since been revised and updated several times, with the latest Version 1.7, of which was used in this research study. It is noted from the user manual for the SPEI package (found on https://cran.r-project.org/web/packages/SPEI/SPEI.pdf) that the Potential Evapotranspiration (PET) is the amount of evaporation and transpiration that would occur if a sufficient water source were available, whilst Reference (ETo) is the amount of evaporation and transpiration from a reference vegetation of grass. Both PET and ETo calculations within the RStudio SPEI-Package were considered to be equivalent. Therefore, the RStudio package has functions within its algorithm to calculate PET using the Thornwaite Equation or ETo using the Hargreaves or Penman-Montieth Equations.

Once the SPEI package was downloaded it was then unzipped and installed within the RStudio program. Thereafter procedures were undertaken to calculate SPI and SPEI for a 31 year period of 1988 to 2020. For the purpose of this research project calculations for SPI and SPEI was conducted to measure and characterize drought occurrence and impacts in the uMngeni and selected Breede-Overberg catchment, over the timescales of 3-month and 6-months. The procedure for the SPI calculation in RStudio firstly involved sorting the 31 year record of monthly rainfall into the text file format as required by the SPEI -Package. Following this, the input data was imported into the RStudio Program. Code scripting was then done within the RStudio platform to calculate SPI over various timescales for both of the selected study sites.

The procedure undertaken to calculate SPEI in RStudio involved firstly sorting the monthly rainfall, Tmin and Tmax data into a text format. This input data was then imported into the RStudio program. Before SPEI can be computed the Reference Evapotranspiration (ETo) is required to be calculated. There are numerous methods available within the SPEI-Package to calculate PET and/or ETo including the Penman-Monteith, Thornthwaite and Hargreaves methods. However, due to the fact that long-term monthly Tmin and Tmax data and the latitude data for the study sites are available, the Hargreaves equation could be used to calculate ETo. Studies by Beguerıa *et al.*, (2014), Ogunrinde *et al.,* (2020) and Nejadrekabi *et al.,* (2022) suggested that in areas where data is poor or not available the use of the Hargreaves Equation for determining ETo (Equation 3.1) is an adequate method that may be adopted.

$$ETo = 0.0023 \times (Ra) \times (Tm+17.8) \times (Tmax-Tmin)^{0.5} \quad (3.1)$$

Whereby, ETo represents the Reference evapotranspiration, Ra is the extraterrestrial radiation (MJ/m2day), Tm is the mean temperature (°C), Tmax is the maximum temperature (°C) and Tmin is the minimum temperature (°C)

Following the calculation of this ETo variable, procedures could then be carried out to determine the climatic water balance within the RStudio program. The climatic water balance was derived through the subtraction of the ETo values from the Rainfall values. The final step undertaken involved codes being scripted within RStudio to calculate the resulting SPEI values at its various timescales (i.e. 3-month and 6-month). The results produced for both SPI and SPEI were then graphically displayed for further analysis.

3.4.3 Calculation of the Vegetation Health Index (VHI)

In order to quantify and evaluate agricultural drought characteristics the Vegetation Health Index was selected for further assessment. Studies by Bento *et al.,* (2018), Gidey et al (2018) and Ekundayo *et al.,* (2020) further indicate that VHI is an appropriate SEO drought index which has the potential to identify agricultural drought characteristics, especially over larger spatial regions.

The Vegetation Health Index developed by Kogan (1996), can be calculated by firstly determining its two components of Vegetation Condition Index (VCI) and Temperature Condition Index (TCI). In order to derive these components satellite-derived variables needed to be acquired namely, the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) data respectively. This information was provided by the datasets of the selected MODIS satellite products. These satellite-derived variables were analyzed, visualized and downloaded using Google Earth Engine (GEE) scripting. It was established that the data would be collected as average variables for a 20 year period (2000 to 2020) over both study sites. Furthermore, with this index both a temporal and spatial analysis of agricultural droughts would be conducted.

During the process of data retrieval from the satellite products it was noted that several adjustments were needed to be made to both the NDVI and LST datasets, within GEE before it could be downloaded in the necessary formats required. In order to adequately represent the values of NDVI

(MOD13A1.006 product) adjustments were made to re-scale the NDVI values/pixel (by a value of 0.0001). The second adjustment made was for the LST data (provided by the MOD11A1 product), whereby it was recognized that initially this product provides values represented by the unit Kelvin, therefore, procedures were undertaken to convert the values/pixels to represent Degree Celsius before the data was acquired.

For the temporal assessment of agricultural drought NDVI and LST values were acquired as average daily values over the entire selected study sites. The information on these variables were then downloaded into a CSV format for further analysis and assessment. Following, the collection of the satellite-derived data, procedures were conducted in excel to sort the data into its monthly aggregate. Thereafter the absolute minimum and maximum values of NDVI and LST were obtained using GEE coding for a 20 year period of 2000 to 2020. Once these absolute values were obtained the data could then be applied to the formulas to calculate the components VCI (Equation 3.2), TCI (Equation 3.3) and the VHI (Equation 3.4). Time-series graphs were then compiled with the results for further evaluation of agricultural droughts experienced at both of the selected study sites.

Where the equation to calculate VCI is derived as follows:

$$\mathrm{VCI} = \frac{\mathrm{NDVI} - \mathrm{NDVImin}}{\mathrm{NDVImax} - \mathrm{NDVImin}} \times 100 \tag{3.2}$$

Whereby, NDVI is derived as the value for the pixel and month. NDVI_{max} and NDVI_{min} are the absolute maximum and minimum values of NDVI respectively, for the considered pixel and month. Similarly to the computation of VCI, the Temperature Condition Index can be derived with the following equation:

$$\mathrm{TCI} = \frac{\mathrm{LSTmax} - \mathrm{LST}}{\mathrm{LSTmax} - \mathrm{LSTmin}} \times 100 \tag{3.3}$$

Whereby LST is the value given for the pixel and month. LST_{max} and LST_{min} are the absolute maximum and minimum values of a given LST pixel and month. Once the values of VCI and TCI are estimated, calculations for VHI can be conducted with the following equation:

$$\mathrm{VHI} = \alpha\ \mathrm{VCI} + (1 - \alpha)\ \mathrm{TCI} \tag{3.4}$$

Where α is a weight parameter that is usually set as a standard value of 0.5 (Kogan, 1996), VCI is the Vegetative Condition Index per pixel/month and TCI is the Temperature Condition Index per pixel/month.

For the spatial assessment of agricultural drought it is noted that a three-step procedures was undertaken. This spatial assessment involved the use of both GEE and GIS-based methods. The first step taken involved acquiring the necessary satellite-derived NDVI and LST data. This information was obtained with the use of GEE scripting whereby, the dataset imagery of NDVI and LST was acquired and downloaded in a GeoTiff format for each month of the selected 20 year period. The GeoTiff data is recognized as a format which enables geo-referencing information to be embedded within an image file. The information stored in these GeoTiff files could then be further visualized and analyzed using the ArcGIS programs.

Following this, the second step undertaken involved using the Spatial Analyst Tools within ArcGIS to calculate and visualize the maximum and minimum values NDVI and LST with the GeoTiff imagery obtained. The cell statistic tool, was utilized in order to determine the maximum and minimum NDVI and LST values for each pixel on the GeoTiff images for each month and year (of the 20 year period). Thereafter, using the cell statistic tool the absolute minimum and maximum values per pixel of the NDVI and LST were calculated for the entire record length of 2000 to 2020.

The final step of the spatial analysis involved deriving and visualizing the components VCI, TCI and VHI. This was accomplished by using the Spatial Analyst Tool of Raster Calculation within ArcMap. The Raster Calculation tool, facilitates the executing of Map Algebra equations on each pixel of a GeoTiff imagery, in order to create an output raster image. This function of ArcGIS was thus applied with the use of Equation (3.1), (3.2) and (3.3) in order to derive VCI, TCI and VHI respectively.

3.5. Drought Propagation Assessment

Following the quantification and analysis of the meteorological drought and agricultural drought a comparative analysis is carried out between the results produced by the SPI, SPEI and VHI indices at both the selected study sites. This comparative assessment is done in order to establish the trends and patterns associated with the characteristics of the drought propagation process (i.e. the transition from a meteorological drought to agricultural drought). In order to calculate the period in which drought propagation occur, that lag time for the onset of the drought was determined. The drought propagation lagging period within this study was noted to be the period of time (months) between the start of one drought type (at a specific time scale) to the start of the next drought type. This assessment will be carried out for a 20 year period from 2000 to 2020 for all three indices across both of the selected study site regions.

4. RESULTS

This chapter will address the results produced from the meteorological and agricultural drought assessment. This chapter will also highlight the evaluation of the drought propagation process within two climatically different study sites namely, the uMngeni Catchment and the Breede-Overberg Catchment. The following aspects of this research will be presented in this Chapter:

- Results from the validation study assessing the applicability of two satellite-derived rainfall products, namely CHIRPS and PERSIANN-CDR and the satellite air temperature product ERA5 Reanalysis against ground-based observations.
- Results from the average temporal quantification of historical meteorological droughts using SPI at both selected research study sites.
- Results on the average temporal quantification of historical agricultural drought using SPEI, averaged VHI and its associated components (VCI and TCI), at both the selected study sites.
- The applicability of SPI-6 in estimating agricultural drought characteristics in different climate regions in comparison to VHI.
- Results on the applicability of satellite-derived drought indices (VHI) through its validation against standardized approaches (SPEI).
- Results and illustrations on the spatial distribution of historical agricultural drought using VHI.
- Results on the comparative assessment between SPI, SPEI and VHI to determine tends and patterns for the drought propagation process at each climatic region.

4.1 Validation of Rainfall Data

The results from the statistical and cross-correlation analysis of rainfall data between the satellite products (CHIRPS and PERSIANN-CDR) and the ground-based measurements can be seen in

Table 4.1, and illustrated with regression scatter plots in Figure 4.1. The results for this analysis indicated that the Pearson Correlation (r) relationship between CHIRPS and the ground-based observations were relatively high with values no less than 0.85 in value. The highest recorded ‘r’ value was experienced at the Oribi and Pietermaritzburg (PMB) stations with a values of 0.90 and 0.89 respectively. Whilst the ‘r’ results from the PERSIANN-CDR satellite indicated that overall, the correlation relationship was reasonably good with three of the locations having an ‘r’ value of 0.82 (i.e. Allerton, Botanical Garden, and the PMB stations). The highest value recorded from this SEO product was recorded at 0.83 for the Darville station, whilst the lowest “r” value was recorded at 0.79 for the Oribi Airport station.

The results of R^2 further indicate that CHIRPS compares most favorably against the Oribi Airport and PMB Station with these stations having R^2 values of 0.80 and 0.79 respectively. It is also noted that the other stations namely, Allerton, Botanical Garden and Darville performed relatively well with R^2 values of 0.73, 0.72 and 0.77 respectively. For the regression analysis on the PERSIANN-CDR Satellite product the results indicate that, from all five locations the best performing station was Darville with an R^2 of 0.69 in value. Whilst the Botanical garden and PMB stations had R^2 values of 0.67 and the Alerton station had a value of 0.66. The lowest performing station with the PERSIANN-CDR satellite data was recognized to be at the Oribi Airport Station with a R^2 value of 0.63.

From the comparison of regression and cross correlation analysis it is recognized that there is a relatively strong positive correlation relationship between SEO rainfall datasets and the ground-based data. However it is noted that even though the PERSIANN-CDR satellite product did perform relatively well, the CHIRPS product was seen to perform more favorably in comparison. Whereby, typically across all five of the selected stations, the CHIRP product typically produced results with both the R^2 and Pearson correlation values closer to the value of 1 than that of the PERSIAN-CDR product.

The Root Mean Square Error (RMSE) was conducted in order to determine the measure of deviation errors between estimated and observed data. Typically the results from this statistical assessment (Table 4.1) showed that at four stations (Botanical Garden, Oribi Airport, Pietermaritzburg and Dareville) the overall comparison on the CHIRPS dataset had a relatively lower RMSE values ranging from 0.15 to 3.69 as compared to the comparison on the PERSIANN-CDR data which ranged from 4.04 to 8.27 in value. However, at the Allerton Station it was noted that the RMSE had a result of 5.39 from the CHIRPS comparison and 0.29 at the PERSIANN-CDR comparison.

Table 4.1: Regression and cross-correlation results for the CHIRPS and PERSIANN-CDR satellite rainfall products, within the U20J sub-catchment

Satellite Earth Observation Rainfall Products										
	CHIRPS Rainfall Product					PERSIANN-CDR Rainfall Product				
Stations	**Allerton**	**Botanical Garden**	**Oribi Airport**	**PMB**	**Dareville**	**Allerton**	**Botanical Garden**	**Oribi Airport**	**PMB**	**Dareville**
Pearson Correlation	0.86	0.85	0.90	0.89	0.88	0.82	0.82	0.79	0.82	0.83
R Square	0.73	0.72	0.80	0.79	0.77	0.66	0.67	0.63	0.67	0.69
Adjusted R Square	0.73	0.72	0.80	0.79	0.77	0.67	0.67	0.63	0.67	0.69
Standard Error	36.22	28.61	22.55	22.76	23.84	40.29	38.66	41.00	38.61	37.38
RMSQ	5.39	0.15	3.69	1.23	2.01	0.29	4.04	8.27	6.52	7.30

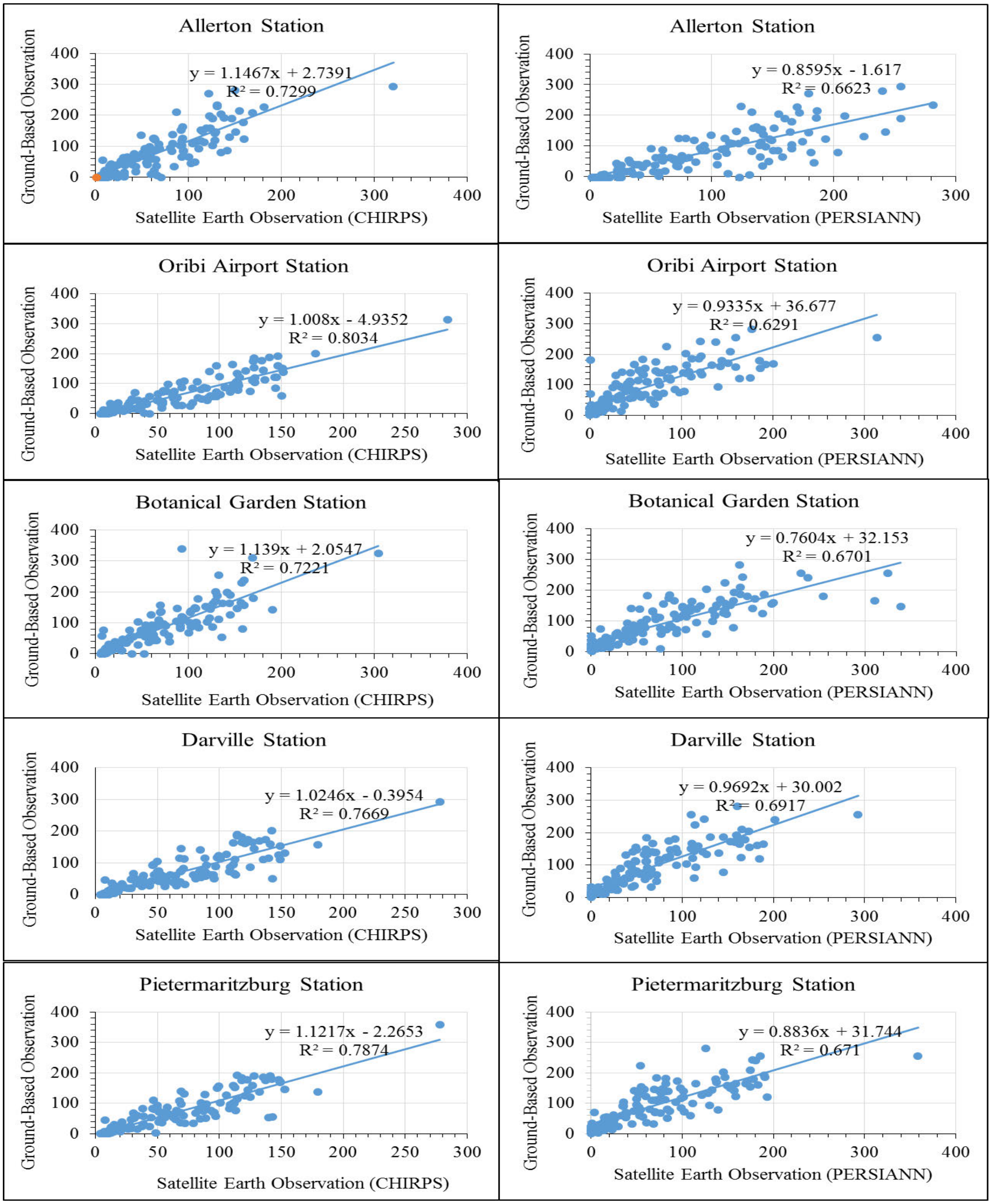

Figure 4.1: Regression graphs comparing ground-based rainfall (mm) data against the CHIRPS and PERSIANN-CDR satellite products, at five stations within the U20J sub-catchment

A paired T-test of sampled means was performed between the ground-based data and the SEO rainfall products (Table 4.2). Results from the CHIRPS dataset indicated that for the evaluations at the Allerton, Botanical Garden, PMB and Dareville stations there was negative t-test values of 3.99, -3.35, -2.18 and -0.55 respectively. This is indicative that the significant difference between the two datasets was small. However, the Mean values of the CHIRPS were lower, relative to the ground-based observations data, this potentially indicates that there is an under-estimation of CHIRPS values experienced. However, it is noticed that at Oribi Airport location there is a slightly greater Mean but a lower value of variance experience by the CHIRPS dataset, which may be a contributor to the positive t-test value of 1.98.

The T-test results performed between the PERSIANN-CDR product and the ground-based observation records indicated that all results were positive with the highest being 9.03, 8.52 and 6.87 at the Oribi Airport, Dareville and Pietermaritzburg stations respectively. Whilst at Allerton had a value of 3.91 and Botanical Garden was 3.49. These results were indicative that the significant difference between the datasets may be relatively small. The Mean value of PERSIANN-CDR data were further noted to be higher than that of the ground-based observation values. It can thus be deduced that the use of the rainfall estimations provided by the PERSIANN-CDR satellite product overestimates its values when compared to the ground-based records of rainfall. However it was also noted that the results produced by the PERSIAAN-CDR datasets had Mean and Standard Deviations values similar across all five selected stations (Table 4.2). Whereby, the Mean values were recorded at 93.01 and the standard deviation of the datasets had a value of 67.06. These similar values may have been accounted for by the course resolution of the satellite product.

The results produced by the statistical values are further supported by the time series graphs at all five stations shown in Figure 4.2, which depicts the monthly rainfall values and further shows the relationship between the ground-based observations, CHIRPS and PERSIANN-CDR datasets. The results from this indicate that overall at all five stations the PRESIANN-CDR values tend to be significantly overestimated as compared ground-based observation values. Whilst generally, on average across the five stations the CHIRPS rainfall product tends to have a slight underestimation of results in relation to the ground-based data. However, the CHIRPS results produced is seen to have a relatively stronger relationship with the ground-based observations than the PERSIANN-CDR dataset.

The results from the validation study points toward the CHIRPS datasets having a closer relationship of correlation with the ground-based data. Therefore, the CHIRPS product is recognized as a Satellite Earth Observation dataset that is able to provide adequate records of long-term rainfall estimations. Thus, following this section the use of the CHIRPS satellite-rainfall product will be the selected for further use in the calculations of the meteorological drought index Standardized Precipitation Index (SPI) and the agricultural drought index of the Standardized Precipitation Evapotranspiration Index (SPEI).

Table 4.2: Statistical and T-test results for the Ground-based observations, CHIRPS dataset and PERSIAAN-CDR dataset

	Rainfall Stations	Mean	Standard Deviation	Skewness	Minimum	Maximum	Paired T-test
Ground-Based Rainfall Observation	Allerton	79.08	70.51	0.93	0	295.4	
	Botanical Garden	80.03	72.19	1.15	0	339.3	
	Oribi Airport	60.34	56.98	1.27	0	314	
	PMB	69.34	62.17	1.19	0	358.8	
	Dareville	65.01	57.54	1.03	0	292.9	
CHIRPS Rainfall Product	Allerton	66.1	48.85	0.47	5.62	320.66	-3.99
	Botanical Garden	68.65	50.89	0.47	0	295.4	-3.35
	Oribi Airport	64.92	47.77	0.41	1.71	281.89	1.98
	PMB	63.89	45.97	0.4	5.94	304.18	-2.18
	Dareville	63.89	45.97	0.4	0	339.3	-0.55
PERSIANN-CDR Rainfall Product	Allerton	93.66	66.9	0.54	1.71	295.4	3.91
	Botanical Garden	93.66	66.9	0.54	1.71	281.89	3.49
	Oribi Airport	93.66	66.9	0.54	1.71	304.18	9.03
	PMB	93.66	66.9	0.54	1.71	339.3	6.87
	Dareville	93.66	66.9	0.54	1.71	281.89	8.52

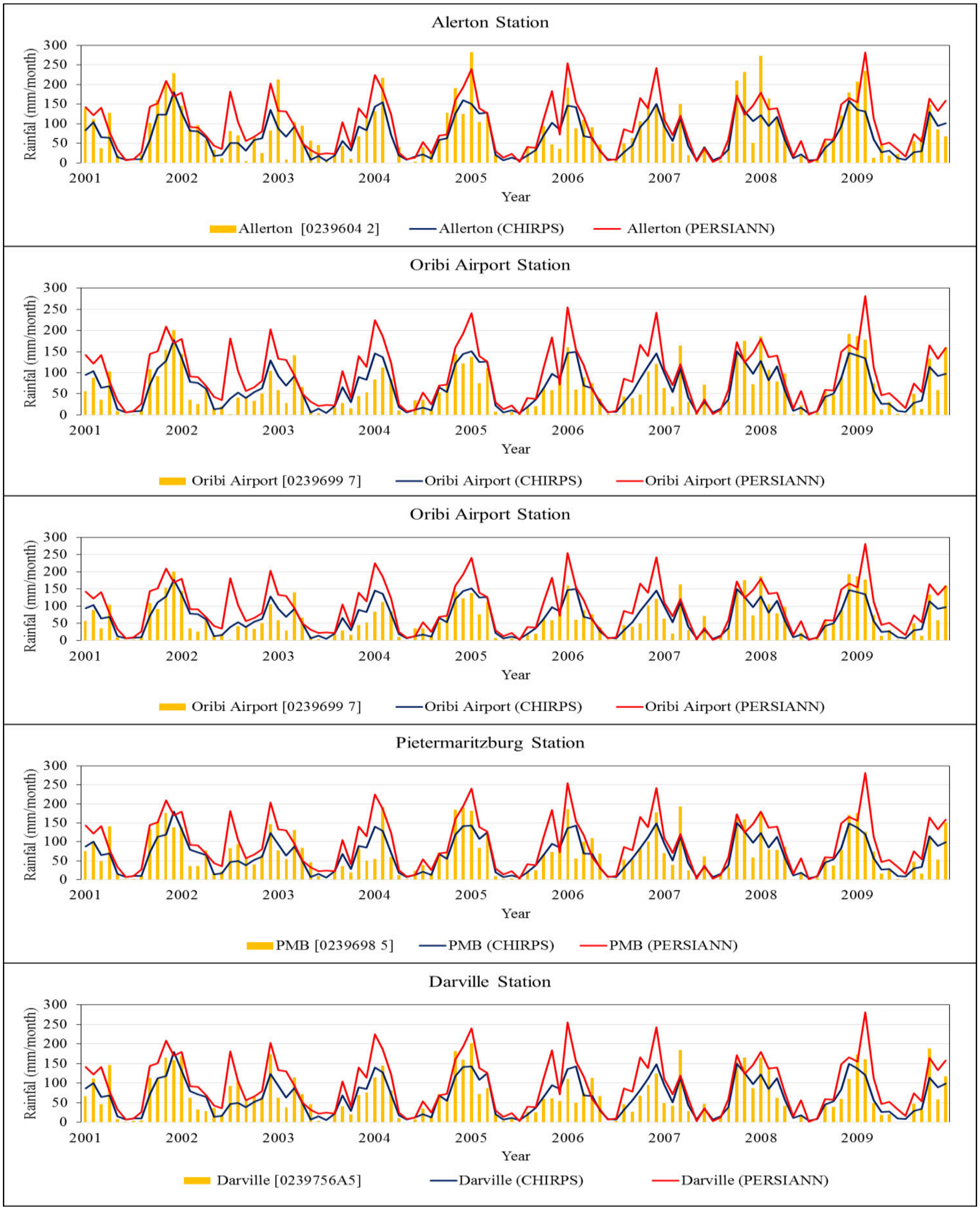

Figure 4.2: Time series graphs depicting the monthly ground-based observations, CHIRPS and PERSIANN-CDR rainfall results at the five selected rainfall validation stations, for an 8-year period from 2001 to 2009

4.2 Validation of Temperature Data

The second variable assessed for the validation component of the study was air temperature (Tmin and Tmax) data. The satellite product under assessment for this variable is the ERA5 Reanalysis product. The results of this variables statistical and cross-correlation is found in Table 4.3. The overall Pearson correlation (r) results from this product indicate that there is a very strong positive relationship between the observed and estimated Tmin and Tmax values. Whereby, both the Tmin and Tmax have 'r' values ranging between a minimum of 0.86 and a maximum of 0.97.

Results on the regression analysis between the ERA5 product and the ground-based observations are shown in Figure 4.3 and Table 4.3. The results on R^2 for this SEO product further supports the fact that there is a strong relationship between the observed and estimated Tmin and Tmax data as on average the R^2 range between 0.75 and 0.93 in value. It is further noted that the lowest 'r' and R^2 values were established to be from the Tmax results at the Hermanus station. Whilst, the other stations (Tmin and Tmax) have R^2 no less than 0.81 in value.

Results from the Root Mean Square Error (RMSE) in Table 4.3, showed that all five stations (Cape Agulhas, Struisbaai, Hermanus, Overberg and Grabouw) had a significantly low values of RMSE. Whereby the values ranged from a high of 0.12 (for the Tmin at the Overberg Station) to a low of 0.01 (for the Tmin at the Cape Agulhas Station). These low values of RMSE provide an indication that typically, there is a significantly small deviation found between the observed data and the predicted date of the ERA5 Reanalysis product. The results produced by the regression and cross-correlation analysis further support that the use of the ERA5 Reanalysis product is an adequate source in obtaining valid Tmin and Tmax data for a continuous long term records, and has the potential to be utilized as an input variable.

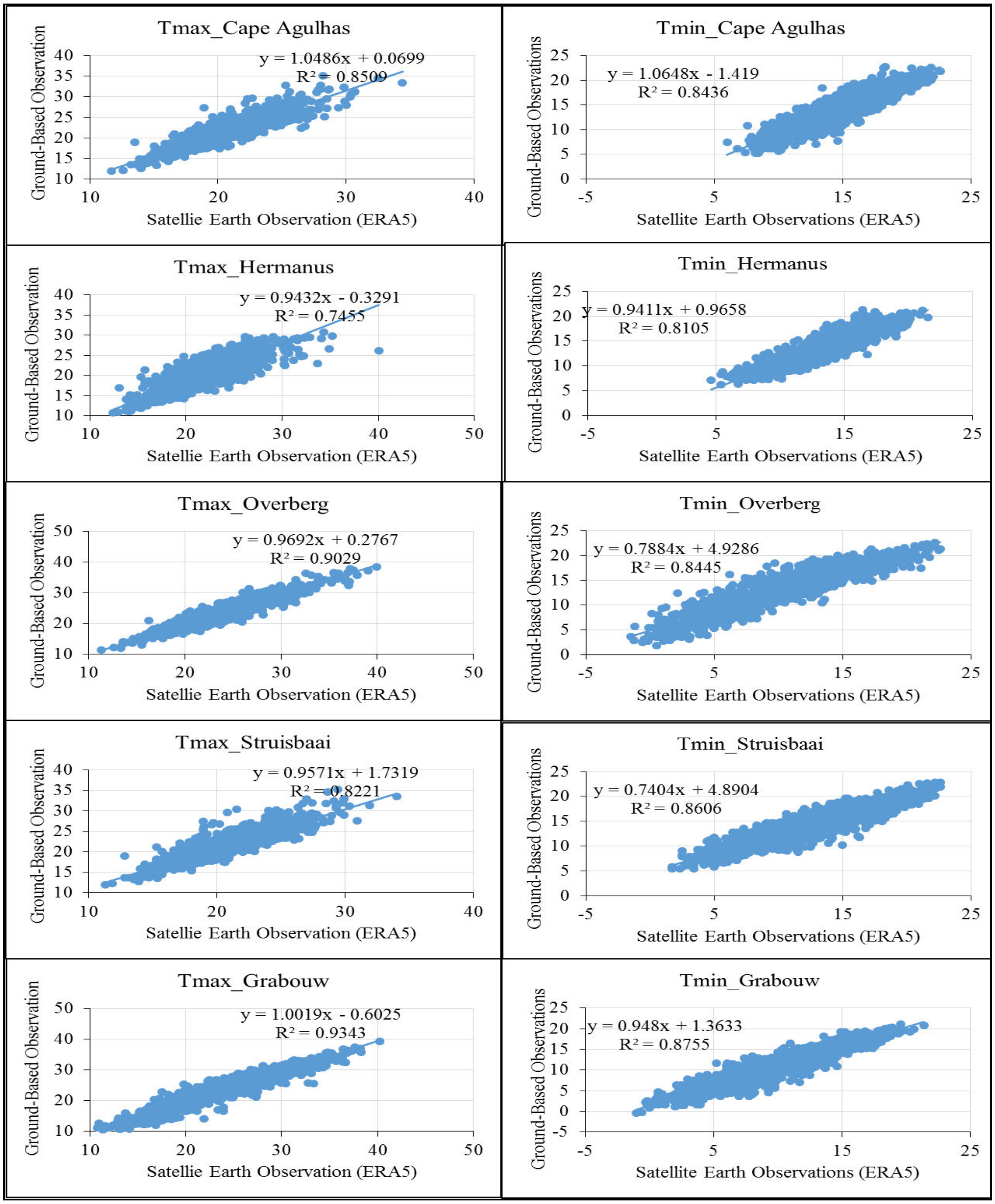

Figure 4.3: Regression graphs between the ground-based maximum and minimum air temperature (°C) observations and the ERA5 Reannalysis satellite product, from five stations within the G40 and G50 validation site

Table 4.3: Regression and cross-correlation results of the Tmin and Tmax data between the ERA5 Reanalysis Satellite product and the ground-based observations at five stations within the G40 and G50 sub-catchment

Temperature Data from the ERA5 Reanalysis Satellite Product										
	Minimum Statistic and Regression Analysis					Maximum Statistic and Regression Analysis				
Stations	**Cape Agulhas**	**Struisbaai**	**Hermanus**	**Overberg**	**Grabouw**	**Cape Agulhas**	**Struisbaai**	**Hermanus**	**Overberg**	**Grabouw**
Pearson Correlation	0.92	0.93	0.90	0.92	0.94	0.92	0.91	0.86	0.95	0.97
R Square	0.84	0.86	0.81	0.84	0.88	0.85	0.82	0.75	0.90	0.93
Adjusted R Square	0.84	0.86	0.81	0.84	0.88	0.85	0.82	0.75	0.90	0.93
Standard Error	1.24	1.70	1.26	1.95	1.48	1.16	1.37	1.75	1.27	1.42
RMSQ	0.01	0.03	0.02	0.12	0.03	0.03	0.02	0.06	0.03	0.05

The results for the T-test between the ERA5 Reanalysis product and the ground-based air temperature observation records are depicted by Table 4.4. The minimum air temperature results indicate that at four stations namely the Stuibaai, Hermanus, Overberg and Grabouw there were positive t-test values (13.49, 1.52, 25.66, and 10.38 respectively). These values of the t-test indicate that on average the significant difference between the two datasets was relatively small. The Mean values from the ground-based data were seen to be on average lower than that of the ERA5 data. This may further indicate that there is a slight overestimation of the minimum air temperature data from the ERA5 product. However, it was also noted that at the Cape Aguhlas station the Tmin values had a negative T-test of -4.99 in value.

For the maximum air temperature t-test analysis, results show that there is a positive relationship at the Cape Aguhlas (value of 16.41) and Stuibaai (value of 10.12) stations. Whilst, at the other stations namely, Hermanus, Overberg and Grabouw there was negative t-test values (-13.04, -4.71 and -5.48 respectively). The overall results from this indicates that there is a relatively small significant difference between the ground-based observations and the ERA5 datasets. However, from the Mean values at the ground-based observations there was on average greater values from the ground-based observations as compared to the ERA5 Reanalysis product. This is further indicative that there is a slight underestimation of the ERA5's Tmax results. Further supporting the results produces by the statistical analysis are the time series graphs of the five stations depicted by Figure 4.4 and Figure 4.5.

Overall from the regression and statistical analysis performed it can be deduced that the ERA5 Reanalysis Product is an adequate SEO product that can be utilized as input data for further drought calculations

Table 4.4: Statistical results and T-test result for the minimum and maximum air temperature data from ground-based observations and the ERA5 Reanalysis Product

Ground-Based Minimum Air Temperature						**Ground-Based Maximum Air Temperature**				
	Cape Agulhas	**Struisbaai**	**Hermanus**	**Overberg**	**Grabouw**	**Cape Agulhas**	**Struisbaai**	**Hermanus**	**Overberg**	**Grabouw**
Mean	15.13	13.23	13.72	10.68	10.31	20.90	21.17	21.33	24.19	23.02
Standard Deviation	3.13	4.54	2.89	4.94	4.18	3.01	3.24	3.46	4.06	5.52
Sample Variance	9.78	20.63	8.37	24.36	17.49	9.06	10.51	12.00	16.52	30.45
Skewness	-0.11	-0.23	-0.30	0.01	-0.20	0.13	0.04	0.52	0.18	0.27
Minimum	6.00	1.70	4.60	-1.50	-1.00	11.70	11.30	12.40	11.30	8.20
Maximum	22.60	22.89	22.60	22.89	21.50	34.40	34.00	40.06	39.90	40.20
	Minimum Statistic and Regression Analysis					**Maximum Statistic and Regression Analysis**				
	Cape Agulhas	**Struisbaai**	**Hermanus**	**Overberg**	**Grabouw**	**Cape Agulhas**	**Struisbaai**	**Hermanus**	**Overberg**	**Grabouw**
Mean	14.69	14.69	13.88	13.35	11.14	21.99	21.99	19.79	23.72	22.46
Standard Deviation	3.63	3.63	3.03	4.23	4.24	3.42	3.42	3.78	4.15	5.72
Sample Variance	13.14	13.14	9.15	17.93	17.96	11.71	11.71	14.32	17.19	32.72
Skewness	-0.22	-0.22	-0.06	-0.28	-0.16	0.13	0.13	0.14	0.15	0.12
Minimum	5.43	5.43	6.25	1.90	-0.35	12.03	12.03	9.69	11.47	8.04
Maximum	22.89	22.89	21.23	22.56	21.08	35.28	35.28	30.69	38.44	39.21
T-test Statistics	-4.99	13.49	1.52	25.66	10.38	16.41	10.12	-13.04	-4.71	-5.48

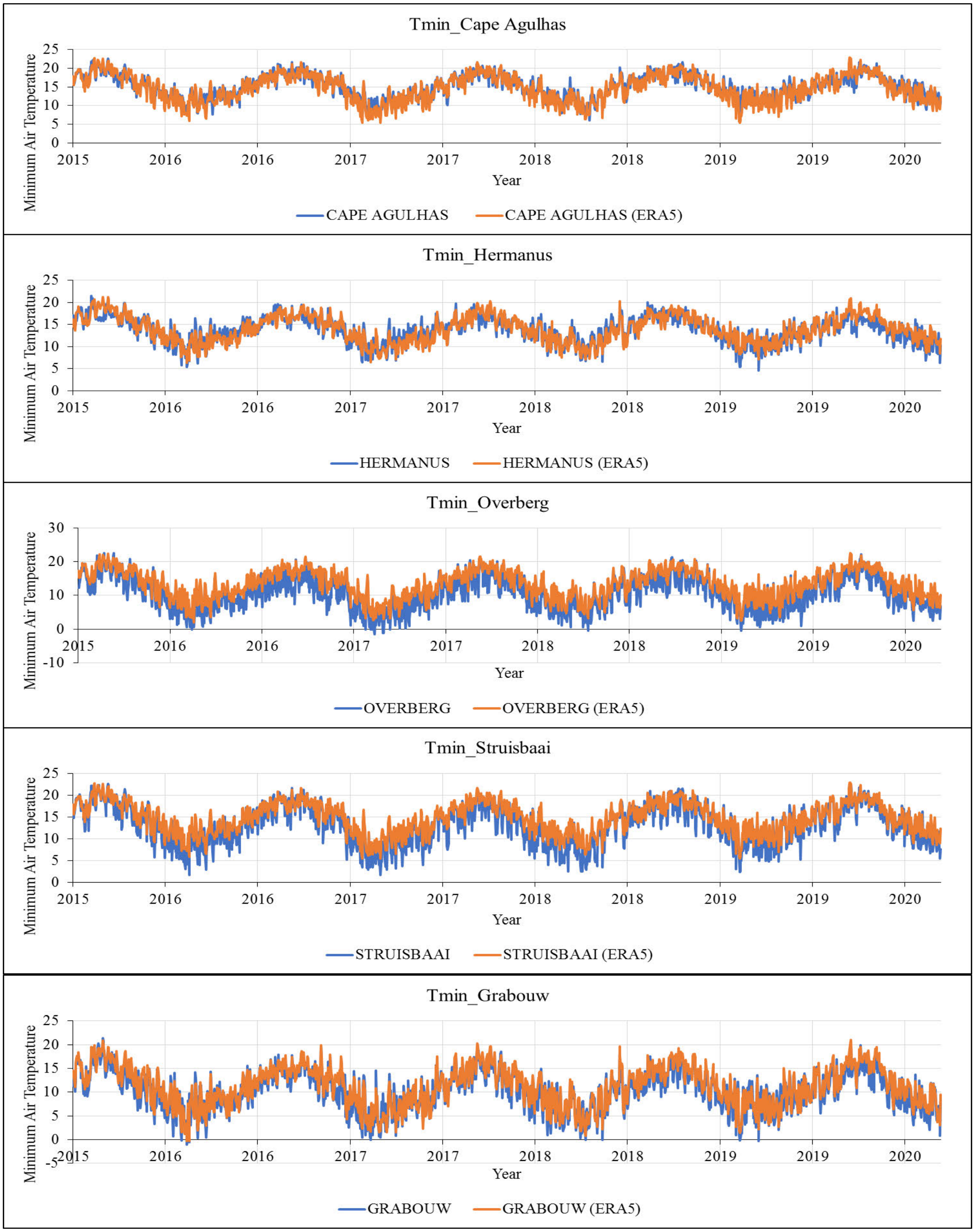

Figure 4.4: Time series graphs of the daily minimum air temperature data at the selected sites (G40 and G50 sub-catchments) for a 5 year period of 2015 to 2020

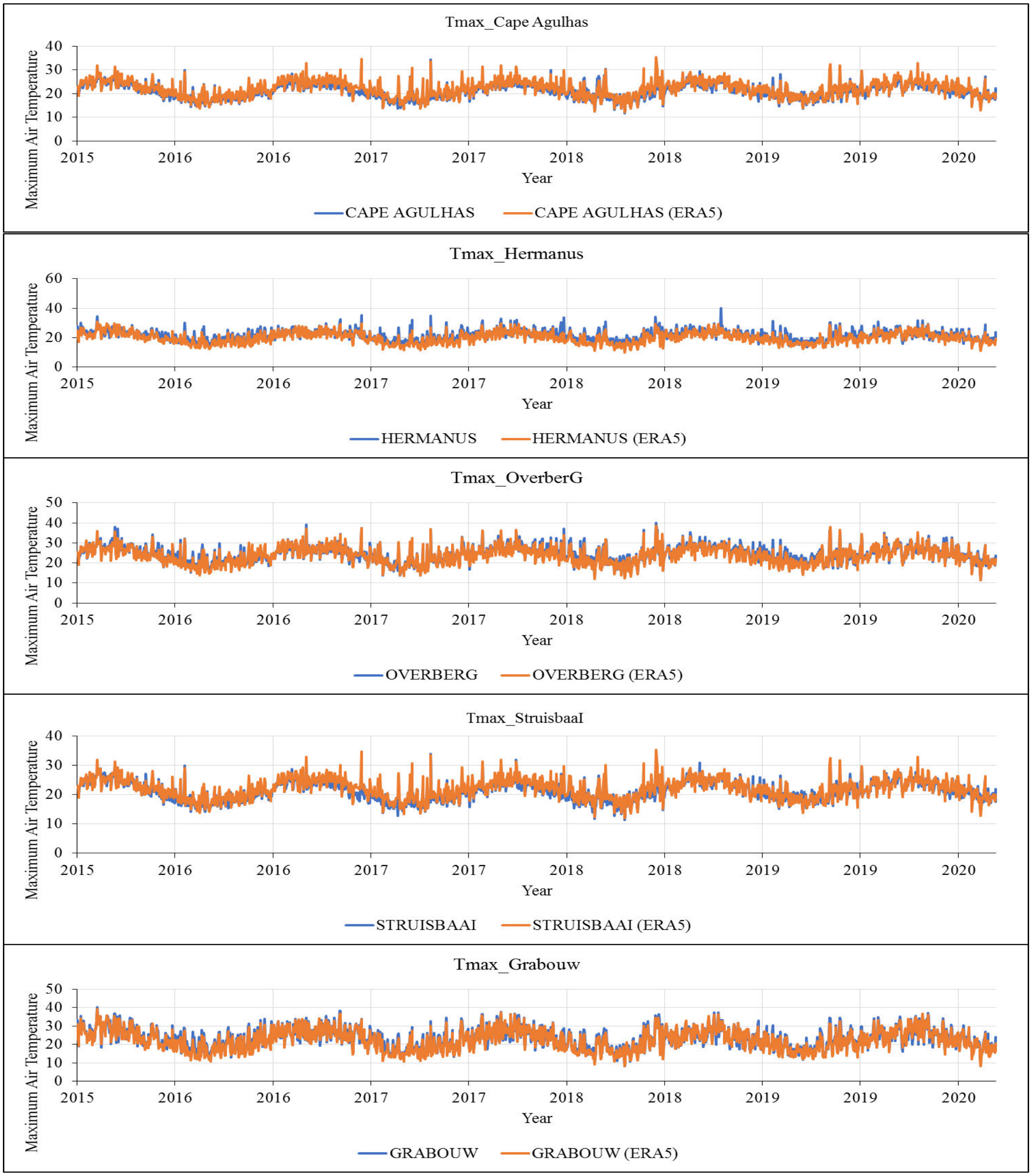

Figure 4.5: Time series graphs of the daily maximum air temperature data at the selected sites (G40 and G50 sub-catchments) for a 5 year period of 2015 to 2020

4.3 Temporal Assessment of Drought Characteristics using Standardized Approaches in the uMngeni Catchment

According to the World Meteorological Organization (2016) and Bijaber *et al.,* (2018), it was acknowledged that the SPI index, has the potential to indicate the characteristics of other drought types when calculated at different timescales. Whereby, shorter timescales (i.e. from 1 to 6 months) are able to detect meteorological and agricultural drought conditions, whilst longer SPI timescales (9 to 36 months) may provide an indication of precipitation anomalies associated with hydrological droughts. It is noted that for the purpose of this research project hydrological drought is not assessed further in detail. However, in order to assess meteorological and agricultural drought conditions SPI at 3-month (SPI-3) and 6-month (SPI-6) timescales were selected for assessed further. According to Table 4.5, it is acknowledged that if SPI values are -1 or lower, a drought event is taking place. Owing to this -1 is set as the drought line indicator for the SPI and SPEI results.

Table 4.5: Classification for the Standardized Precipitation Evapotranspiration Index (SPEI) values (McKee *et al.,* 1993; Vicento-Serrano *et al.,* 2010)

SPI / SPEI VALUE	DROUGHT CATEGORY
≥ 2	Extreme Wet
1.5 to 1.99	Severe Wet
1 .0 to 1.45	Moderate Wet
-0.99 to 0.99	Normal
-1.0 to 1.49	Moderate Drought
-1.5 to -1.99	Severe Drought
≤ -2	Extreme Drought

From Figure 4.6 and Figure 4.7, it is apparent that during the 20 year period, there were four major drought events that occurred within the uMngeni catchment at a 3-month and 6-month timescale. These drought events were recognized to have occurred during 2011-2012, 2014, 2015-2016 and 2019-2020. Findings of the SPI-3 assessment, (Figure 4.6), further noted that the moderate droughts events (values of -1.0 to 1.49) typically occurs for a period of approximately one to three months. Whilst the duration of severe drought events (values of -1.5 to -1.99) tended to occur for a period of approximately one to two months. In the 2011-2012 drought event the SPI-3 results indicated that there was a moderate event that occurs over a period of 2 months which then developed into a severe drought lasting for one month before the event recovered slightly back to a moderate drought in the following two months. The results SPI-3 also indicated that the most extreme drought events occurred in 2015-2016 and 2019, with the SPI-3 values from these years reaching values lower than -2. These extreme events in this catchment were seen to last for a period of approximately one to two months before the drought event slightly recovers to a moderate and/or severe drought event.

Further supporting the results of SPI were, studies conducted by Blamey *et al.*, (2018), Ndlovu and Demlie, (2020), whereby these studies were able to adequately detect the occurrence of meteorological drought conditions similar to the results produced in this study. It was further noted that in both studies the 2015-2016 drought event (during the austral summer months) was identified as a significant drought event in the Kwa Zulu-Natal province region. Therefore, from the results produces in this research project, it can be deduced that the SPI is an effective index to quantify meteorological drought characteristics, especially at a 3-month timescale. This index further indicates that it is able to provide a representation of the average rainfall distribution and variability experienced in the catchment.

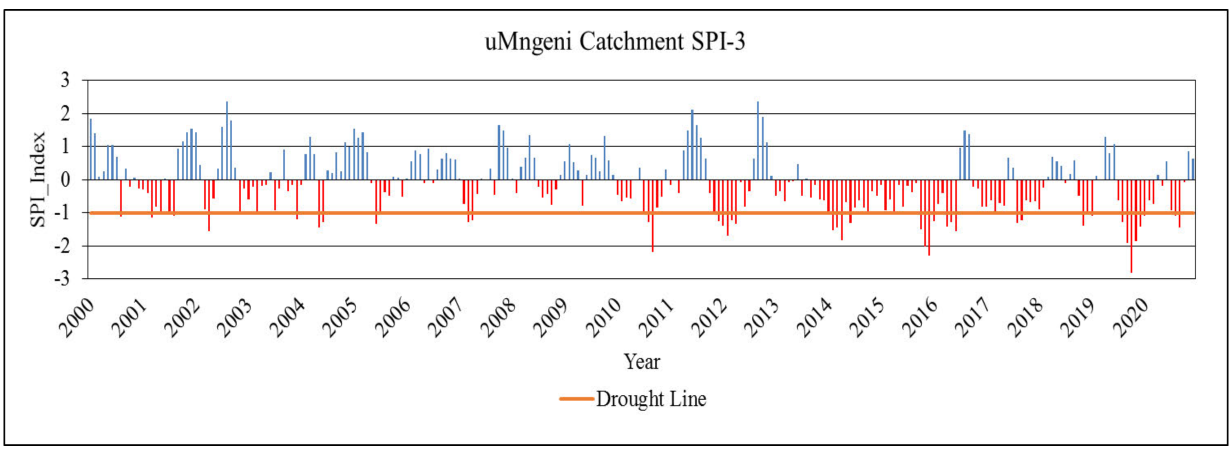

Figure 4.6: Standard Precipitation Index (SPI) results across the uMngeni Catchment at a 3-month timescale (SPI-3), for a 20-year period (2000 to 2020)

The results from Figure 4.7, shows that the typically at a slightly longer timescale (i.e. 6-months) the severity and duration of droughts had slightly increased to depict more moderate to severe drought events, especially for the years 2012, 2014 and 2016. However, it was also noted that at

2019 there were slightly lower values of SPI-6 as compared to the initial assessment of SPI-3. The duration of the 2012 and 2019-2020 drought period it was apparent at the SPI-6 timescale was also seen to have a lagging period of two months as compared to SPI-3 timescales.

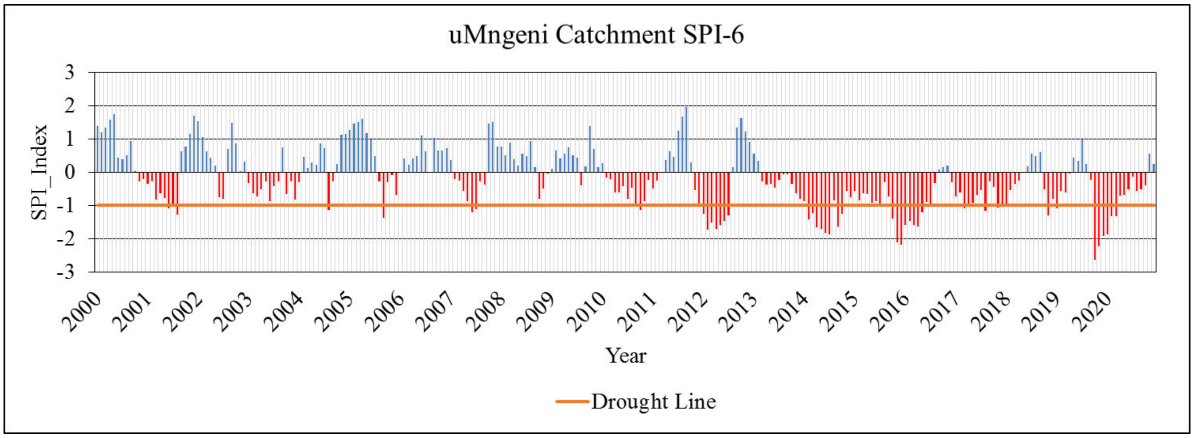

Figure 4.7: Standard Precipitation Index (SPI) results across the uMngeni Catchment at a 6-month timescale (SPI-6), for a 20-year period (2000 to 2020)

The Standard Precipitation Evapotranspiration Index (SPEI) was selected the second drought index for evaluation. This is an index similar to SPI in the sense that it is able to detect drought through a multi-scalar standardized approach. However, SPEI takes into account the climatic water balance and is thus, able to evaluate both meteorological drought, agricultural drought (Begueria *et al.*, 2014). Similarly to SPI, the analyses of SPEI was performed on a 3-month (SPEI-3) and 6-month (SPEI-6) timescale across the uMngeni Catchment, as shown in Figure 4.8 and Figure 4.9 respectively.

The results from the SPEI-3 timescale (Figure 4.8), indicates that the agricultural drought events at a 3-month timescale typically occur for a period of 1 to 7 months. The most extreme drought event was seen to have taken place in 2015 for the month of December (-2.09), and in 2019 for the months of August (-2.12) and October (-2.41). The longest duration of agricultural drought took place in 2011-2012 which lasted for a period of 6 months, and in 2019-2020 which lasted for a period of 7 months. One of the apparent trends found from this analysis was that moderate drought events takes place for approximately one to three months, if the precipitation deficit persist conditions can potentially increase to a severe drought event, which lasts for approximately one month before the drought event can begin to recover back to a moderate drought event. However, in the case of the extreme drought events, such as for the 2015-2016 and 2019-2020 drought event, the trend observed indicated that if water deficits and anomalies persist during the occurrence of severe droughts event, there is potential for the onset of extreme drought event to occur. Typically these extreme drought events last for a period of one to two months.

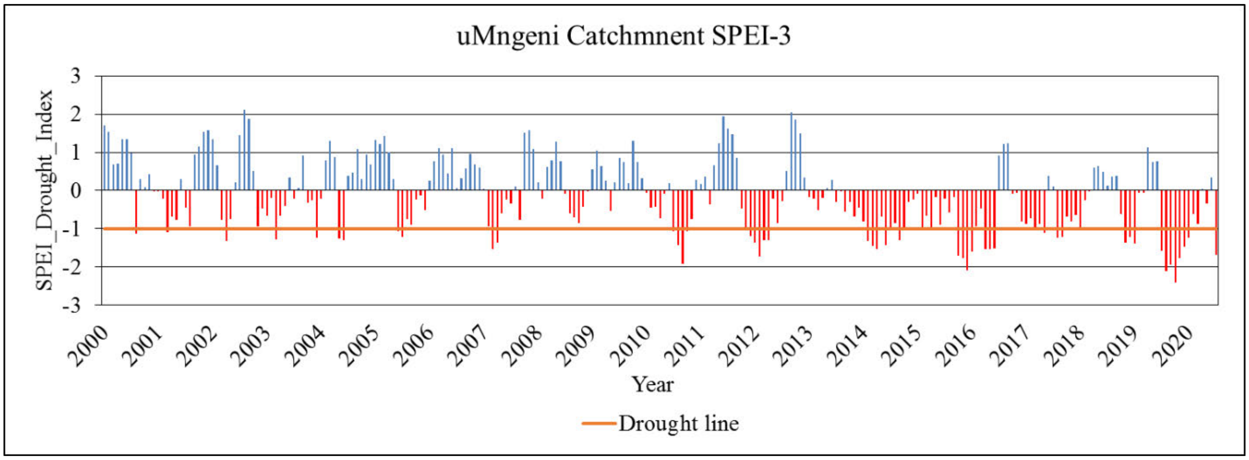

Figure 4.8: Standard Precipitation Evapotranspiration Index (SPEI) results across the uMngeni Catchment at a 3-month time scale, for a 20-year period (2000 to 2020)

From the SPEI-6 analysis as shown in Figure 4.9, it was noted that the moderate and severe agricultural droughts events typically become slightly more intensive and occur at an increased duration as compared to the results produced by SPEI-3 (Figure 4.8). Whereby the longest drought event at a SPEI-6 interval occur in 2015-2016 (for 10 months), 2012 (for 7 months), and 2014 (for 6 months). The most extreme event is recognized to occur in 2019 for the month of October with a SPEI value of -2.12. It is noted that there was a slight decrease in the intensity of the SPEI-6 extreme drought event as compared to SPEI-3. The results presented also indicate that in 2010, 2012 and 2019-2020 there is a lagging period of 2 to 3 months.

Whilst in 2014 and 2015-2016 results indicated that no lagging period was experienced, however, it was recognized that there was an increase in the duration of the drought event by approximately one to two months. Similar results of agricultural drought conditions in this region was found in the conducted by Adisa *et al.*, (2021). Furthermore, articles by The Witness (2015), further describing the impacts agricultural drought had on the livestock and crop yield production during 2015-2016.

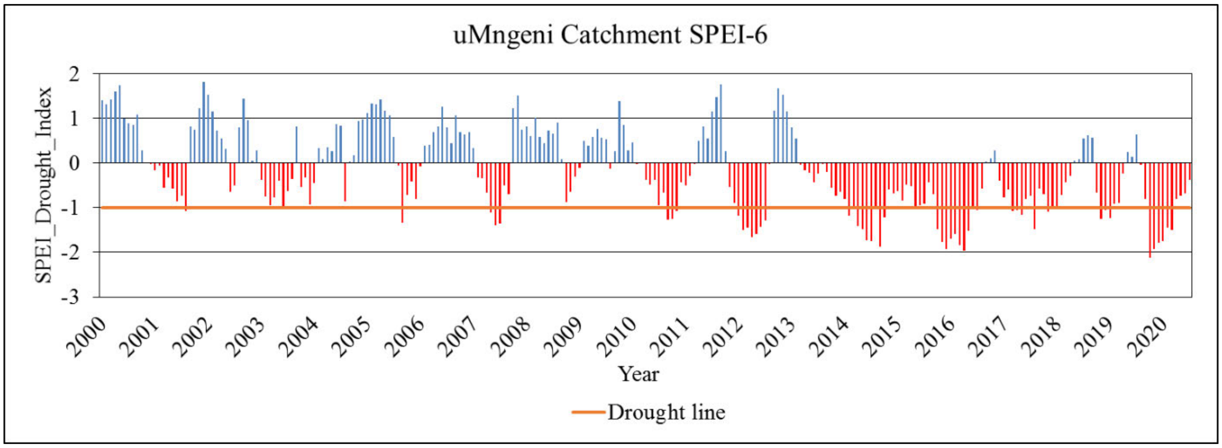

Figure 4.9: Standard Precipitation Evapotranspiration Index (SPEI) results across the uMngeni Catchment at a 6-month time scale, for a 20-year period (2000 to 2020)

A comparative assessment was conducted, for a 10 year period (2010 to 2020), in order to determine the applicability of SPI and SPEI in determining agricultural drought characteristics (Figure 4.10). Results indicate that in 2010, 2012 and 2019 typically the SPI-6 results were able to detect the agricultural drought conditions however, during these drought years there was a lagged response time in the events onset for a period of approximately two to three months as compared to the SPEI-3 results at these years. Overall the results produced from this assessment indicates that on average the SPI-6 results tend to have a better relationship with the SPEI-6 values as compared to the SPEI-3 values. With the SPI-6 values only slightly overestimating its values in comparison with the SPEI-6 values throughout the entire selected record period. This overestimation may be accounted for by the fact that SPI only incorporates rainfall data and does not take into consideration other processes such as the climatic water balance. Overall the comparison indicates that SPEI-3 timescales may be more sensitive to changes in drought as the onset period is shown to be detected earlier than that of the SPI-6 and SPEI-6 timescales.

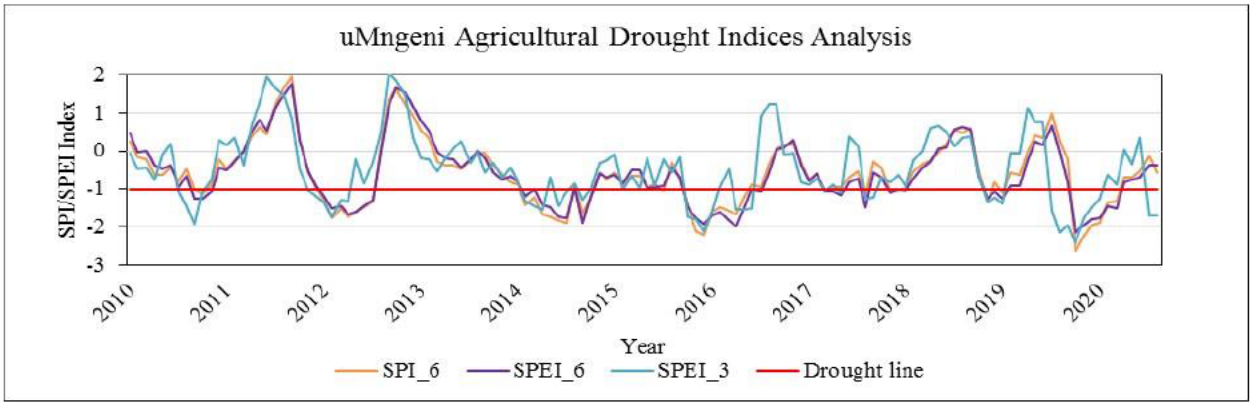

Figure 4.10: Comparative temporal assessment between SPEI-3, SPEI-6 and SPI-6, across the uMngeni Catchment for a 10-year period

4.4 Temporal Assessment of Agricultural Drought Indices in the uMngeni Catchment

For the Satellite-based Agricultural drought assessment, a time-series graph as depicted by Figure 4.11, was created in order to show the results of the average temporal extent of averaged VCI, TCI and VHI across the uMngeni catchment. Typically according to the classification system by Kogan, (1996) (Table 4.6), a light drought event occurs if VHI values are below 40 and the severity of this is likely to increase when values are below 30. Therefore, for the purpose of this study a drought line threshold of VHI was identified to be set at a value of 40.

Table 4.6: Classification System for Vegetation Condition Index, Temperature Condition Index and the Vegetation Health Index (Kogan, 1996)

Vegetation Condition Index/ Temperature Condition Index/ Vegetation Health Index Classification	
Value	**Category**
> 40	No Drought
30 – 40	Light Drought
20 – 30	Moderate Drought
10 – 20	Severe Drought
0 – 10	Extreme Drought

The results from Figure 4.11, show that there is an inverse relationship found between the VCI and TCI average values. The most severe decrease of the VCI component, below the drought threshold is seen to be during the winter months. It should be noted that the NDVI values used to calculate VCI, are subjected to the density of vegetation growth of an area during particular seasons. Owing to this, the summer months in this region may have more favorable climatic conditions to facilitate the growth of vegetation in the area.

With regards to the TCI experienced in the uMngeni catchment, it is apparent that during the summer months there are lower average values of TCI experienced and higher average TCI during winter. Typically in this area temperature conditions tend to be much cooler and dryer in winter, with lower temperatures being experienced, it may thus be deduces that owing to the lower temperatures the likelihood for evapotranspiration may not be as high, as it would be during the summer months

Results of the averaged VHI from Figure 4.11, further indicate that on average the catchment does not experience any severe drought event for the entire 20 year record period. The VHI values are typically lower during the winter months in this catchment, with the lowest being recorded at a value of 31. Even though most of the averaged VHI values do not fall below the threshold drought line, the years seen to have experienced light drought events are identified as 2000, 2010, 2014, 2015 and 2019. These results of the averaged VHI calculation further indicate that the drought events last for a period of 1 to 3 months.

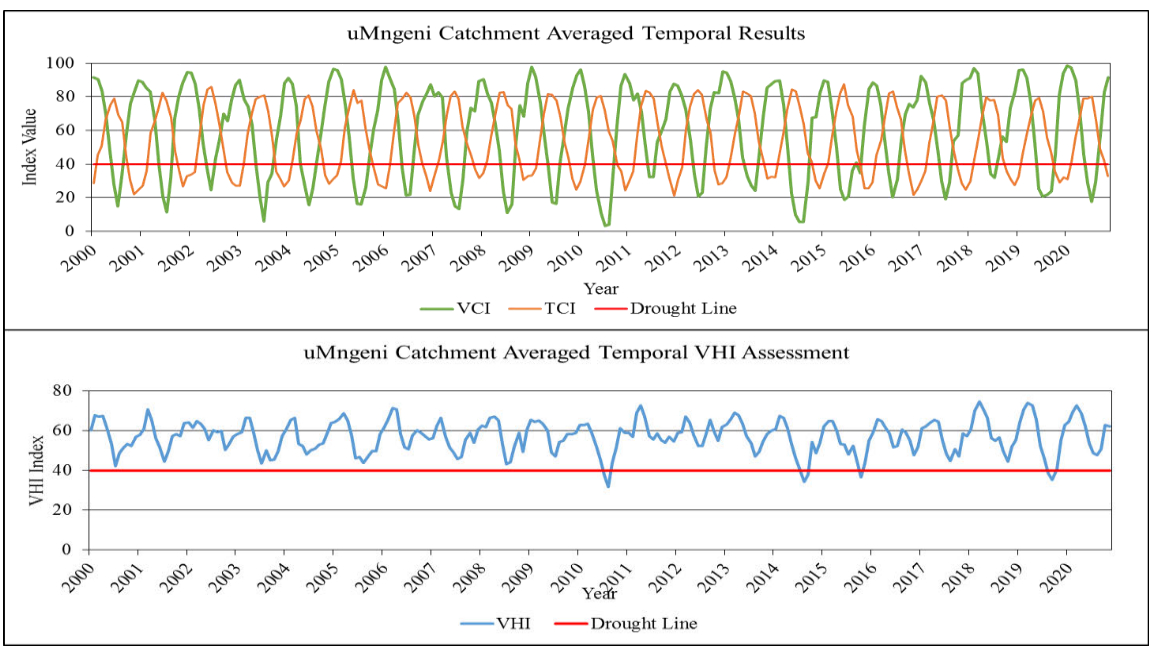

Figure 4.11: Agricultural drought assessment results on the averaged components VCI, TC and VHI across the uMngeni Catchment

From the comparative analysis between the SPEI-3, SPEI-6 and VHI (Figure 4.12), the findings indicate that on average the VHI results tends to be highly underestimated as compared to the results from SPEI-6. In the cases of the drought events that occurred in 2012, 2015-2016 and in 2019 the results of the SPEI-6 indicated that during these drought years, there were moderate-to-extreme agricultural drought events that occurred and lasted for a duration of 6 to 10 months. Whilst for SPEI-3 it was notes that the duration of the drought had a relatively shorter duration, greater intensity, and an earlier onset of the drought. For the same drought years the results from the averaged VHI assessment indicated that there was light agricultural drought events taking place, with VHI ranging between 31.75 and 38.76 in value. The averaged VHI assessment during these years further indicated that the drought events only lasted for a period of one to two months in length.

Supporting the agricultural drought finding for the 2019 drought event identified in this study, was a media release statement by The South African Weather Services. This statement reported on the state of drought for the summer of 2019, whereby it was acknowledged that during this period there was already low levels of soil moisture available to support the production of crops, the persistence of these water deficits have further led to the development and impacts of agricultural droughts.

For the drought event that occurred in 2010, the averaged VHI assessment identified a light drought event which occurred for two months in August (at a value of 37.54) and September (at a value of 31.75). However, for the same 2010 drought event the SPEI-6 results indicated that a moderate-drought event took place over a period of four months from July to October. And SPEI-3 identified the drought even as a severe drought event.

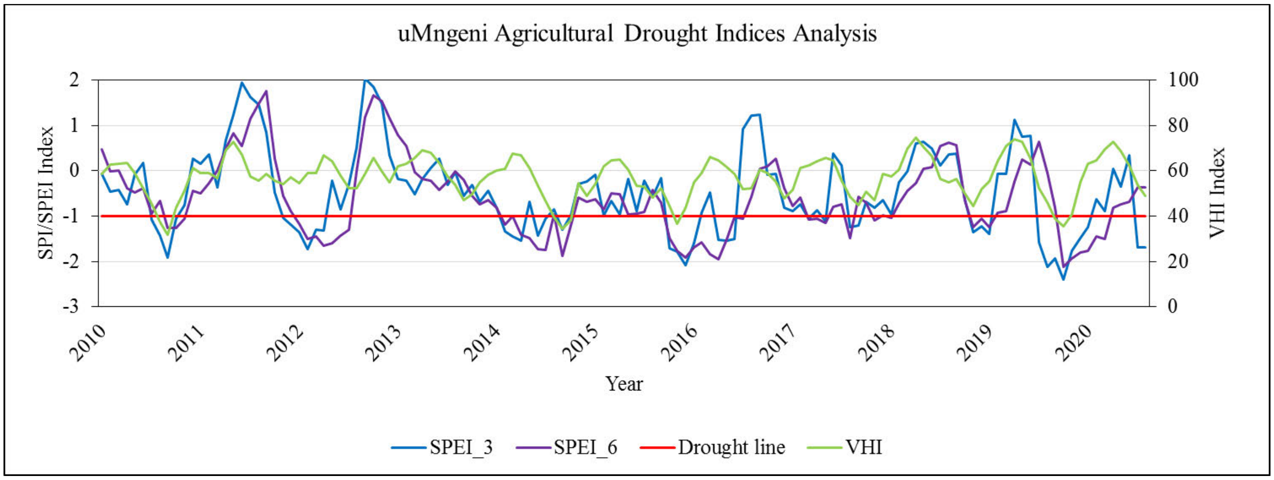

Figure 4.12: Comparative temporal assessment between SPEI-3, SPEI-6 and the averaged VHI, across the uMngeni Catchment for a 10-year period

Overall from the agricultural drought assessment it should be noted that the VHI results were calculated based on catchment averages and may not be a true representation of the conditions occurring at a more localized level. Therefore, a spatial assessment of VHI was conducted in order to better represent the conditions of agricultural drought occurring in this region.

4.5 Spatial Assessment of Agricultural Drought in the uMngeni Catchment

A spatial assessment was conducted at the uMngeni Catchment study site using the satellite-derived drought index VHI. This analysis was done in order to assess the spatial extent of agricultural drought as it appears across the catchment. It is important to note that the results indicated by this spatial assessment showed the average VHI values per pixel/month, across the entire study site.

This assessment was carried out for a wet year of 2012-2013 (Figure 4.13) and a dry year of 2015-2016 (Figure 4.14). The selection of the wet and dry periods was made based on the results of the SPI and SPEI from this study. Further supporting the selection of the dry periods was the study by Blamey *et al.*, (2018). Whilst a study by Olanrewaju and Reddy (2022), identified the year 2012 as one of the wettest periods experienced in this region.

For the spatial assessment of the wet year (Figure 4.13), trends were observed whereby, during the months September, October and November of 2012 the results indicate that the eastern-most part of the catchment experienced VHI values above 40 (as indicated by the yellow-to green color on the Figure 4.13). Thus, indicating that there are wetter conditions experienced on the eastern portion of the catchment as compared to that of the central and western part of the catchment. The results from Figure 4.13 further indicates that even though the selected period was for a wet-year, the occurrence of drought events was still evident, especially on the western part of the catchment. During September to November 2012 the western and central part of the catchment is recognized to experience light-to moderate drought events.

However, from December 2012 to April 2013 the results show that at certain sections of western part of the catchment there is a slight recovery period of the drought events, as its intensity is seen to have been reduced and more yellow to green patches are seen on this portion of the catchment. However, this recovery period is not the case for the entire catchment, as it is apparent that the occurrence of drought events becomes more intensified along to central parts of the catchment with moderate to severe conditions experienced (as indicated by the orange to red patches) during these months. There are also patterns that indicate that the drought events spread along to the eastern part of the catchment during this period. With the conditions at the eastern part of the catchment ranging from a moderate to severe drought event.

During the months of May and June 2013 it is recognizes that the drought events at the eastern most part of the catchment had recovered from the drought events from the previous months (as indicated by the green to yellow color on Figure 4.13). However it is noted that light to severe drought events conditions are experienced at a wider spatial extent along the western part of the catchment.

For the spatial assessment of the selected dry year 2015-2016 (Figure 4.14), it is apparent that, in the months of September, October and November and December 2015, there is a greater extent and severity of the drought conditions experienced along the central portion of the catchment, with moderate to extreme events occurring. Further supporting the results that an extreme event occurred in December 2015, was the SPEI-3 values obtained within this study (refer to Figure 4.8).

during this period it is also recognized that light to moderate drought events occur along the western and eastern most parts of the catchment (as indicated by the light orange color).

For the selected dry period, it is noted that during the months of January to April 2016 (Figure 4.14) moderate to extreme droughts occur especially along the central and lower portions of the catchment. Similar to the trends experienced in the wet year, it is acknowledged that during these months the eastern most tip of the catchment experiences a significantly greater intensity of drought conditions, with this section of the catchment experiencing severe-to-extreme drought conditions. During the months of May and June 2016, the spatial assessment of agricultural drought indicate that the intensity of droughts have recovered slightly. However, during these two months it is apparent that in the uMngeni catchment there is light conditions of drought experienced along the central and eastern part of the catchment, whilst the western part of the catchment experiences moderate drought conditions.

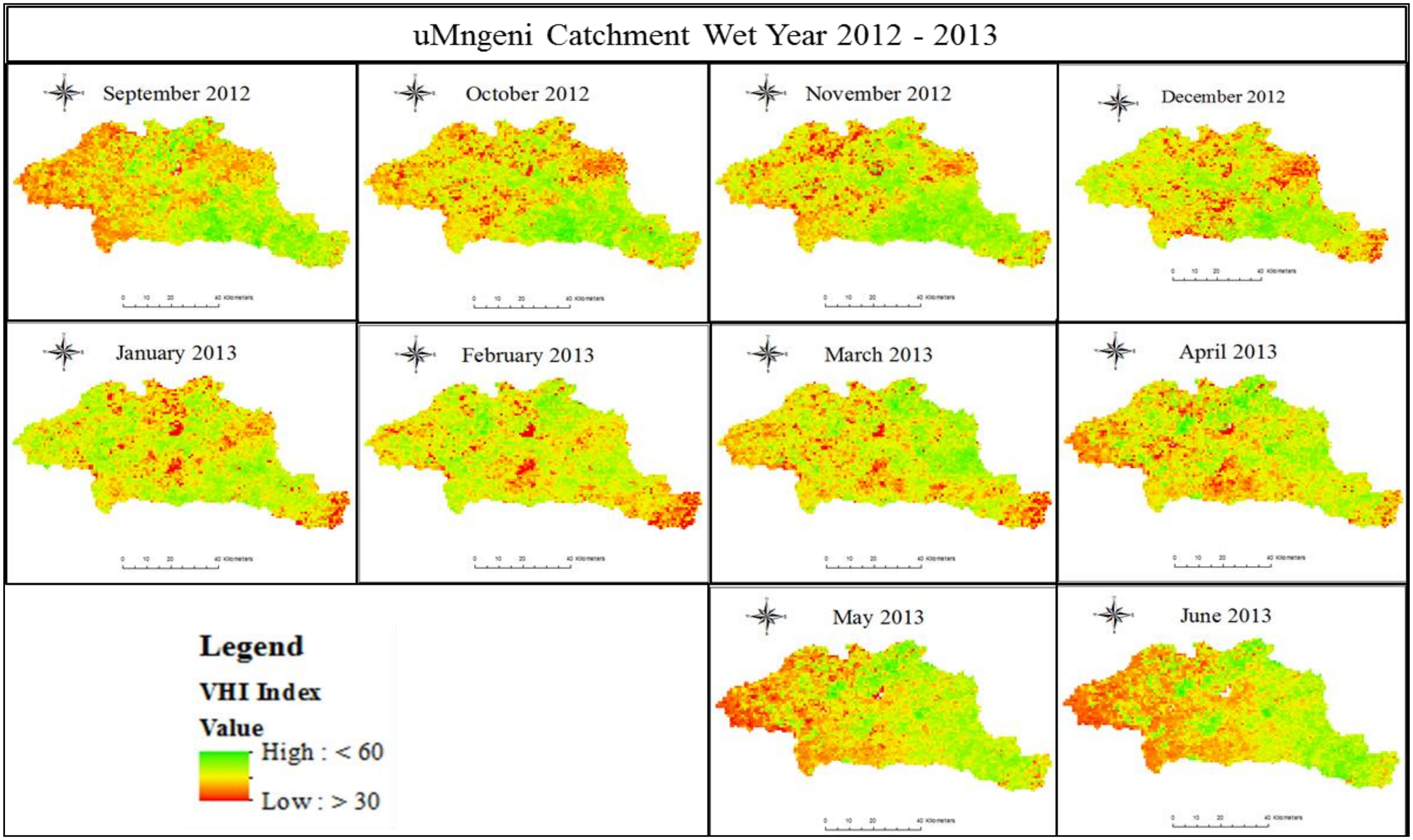

Figure 4.13: Spatial assessment of agricultural drought using the Vegetation Health Index (VHI) across the uMngeni Catchment, for the selected wet year (2012-2013)

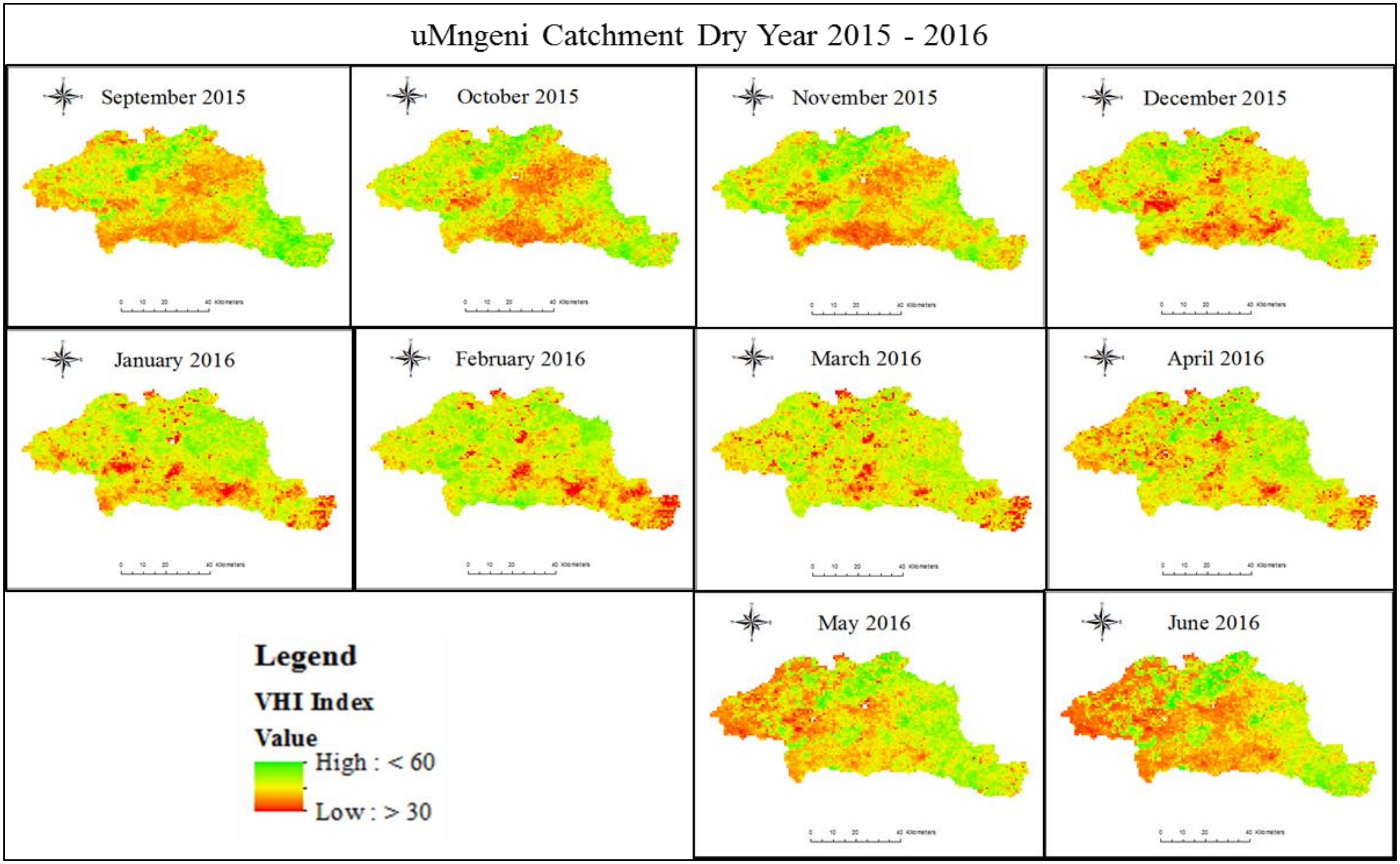

Figure 4.14: Spatial assessment of agricultural drought using the Vegetation Health Index (VHI) across the uMngeni Catchment, for the selected dry year (2015 – 2016)

4.6 Temporal Assessment of Drought Characteristics using Standardized Approaches in the Breede-Overberg Catchment

For the meteorological drought assessment within the Breede-Overberg Catchment, similar to Section 4.3, SPI was determined for a 3-month (SPI-3) and 6-month (SPI-6) timescale. The Breede-Overberg area is recognized as a region which experienced significant variability with regards to rainfall distribution and occurrence. Therefore, it is assumed that the occurrence of drought and its impacts are also variable.

From the results of SPI-3 calculations (Figure 4.15) it is apparent that the most extreme event of drought took place in 2003, with its value reaching below -3. It is also noted that other extreme events of drought took place in 2016 for the month of December (at a value of -2.01) and in 2017 for the months of May (at a value of -2.43) and July (with a value of -2.00). Typically, these extreme drought events had a duration lasting for around one month. Other noticeable drought event that occurred at a SPI-3 timescale, in this catchment was during 2000, 2003, 2010, 2011, 2017-2018.

The results from this timescale identified that the longest duration of drought occurred in 2017-2018, which lasted for a period of 12 months. This 2017-2018 drought event was recognized to have a mixed intensity level with moderate, severe and extreme values. In 2000 results indicated that there was a drought event that lasted for a period of 5 months (April to August), which had an intensity starting as a moderate drought of two months and further developed into an extreme event (lasting one month) before the drought recovered into a severe event (lasting two months).

From the results on the assessment of SPI-6 in the Breede-Overberg Catchment (Figure 4.16) one of the noticeable difference seen was that the 2003 drought event experienced a significant reduction in intensity, whereby, it was identified to be a moderate drought event. In 2000, 2010, 2011-2012 and 2015 the drought events were recognized to have an increased duration of approximately one to four months. However, this was not the case for the 2017 drought event, whereby the SPI-6 values indicate that an extreme drought event had an estimated duration that did not increase but rather remained at 12 months, however its intensity of event had significantly increased, with the values ranging from approximately -2.27 to -2.86. It was noted that typically there was a lagging period of one to two months between the SPI-6 and SPI-3 results. Overall from the analysis of SPI it is apparent that at a 3-month timescale there is a greater sensitivity of the index to determining the magnitude of meteorological drought events as compared to the SPI at a 6-month timescale.

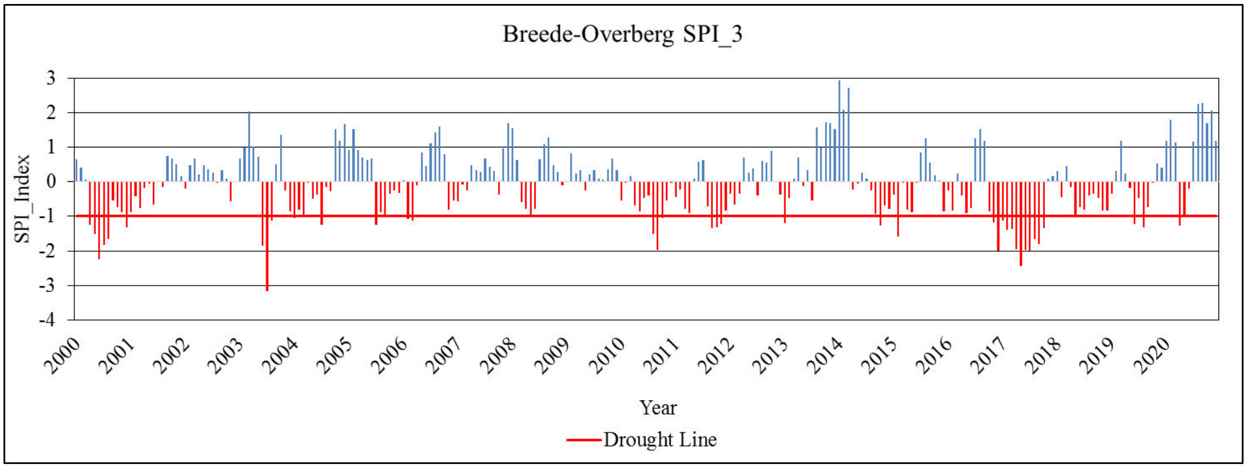

Figure 4.15: Standard Precipitation Index (SPI) results across the Breede-Overberg Catchment at a 3-month timescale, for a 20-year period (2000 to 2020)

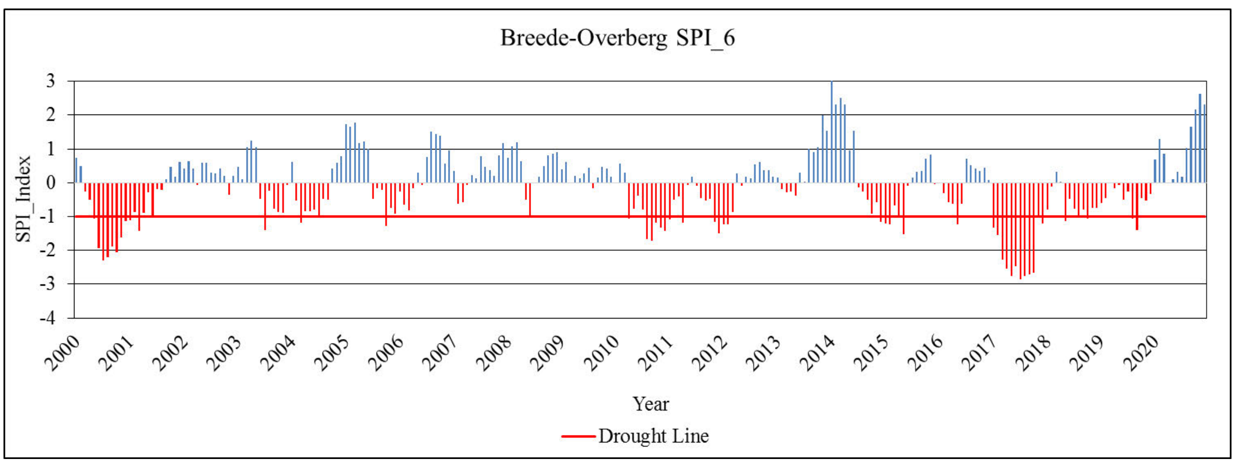

Figure 4.16: Standard Precipitation Index (SPI) results across the Breede-Overberg Catchment at a 6-month timescale, for a 20-year period (2000 to 2020)

Results of the SPEI assessment at a 3-month timescale (SPEI-3) is shown in Figure 4.17. The results indicate that the most significant agricultural drought occurs in the years 2016-2017 with the duration of this event lasting for a period of 13 months. This drought period consisted of extreme drought conditions, ranging from SPEI values of -2.34 and -3.10, it is also noted that the extreme drought event persisted for a period of 6 months (January to June) before it recovers to a severe drought state. Other identified agricultural drought years were 2000, 2003, 2015-2016 and 2018, the results from these years had drought periods that occurred for a period of 1 to 3 months and ranged from severe to moderate drought conditions.

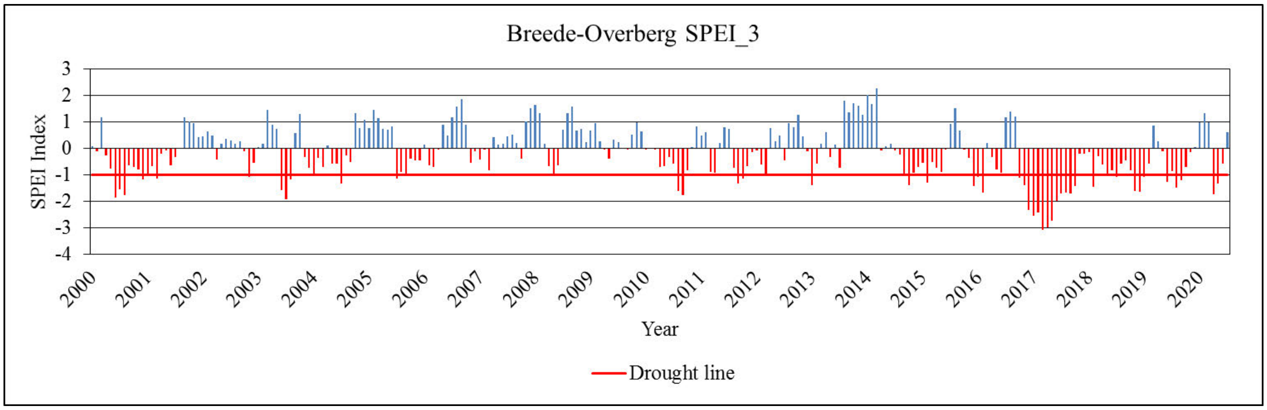

Figure 4.17: Standard Precipitation Evapotranspiration Index (SPEI) results across the Breede-Overberg Catchment at a 3-month time scale, for a 20-year period (2000 to 2020)

For the SPEI-6 assessment (as shown in Figure 4.18), the results produced indicated that there were several moderate drought events that occurred within the Breede-Overberg catchment, of which were for the years 2014-2015, 2016, 2018-2019 and lasted for a duration of three to six months. The results from the SPEI-6 analysis also indicated that there were two significant agricultural drought events that occurred in this catchment namely, for the years 2000-2001 and for 2017. The 2000-2001 drought event at a SPEI-6 timescale was recognized to last for a duration of 8 months. The results further indicate that for this event the conditions experienced were moderate and occurred for a period of one to two months, whilst the severe drought conditions for a period occurred for a period of five months. The SPEI-6 results in 2000-2001 were also seen to have a longer duration of occurrence by approximately three months, as compared to the SPEI-3 results produced.

With regards to the 2017-2018 drought event, the results indicated that this was one of the most extreme agricultural drought event to occur in the Breede-Overberg Catchment. At the SPEI-6 timescale, the 2017-2018 drought event was recognized to last for a duration of 12 months. The extreme drought months were persistent for a 13 month period with its extreme conditions ranging from -2.03 to -3.05 in value. Following the extreme months, the results produced showed that the 2017 drought event slowly began to recover to a moderate drought event in December. It should be noted that for this drought event there was a lagging period of 3 months in the SPEI-6 results as compared to the SPEI-3 results.

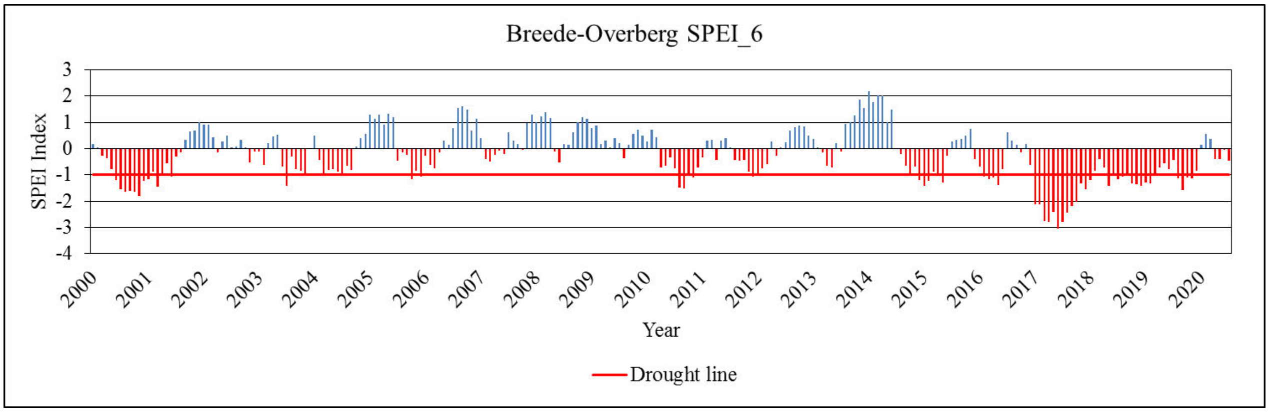

Figure 4.18: Standard Precipitation Evapotranspiration Index (SPEI) results across the Breede-Overberg Catchment at a 6-month time scale, for a 20-year period (2000 to 2020)

The 6-month timescale of SPI, is typically representative of short term conditions associated with rainfall deficits, however it is able to detect the conditions of agricultural drought to some degree. This is further supported by the comparative assessment was conducted between standardized indices SPI-6, SPEI-3 and SPEI-6 (Figure 4.19). The results of the comparison between SPI-6 and SPEI-6, indicates that on average there is a relatively good relationship found between the two indices. The results further showed that for the 2011-2012, and 2017-2018 drought events the SPI-6 values were slightly overestimated as compared to the results of the SPEI-3 index. However this trend is not always the case, for example, in 2013, 2018-2019 and 2020 it was apparent that the SPI-6 values were underestimated as compared to the SPEI-3 values.

One of the most significant drought events that occurred in this catchment was in 2017-2018, the comparative results during this period indicated that SPI-6 had a lagging period of approximately four months and a lower severity as compared to SPEI-3. From the comparison between SPI-6 and SPEI-6 it was apparent that for the 2017 agricultural drought event, there was a greater intensity experienced at the SPEI-6 timescale with extreme drought conditions persisting. It should also be noted that in 2015, 2016, 2018 and 2019, the agricultural drought events were acknowledged to have a greater duration and intensity experienced at the SPEI-6 timescale as compared to SPEI-3.

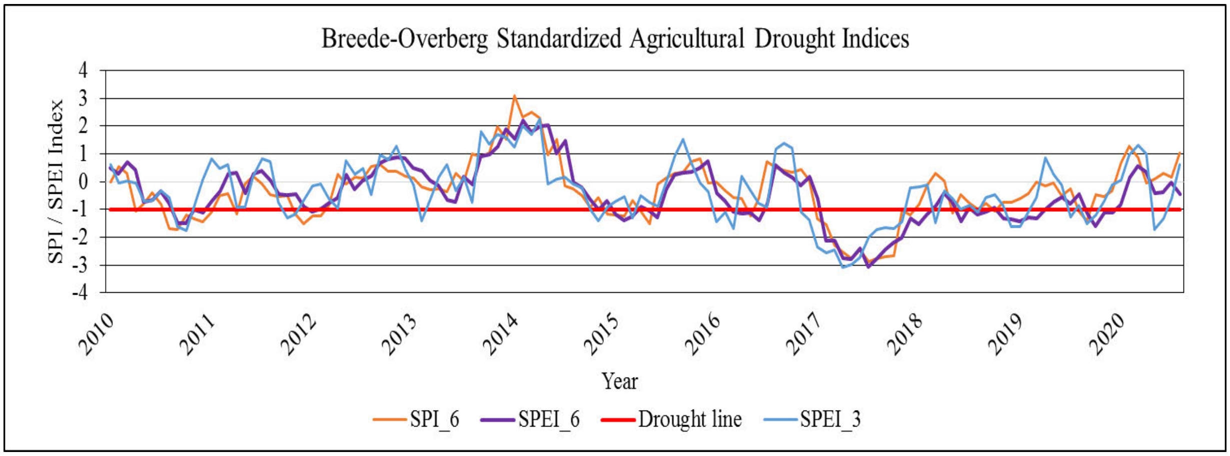

Figure 4.19: Temporal assessment of selected agricultural drought indices, namely the SPEI-3 and SPI-6, across the Breede-Overberg Catchment

4.7 Temporal Assessment of Agricultural Drought Indices in the Breede-Overberg Catchment

Figure 4.20, shows the average temporal extent of VCI, TCI and VHI within the Breede-Overberg catchment. The results from this region indicates that there is a directly proportional relationship found between the VCI and TCI average values. Furthermore, from the information provided by Figure 4.20, it is acknowledged that typically during the summer months the both the VCI and TCI values are typically low. This proportional relationship between the VHI components may be accounted for by the regions temperate climatic conditions. Whereby, in this area during winter months there is likely to be greater rainfall conditions and have more favorable conditions to promote the growth of vegetation in this region. During the summer when temperatures are high there is greater potential for processes such as evapotranspiration to take place, this couples with the low rainfall during this season may influence the potential for agricultural droughts to occur.

Figure 4.20, also depicts a time-series analysis for the average Vegetation Health Index (VHI) values experienced within the Breede-Overberg Catchment. Results from this graph indicate that on average the catchment is prone to experiencing agricultural drought especially during the summer months (November to March). The results further indicate that the duration of averaged VHI drought events last for a period of three to five months. During summer in this climatic conditions are already recognized as hot and dry, with little to no rain occurring during this period. The results from this assessment further indicate that on average an agricultural drought occurs periodically for each year and has severity levels ranging from light events to extreme events. Some of the identified extreme drought event by the averaged VHI indices was for the years 2000, 2016, 2010, 2011 and 2012.

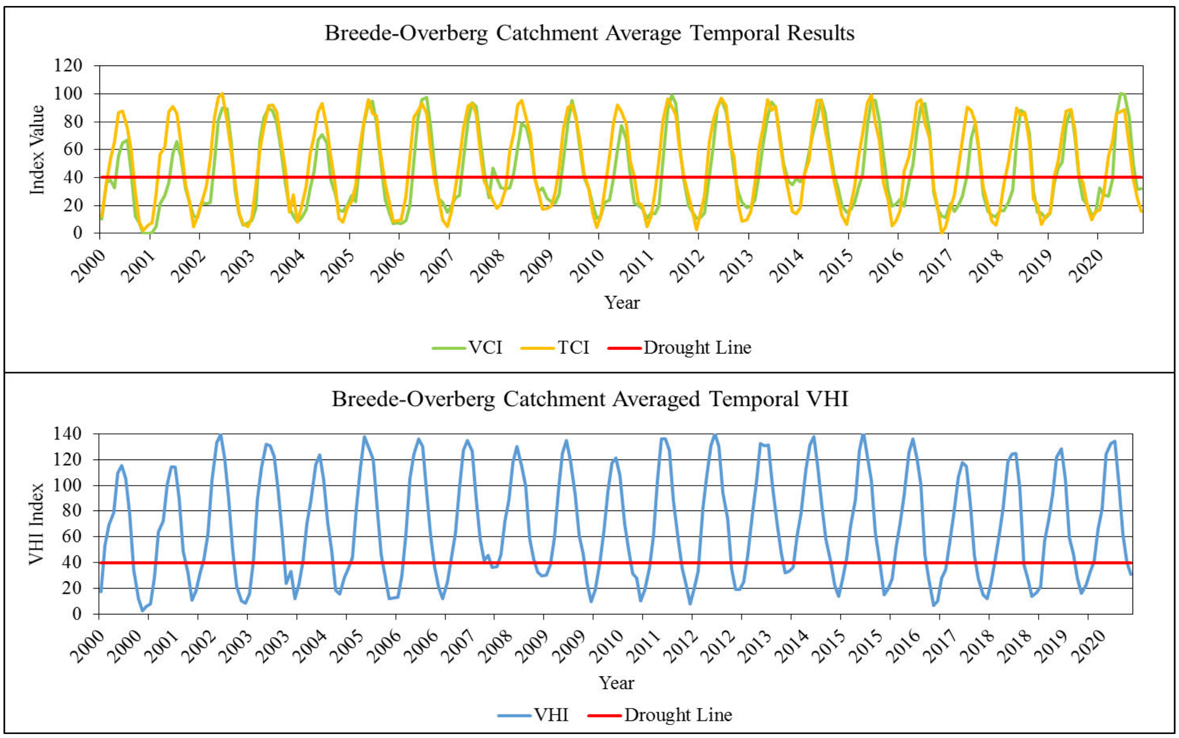

Figure 4.20: Agricultural drought assessment results on the averaged VCI, TCI and VHI across the Breede-Overberg Catchment.

Agricultural drought comparisons were conducted between the averaged VHI, SPEI-3 and SPEI-6 values (Figure 4.21), it is noted that the averaged VHI results typically depict periodic drought conditions for the summer months. Moderate droughts by SPEI is typically indicated by values between -1.0 to -1.45, whilst for VHI moderate drought are indicated by values ranging from 20 to 30. For the 2010 drought events, it was observed that there was a lagging period of VHI values of approximately 2 to 3 months, when compared to the SPEI-3 and SPEI-6 timescales. Typically the averaged VHI results indicate that drought occurs annually and during the months of November to March. However, it was noted that in the 2010 drought event there was an underestimation of drought by the averaged VHI. Whereby, the VHI values indicated that a moderate drought occurred during this period and persisted for 5 months, however at the SPEI-3 and SPEI-6 timescales the results depicted that a 2 month drought event took place with a severe drought conditions.

It was indicated by this study that one of the most extreme agricultural drought event that took place in this catchment occurred for the period of 2016-2017. The comparative assessment at this dry period indicated that VHI was able to detect the intensity of the drought event. Whereby, the results of averaged VHI during the 2016-2017 agricultural drought event was recorded to experience severe-to-extreme conditions lasting for a period of 4 months. At the SPEI-3 timescale it was noted that severe-to-extreme drought conditions persisted with this event lasting for a period of 13 months. Whilst at the SPEI-6 timescale the 2017 agricultural drought event had persistent conditions of extreme-to-severe, which lasted for a period of 12 months. It should also be noted that for this drought event there was had a lagging period of the SPEI-6 timescale approximately 3 months in relation to the SPEI-3 timescale. For the 2018-2019 agricultural drought the results showed that the averaged VHI identified the occurrence of light-to-severe conditions at a duration of 5 months, whilst the SPEI-3 indicated that there was severe conditions lasting for 3 months, and the SPEI-6 timescale indicated that moderate conditions persisted for a period of 6 months.

Supporting the results achieved was a study by Theron *et al.*, (2021), looked at wheat production during 2015-2018 agricultural drought within the Western Cape. The results produced by this study indicated that there was multi-year severe drought conditions experienced between the years 2015-2018. Further supporting the results produces in this research project, was a media statement (released in January 2018) by the South African Weather Service (SAWS), which stated that in the Western Cape province 2017 was recorded as the 1st driest year (since 1921), 2015 was the 2nd driest year (since 1921) and 2016 was the 14th driest year (since 1921). The results therefore, show that the VHI has the potential to identify the severity of the drought event in this region however, the averaged values of VHI may not adequately estimate the duration of the event as well as the SPEI-3, and SPEI-6 results. It can further be deduced from the results produced that typically SPEI-6 is capable of detecting agricultural droughts relatively better than SPEI-3.

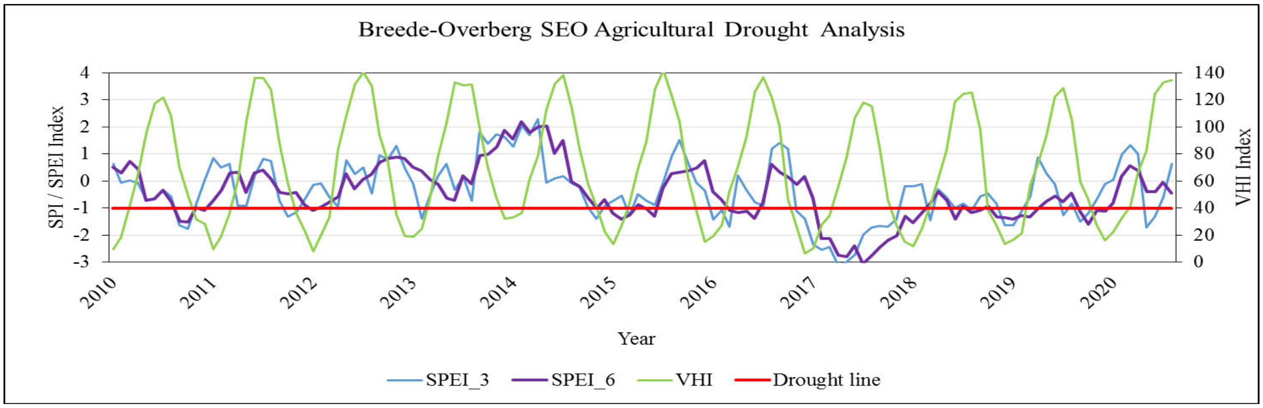

Figure 4.21: Time series graphs depicting the results of the temporal assessment of selected agricultural drought indices, namely the SPEI-3, SPEI-6 the averaged VHI, across the Breede-Overberg Catchment

Similarly to the VHI results produces in Section 4.4, it is noted that the VHI results were calculated based on catchment averages and may not be a true representation of the conditions occurring at a more localized level. Therefore, a spatial assessment of VHI within the Breede-Overberg catchment was conducted in order to better represent the conditions of agricultural drought occurring.

4.8 Spatial Agricultural Drought Assessment in the Breede-Overberg Catchment

A spatial assessment was conducted at using the Vegetation Health Index (VHI) within the Breede-Overberg catchment, in order to identify trends and patterns associated with agricultural drought. From the temporal assessment of agricultural drought in this region it was identified that that the drought months in this area is typically during the summer months. A wet year of 2013-2014 (Figure 4.22) and a dry year of 2016-2017 (Figure 4.23) was selected for the spatial assessment.

Results on the spatial assessment from Figure 4.22 indicated that despite the fact that 2013-2014 was identified as the wet year, the occurrence of drought conditions was still persisted in certain parts of the catchment. For example during September and October 2013, the upper Breede portion of the catchment experienced dry conditions (ranging from light to severe conditions), whilst the lower Overberg part of the catchment experiences wetter conditions (as indicated by the green color). However, in November and December of 2013 it is apparent that the drought event spread out more towards the central portion of the catchment, with light to moderate drought conditions occurring (indicated by the yellow to light orange color).

In the month of January 2014, it appears that the severity of the drought has marginally decreased across the catchment, which indicates that there is a recovery period of the drought event experienced. However, this does not last for long as in March to May 2014, it is apparent that the intensity of drought events have significantly increased (to moderate and severe conditions) especially in the central part of the Breede-Overberg Catchment. On average the Upper Breede and lower Overberg areas during these months are seen to experience either no drought, light drought or moderate drought events (as indicative by the green and yellow color). The trend acknowledged across the months of June to August 2014 (winter months), was that the central part of the catchment is seen to have recovered from the previously intense drought events, this may be owing to the fact that this is a winter rainfall region. It is also acknowledged from Figure 4.20 that during these months there is an increase in the severity of droughts in certain portions of the Upper Breede.

For the spatial assessment of the selected dry year of 2016-2017 (Figure 4.23), it was acknowledged that in September 2016, mainly the Upper Breede portion of the catchment experiences the occurrence of drought events, whilst the Lower Overberg portion is seen to have mostly green patches which are indicative of no drought conditions occurring. However, from October 2016 to January 2017 it is apparent that the severity and duration of drought events is persistent especially over the central portion of the catchment, with the drought conditions being severe to extreme.

Supporting the results from this are the SPEI-3 values in which November to January was determined to be a month that experiences extreme drought conditions. For the months of February to May 2017, it is apparent from the VHI assessment that there was a slight reduction in the severity of drought across the central part of the catchment with moderate to severe droughts occurring. However, it should be noted that the SPEI-3 values indicated that extreme drought occurred for the months of February to April. For the months of June to August 2017 it is recognized that across the Lower Overberg part of the catchment light to no drought conditions are experienced. Whilst there were patches of moderate to severe drought events that occurred in the Upper Breede portion of the catchment. Overall the results produce by the VHI index, indicates that VHI is capable of detecting agricultural drought events better when conducted at a spatial assessment (based on averages values per pixel per month) as compared to VHI assessments based on monthly catchment averages.

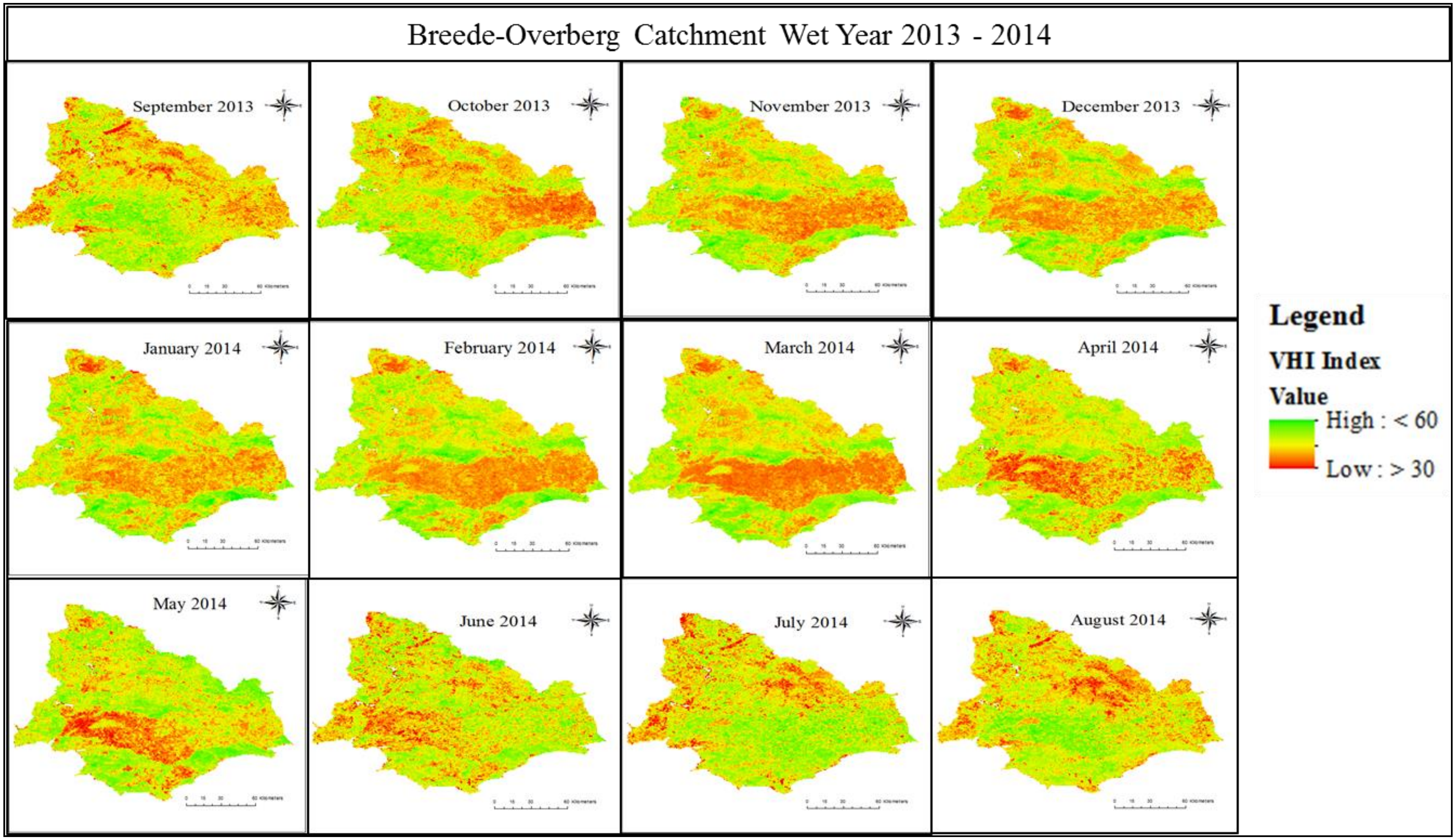

Figure 4.22: Spatial assessment of agricultural drought using the Vegetation Health Index (VHI) across the Breede-Overberg Catchment, for the selected wet year (2013 - 2014)

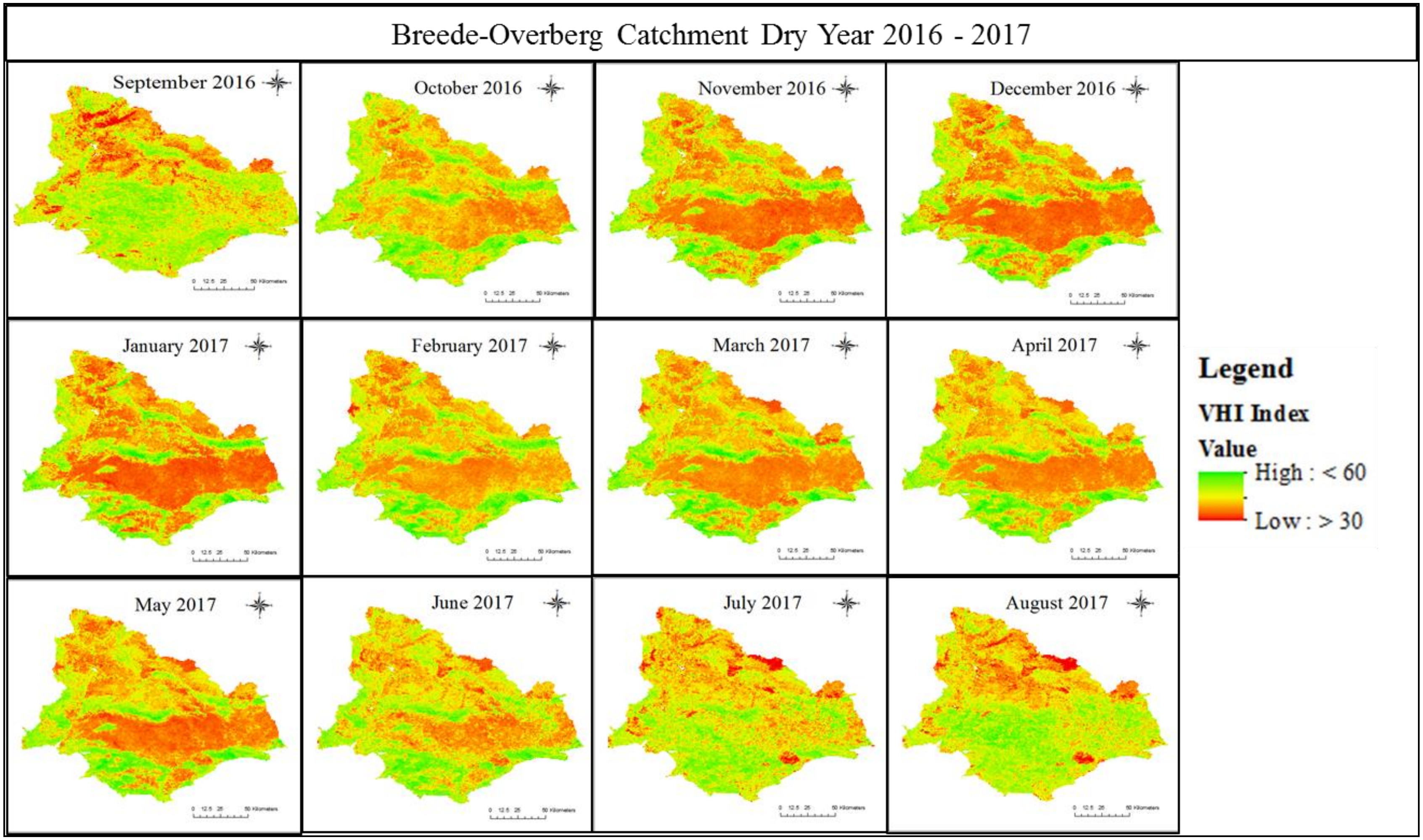

Figure 4.23: Spatial assessment of agricultural drought using the Vegetation Health Index (VHI) across the Breede-Overberg Catchment, for the selected dry year (2016 - 2017)

4.9 Drought Propagation Study in the uMngeni Catchment

Drought propagation refers to the transition of drought from one form to another. This section of Chapter Four seeks to address two of the objectives set out by this research study, where the first objective was to evaluate and quantify the spatial and temporal patterns and trends associated with the transition of drought from meteorological drought to agricultural drought using commonly applied drought indices. The second objective set out was to evaluate the characteristics of the drought propagation process between two different climatic regions.

In order to assess the characteristics of the drought propagation process comparisons are made between the meteorological drought index SPI and the agricultural drought index VHI. Both these results were plotted on a time-series graph (Figure 4.24). The results from this graph indicate that the occurrence and severity of meteorological droughts are greater especially in the years 2010, 2015-2016 and 2019, with these events being recorded to have moderate to extreme conditions of drought experienced. The occurrence of agricultural drought in this area on average is depicted as a light drought event, as its VHI values are between 30 and 40.

The patterns associated with the onsets of agricultural drought in this area is seen to have a lag period of about 1 to 5 months. The lag period in 2010, 2015-2016 and 2019 had a value of 1-month, while the drought event in 2014 had a lag period of 5 months. It was noted that for the results of this projects assessment the 2011-2012 drought event had averaged VHI values indicated that there was potentially no drought that occurred during this period. From the results presented in this temporal assessment it is acknowledged that in this catchment, when an agricultural drought (accounted for by VHI) is persistent, the meteorological drought is also persistent at the same time.

The 2015-2016 was recognized as one of the most severe droughts to have occurred in KwaZulu-Natal. Whilst the results of the temporal assessment of averaged VHI for the 2015-2016 drought event was identified as a light drought events. However, it should be noted that the results from Section 4.6 indicated that the temporal assessment of averaged VHI may not provide relatively accurate depictions on agricultural drought happening across the catchment. The spatial assessment indicated that potentially during the drought year of 2015-2016, the occurrence of agricultural drought was variable across different parts of the catchment, with the areas most affected experienced drought severity of moderate to extreme conditions.

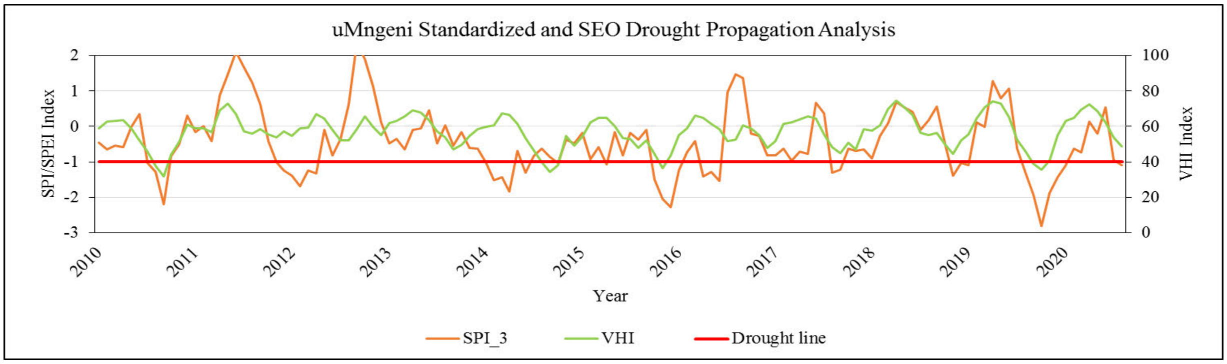

Figure 4.24: Temporal results on the propagation of meteorological droughts to agricultural droughts using SPI and VHI, across the uMngeni catchment

Figure 4.25, depicts the drought propagation process between two standardized approaches namely SPI-3 and SPEI-3 and SPEI-6. SPI at a 3-month timescale had shown capabilities of adequately quantifying meteorological drought conditions. From the results it was apparent that SPEI-6 compared very closely to SPI-3 in this region. Therefore, indicating that at a 3-month timescale of SPEI may not be able to adequately detect changes in agricultural drought conditions as compared to SPEI-6. Therefore, SPEI-6 was be set as the baseline timescale to represent agricultural drought conditions for this region.

The findings from this propagation study indicated that in the years 2010, 2012-2013, 2014 and 2019 the onset of the agricultural drought occurs with a lagging period of 2 months after the occurrence of the meteorological drought. The results from SPEI-6 further indicate that in 2012, 2014, 2015-2016 and 2017 the duration of the agricultural drought was longer than the meteorological drought by a period of 1 to 3 months. It was noted that when the meteorological drought period ends the agricultural drought is still persistent in this region for a period of approximately 2 to 3 months before the drought event can begin to recover to normal conditions. It should also be noted that in 2017 the results of this study indicated that an agricultural drought event of 2 months occurred as an isolated event and not through the propagation from a meteorological drought.

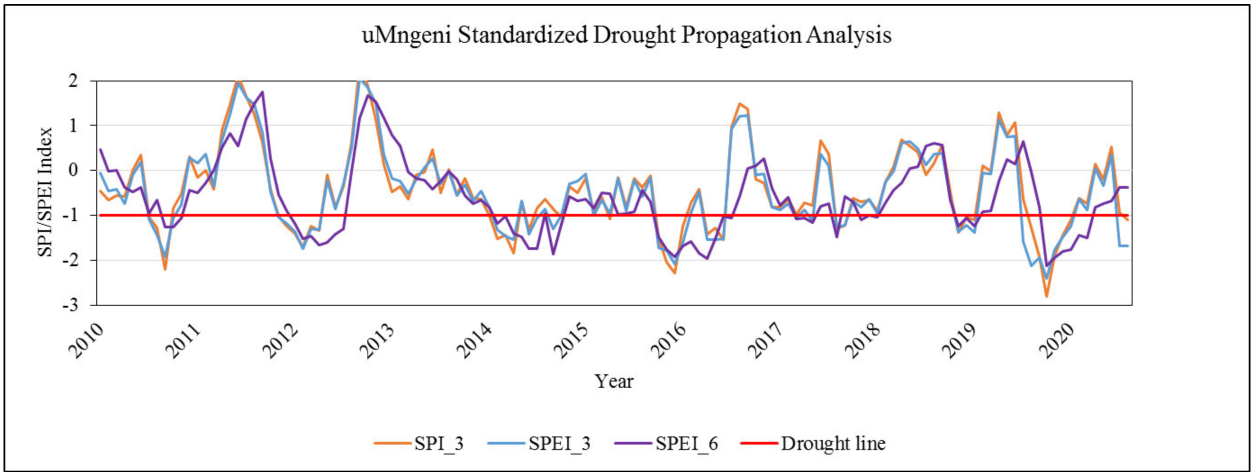

Figure 4.25: Temporal results on the propagation of meteorological droughts to agricultural droughts using SPI-3, SPEI-3 and SPEI-6, across the uMngeni catchment, for a 10 year period of 2010 to 2020

4.10 Drought Propagation Study in the Breede-Overberg Catchment

The second region assessed in this section of the results was the Breede-Overberg Catchment located in a winter rainfall region. Similar to section 4.9, time series graphs were created to compare and identify trends and patterns for the temporal drought propagation process. From these graphs it should be noted that the drought threshold line for SPI and SPEI was set at a value of -1, whilst VHI was set at a value of 40.

Results from the drought propagation study between meteorological drought index SPI-3 and agricultural drought from VHI within the Breede-Overberg catchment (Figure 4.26), indicates that VHI typically depict agricultural drought events to occur for a period of 3 to 5 months during the summer season. Within the selected 10 year period some of the significant meteorological drought events identified by this study were in the years 2010, 2011 and 2017-2018. During the 2010 drought event the meteorological drought had a duration of 3 months and had an intensity of moderate-to-severe conditions, whilst the averaged VHI values indicated that once the meteorological drought in this year ended the agricultural drought started and lasted for a period of 5 months with light-to-severe conditions. In the year 2011-2012, the meteorological drought lasted for a period of 3 months (moderate conditions), it was noted that there was a lagging period of 2 months before the VHI drought event started and persisted for a 5 month period with light-to-severe conditions.

One of the most extreme drought event to occur in this catchment was identified for 2017. The meteorological drought was seen to last for a period of 10 months with moderate, severe and extreme conditions occurring. The results from VHI indicate that the agricultural drought only lasted for the summer months with light-to-extreme conditions occurring. It was noted that at the end of the meteorological drought in 2017, the averaged VHI results indicated that an agricultural droughts began and lasted for a period of 4 months.

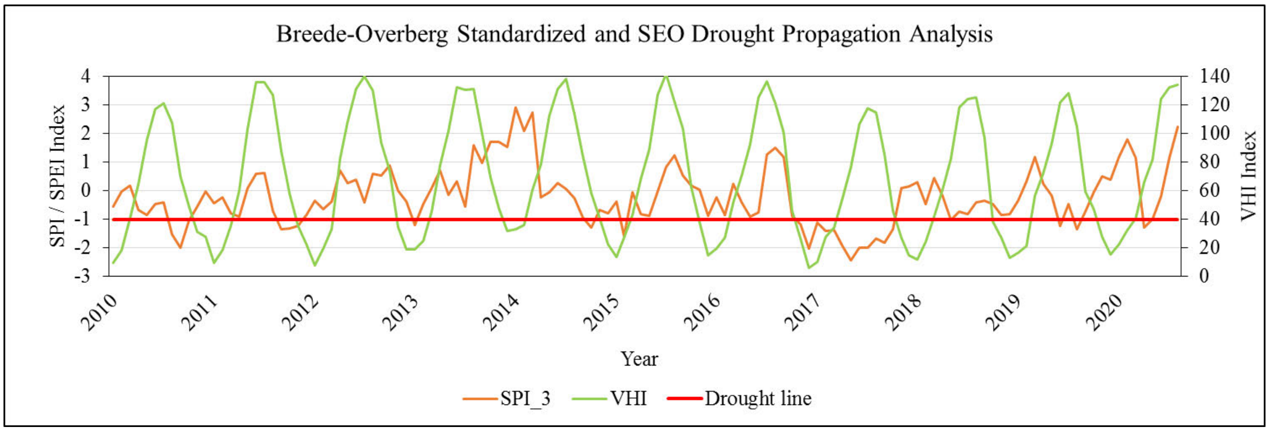

Figure 4.26: Time-series comparing the drought propagation process between SPI-3and averaged VHI in the Breede-Overberg catchment

For the drought propagation assessment using standardized indices SPI-3 and SPEI-3 (Figure 4.27), it was apparent from the results that, for the 2010 and 2011 drought event, the onset of agricultural drought for the SPEI-3 timescale had a lagging period of 1 month. The meteorological drought during this period was seen to last for 3 months. It was also indicated that during 2010 and 2011, the agricultural drought event ended simultaneously with the meteorological drought event. Results produced by these drought years indicated that there was a greater intensity experienced by the meteorological drought event during this period.

2016-2017, was considered to have one of the most significant and extreme drought events within this region. The propagation results during this period indicated that typically there was a simultaneous onset of both meteorological and agricultural drought. The intensity of this 2016-

2017 drought event was seen to be more severe in the agricultural drought conditions with extreme events having a high of -3.10 in value. It was further evident from the results of this study that when the meteorological drought event recovered agricultural drought was still persistent for 1 month. From the SPEI-3 results it was also apparent that isolated agricultural drought events were persistent especially in the years 2016 and in 2018-2019.

The drought propagation assessment between SPI-3 and SPEI-6 was depicted by Figure 4.27. The results from this assessment indicated that on average agricultural drought experience a lagging period in their onset of drought in relation to meteorological droughts. Whereby, for the 2010 there was a lagging period of 1 month. Whilst for the 2017-2018 drought event there was a 3 month lagging experienced. The 2017-2018 was recognized to be one of the worst drought event experienced in this region. It was noted that when the meteorological drought recovered to normal conditions the agricultural drought was still persistent for a further 4 months.

It should also be noted that at the SPEI-6 timescale in 2011 no agricultural drought was recorded however there was presence of a 3 month moderate drought event. From 2015 to 2019 it was apparent that there was an increase in duration and intensity of agricultural drought conditions within this region. In 2015, the results indicated that a meteorological drought occurred 1 month after the occurrence of an agricultural drought event. It was further recognized that for the 2015 drought event, the agricultural drought persisted for a period of 1 month after the meteorological drought ended. There were several agricultural drought events that occur as isolated events rather than through the propagation process especially in the years 2016 and 2018-2019.

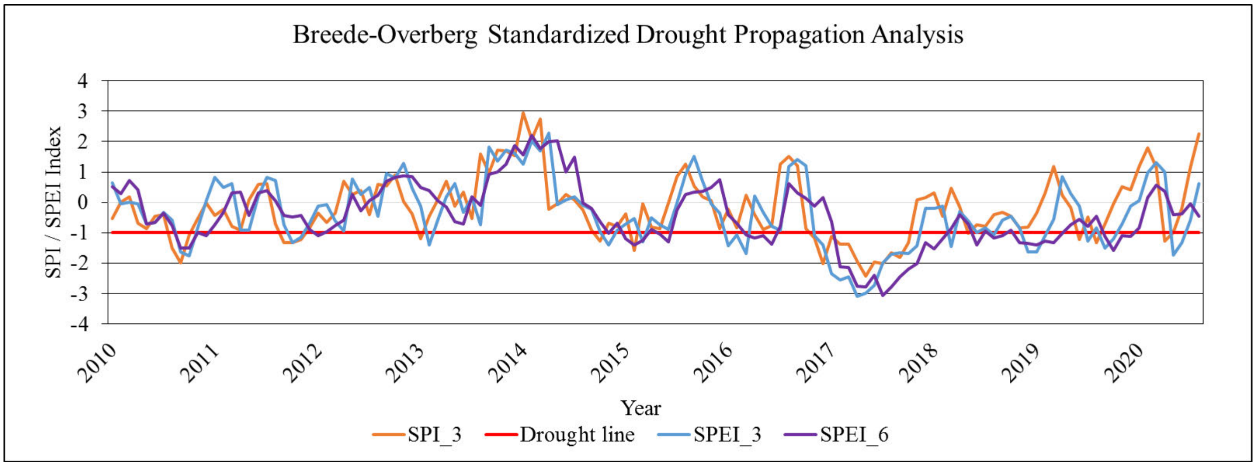

Figure 4.27: Time-series graph of the drought propagation process between SPI-3 SPEI-3 and SPEI- within the Breede-Overberg catchment, over a 10 year period

5. DISCUSSION

5.1 Validation Study Discussion

From the validation assessment it was acknowledged that Satellite Earth Observation products provided an adequate means of acquiring drought related variables such as rainfall and air temperature data. The validation indicated that the overall best performing satellite rainfall product in relation to the ground based observations was the CHIRPS product. Whilst the PERSIANN-CDR was able to perform relatively well in the cross-correlation assessment, it was noted that at several of the selected stations recorded the same resulting SEO values of rainfall. These similar records may be accounted for by the course spatial resolution provided by the PERSIANN-CDR satellite product, whereby, if the stations were close enough they may have been detected by the same pixel coverage of satellite data. The overall results from the validation study indicated that there was a very strong relationship found between the ground-based observations and the selected SEO data. Thus further indicating that SEO products have the potential to provide long-term data which can be utilized in drought studies. However the scaling factor, resolution and specifications of the type of satellite used needs to be carefully considered during the selection process.

5.2 Drought Analysis of Standardized Indices

In general within both the uMngeni and Breede-Overberg Catchments, SPI and SPEI showed a good capability, with regards to successfully detecting several drought conditions persisting in these catchments. The temporal assessment from these standardized indices were acquired at different timescales (i.e. 3-month and 6-month), and the overall, results indicated that at both the study sites the variability of drought events at each timescale were relatively consistent, however the duration and magnitude of the drought events differed for the various timescales.

Overall, looking at the results produced from the temporal evaluation of meteorological drought assessment it can be deduced that in both the uMngeni and Breede-Overberg catchments SPI was able to adequately detect the presence of historic drought events. It was further noted that at a 3-month timescale SPI tended to be more sensitive to detecting the change in severity of drought events (such as extreme conditions), as compared to the 6-month timescale.

In the uMngeni Catchment, it was acknowledged from the results produced that the most severe drought event that occurred in this region was for the years 2015-2016. The occurrence and impacts of this extreme drought events may due to factors like the contributions of changes to climatic characteristics, which may affect rainfall patterns or changes in the dynamics of ocean-atmospheric interaction such as, the El Nino Southern Oscillation. Further supporting the finding of this study, were assessments by Ndlovu, and Demlie, (2020) and Blamey *et al.*, (2018) whereby, they acknowledged that in 2015/2016 there was a significant influence of ENSO on the occurrence of drought. Furthermore, media statements were made by News24 (2015), stating that during 2015-2016, there was a crippling drought which affected KwaZulu-Natal. Typically the conditions associated with ENSO, may lead to the early onset weakening of mechanisms that drive moisture convergence and the development of precipitation cloud formation, thus resulting in the occurrence of precipitation deficits and drought events. It should be noted however that not all El Nino events lead to the occurrence of drought.

However in the Breede-Overberg Catchment, it was established that one of the most significant and extreme drought event to occur in this area was in 2017. SPI was able to detect the occurrence of meteorological drought in this area relatively well. Further supporting the findings of the temporal assessment were the widespread acknowledgement of drought occurrence during this period by the media as well as through studies by Theron *et al.*, (2021). The variable nature of rainfall in the Breede-Overberg catchment may be accounted for by the presence of the cold Benguella and Agullus current flowing along the Oceans bordering the Western Cape. These currents generally flow from the poles, and bring cool water along with it. Due to its cold nature ocean-atmospheric interactions and circulations may not have enough energy and potential to allow for condensation to occur, clouds to form or rainfall to take place as often as those regions on the eastern side of the country.

It was acknowledged from the literature review that SPI, when assessed at a short-term timescale (i.e. 1 to 6 months) it may be capable of predicting agricultural drought conditions. It was assumed that agricultural droughts are likely to occur after prolonged dry spells, therefore a 3-month period may not be able to adequately represent the prolonged drought of agricultural drought. Owing to this it was deduced that a 6-month timescale of SPI would likely provide the potential to detect agricultural drought. Assessments were thus, conducted to assess the potential of SPI-6 in terms of depicting agricultural drought. This was done by comparing SPI-6 with SPEI at both study sites. The overall results from this assessment indicated that in both the catchments SPI-6 had a closer relationship with SPEI-6 rather than SPEI-3. The results further suggested that SPI-6 may has the potential to detect agricultural drought. It is also important to note that since SPI only uses precipitation data as in input parameter it cannot take into account other agricultural drought features such as temperature anomalies, evapotranspiration, vegetation stress or streamflow discharge.

5.3 Agricultural Drought with VHI

With regard to the VCI and TCI results produced in this study it was apparent that in the summer rainfall region (uMngeni Catchment), that these components had an inversely proportional relationship. Whilst the winter rainfall region (Breede-Overberg Catchment) experienced a directly proportional relationship between VCI and TCI. Under normal conditions one would expect to have an inversely proportional relationship between these two components whereby, when vegetation conditions depicted healthy, thick, dense vegetation cover one would also expect for the land surface temperatures to be relatively low, due to the shading effect associated with crop and vegetation growth.

However, this is not the case in the Breede-Overberg Catchment. It is important to firstly note that VHI takes into account the density, growth and health of the vegetation in terms of temperature conditions (as accounted for by the input variables NDVI and LST), in order to estimate the potential for agricultural drought to occur. This being said it was acknowledged that for TCI, in the summer months for this region the land surface temperatures may have been high due to the influence of the climatic conditions experienced in this region. Furthermore, the patterns of TCI experienced is indicative that temperature stress on vegetation plays a significant role in this region. During summer, the conditions which influence ET rates are favorable and one would expect greater ET during this period and a greater likelihood for agricultural drought to occur. There is further potential for this area to experience limited soil moisture recharge, resulting in soil moisture stores being more readily depleted, thus providing the potential for the occurrence of agricultural droughts to take place. The vegetation growth in this catchment, was seen to be greatest during the winter months, this growth and vegetation density may be owing to the winter rainfall conditions experienced in this region providing greater potential for growth during this season.

Overall the VHI results presented by this study suggested that there is a scale influence within the results. Whereby, the averaging of VHI across the both the uMngeni and Breede-Overberg Catchments, were not able to provide an adequate temporal representation of agricultural drought experienced over the area as compared to SPEI. By using the coarse spatial resolution data at an averaged temporal catchment scale the results may have led to small- or medium-scale (light-to-moderate conditions) drought events not being adequately captured and represented. Furthermore, the results presented herein may not have adequately accounted for the spatial heterogeneity in climatic and land use conditions within the catchment and therefore it should not be assumed that these results are applicable at all scales throughout the catchment.

However from this spatial assessment of VHI it was apparent that in both the uMngeni and Breede-Overberg catchment, there was a better and more comprehensive understanding of agricultural drought and it spatial variability and distribution within the different parts of the catchment. This may be due to the scaling of values used whereby, the spatial assessment considered drought conditions based on averages per pixel per month, whilst the temporal assessment was based on monthly averaged values across the catchment study site area. Conclusions can further be made that from the spatial scale assessment of VHI, that there is a seasonal variability associated with the occurrence of agricultural droughts, as certain areas across both catchments were found to be more susceptible to the occurrence of droughts during certain months and seasons. The spatial assessment of VHI was able to further assist in identifying the trends, and patterns of the areas most likely to be susceptible to the occurrence of agricultural drought especially as the month's progress in the year. It was further acknowledged from the spatial assessment of VHI, in both study sites that due to the heterogeneous nature of variability experienced in a catchment certain areas in both study sites were likely to experience some degree of dryness conditions experienced even during a considered wet year period.

5.4 Drought Propagation Discussion

For the propagation assessment it was apparent at both catchment sites, that the SPEI-3 timescale did not adequately represent the conditions favorable for the occurrence of agricultural drought as the results produced were very closely correlated to the values of SPI, whilst the VHI results produces in its averaged temporal assessment may have been misleading due to it accounting for catchment averages. However, at a 6 month timescale SPEI was able to be detect the characteristics and occurrence of agricultural drought relatively well. Therefore the simultaneous comparison of results between SPEI-6 and SPI-3 were seen as the most appropriate indices capable of evaluating and quantifying the drought propagation characteristics across both of the selected study sites

In the uMngeni Catchment, for the severe-to-extreme meteorological events the trend identified was that typically, there is a lagging period of 1 to 2 months before the onset of the agricultural drought. Typically in this region the severity of the agricultural drought events were identified to have lower intensities as compared to the meteorological drought events. Whereby, on average the magnitude of the agricultural drought event in this case tends to have moderate-to-severe conditions experienced. A general trend observed for the propagation process in this region, was that despite the magnitude of the drought event in this catchment it was apparent that when the meteorological drought recovers to normal conditions the agricultural drought is still persistent. A key finding in this catchment was in 2017 whereby the results indicated that an agricultural drought event of 2 months occurred as an isolated event before the meteorological drought occurred. Possible reasons for this may be due to human interventions and actions (such as over-abstraction of water during this period) occurring prior to the deficit in rainfall. During this period it was also noted that the agricultural drought ended whilst the meteorological drought was still persistent. Possible reasons for this type of event may likely be due to water mitigation strategies being applied, such as inter-basin transfers or water use restrictions may have been implemented to ensure water was provided to the agricultural sectors.

The drought propagation study in the Breede-Overberg Catchment indicated that the trends of propagation are highly variable in this catchment whereby, there were cases in which agricultural droughts persisted even after the meteorological drought event ends. However, there was also a cases where an agricultural drought were persistent as isolated events. A possible reason for this event occurring may be owing to anthropogenic interference such as over abstraction of water leading to reduced water available to recharge the soil water that facilitate the growth of crops. Furthermore, results also suggested that on average the meteorological droughts tend to recover faster, however in this region the agricultural drought still persisted for a few more months. On average the Breede-Overberg catchment is more significantly impacted by the occurrence and characteristics of agricultural drought rather than meteorological drought. A contributing factor towards this may be the climatic conditions experienced in this area. The occurrence of isolated agricultural drought events may further indicate that the deficits in the evapotranspiration and declining soil moisture may be highly significant in this region.

It should further be noted that typically the impacts and characteristics of meteorological drought tend to be more severe in the uMngeni catchment. Whilst the Breede-Overberg catchment tends to experience more severe and frequent agricultural drought conditions. The severity of drought events in the Breede-Overberg catchment may be due to this region experiencing Winter Rainfall. The absence of rainfall in this region may not be an issue during the winter period however, the effect in summer when temperatures are hotter may result in dry spells being amplified. This may further be owing to the lack of recharge occurring in the system. Therefore, the severity of drought events may differ to that of the conditions experienced in the uMngeni catchment which is a summer rainfall region.

Overall the results obtained from this comparative assessment of drought propagation, in both the selected climatic regions, further iterated that the use of a single index during drought assessments may not be suitable to identify the propagation of drought and how it manifests itself within a catchment. Therefore a comprehensive and integrated assessment of quantifying the drought propagation process is important. From a management perspective the use of information from more than one type of drought and/or index may assist in forming a more robust understanding of the impacts associated with the propagation process and thus, facilitate the adaption of more applicable strategies than one would make if only a single drought type was assessed.

6. CONCLUSION AND RECOMMENDATIONS

Drought is highly recognized as a phenomena that has the potential to impact on numerous sectors, namely, the environmental, agricultural and socio-economic sectors. They can be categorized into 4 different types namely, meteorological, agricultural, hydrological and socio-economic droughts. These drought events can occur as isolated events, a mutually exclusive event or through the progression from one form to another. The transition of drought from one type to another is known as drought propagation. Typically the impacts faced by drought events are recognized to change as it evolves into its various types.

The findings from this study further emphasize the variable nature of droughts and indicate that drought management decisions should be take into account as a holistic approach, especially for disaster, water and agricultural management. This research study was conducted to add to the theoretical knowledge of the drought propagation process and its associated characteristics. By understanding the drought propagation process, the management and mitigation strategies applied may be more effective in coping with the impacts of droughts. Typically if areas are well informed about the potential of a drought event occurring, it would allow for people to be more prepared for the consequences of the likely impacts they will be faced with. For example people would be aware to stock up on resources such as water and food supplies, or make arrangements to ensure crop productivity does not severely decline. Furthermore being better informed about the occurrence of droughts may reduce the vulnerabilities faced across all sectors of society.

Understanding droughts and their propagation, through a historical perspective may aid in the forecasting of future drought events, thus allowing for people to be more aware and prepared for the impacts of drought events before or during the early stages of the droughts occurrence. Evaluating droughts from multiple perspectives may provide further insight on drought characteristics, spatial extent, potential impacts and its propagation process (e.g., from meteorological to agricultural drought). Thus, facilitation the better informed knowledge on drought conditions that can be utilized in disaster, agricultural and water resource management.

A key finding observed, was that understanding the patterns and trends associated with the drought propagation process can contribute imperative knowledge to the disaster, water and agricultural decision making process. It was acknowledged that droughts are a complex phenomenon. It was identified by this study that in both catchments, despite the different climatic conditions, there were trends observed where the propagation from a meteorological drought to agricultural drought had periods where these two droughts occurred simultaneously before either of the drought types could recover. This finding further emphasizes that typically even though a meteorological drought event may have ended, the effects and impacts of the agricultural drought may still be persistent. It can thus be concluded that there is a close interrelationship found between the conditions and impacts of the different drought types. Therefore, if the use of only one type of drought or index was considered in the indication for the decision making process, there might be a false perception of the conditions happening on the ground.

It was further acknowledged from this study that the use of Satellite Earth Observation Products is able to address the limitations presented by traditional methods of acquiring data on the various hydro-climatic variables for drought assessments. However this being said, ground based information provides invaluable insight on what is happening on the ground. Therefore future studies on drought propagation should consider the use of Ground-based information as far as possible

Furthermore, it was noted that the adoption of satellite derived-drought indices have the potential to evaluate droughts, especially through a spatial scale context. Whereby it was noted that for the temporal drought assessment conducted with the VHI, one of the main limitations acknowledged was that by assessing this drought index using catchment averages, the results produced were possibly misleading in their calculation. This may be owing to the fact that the recommended constant may not have been applicable in the region of study. However when assessing VHI in a spatial context it was apparent that localized drought events were detected throughout both of the catchment. The results from this further suggested that the averaging of results over large areas may lead to the miss-capturing of localized drought events.

Owing to this, a recommendation proposed for future studies, would be to look at understanding a more localized context of drought propagation. Insights on this type of study may further allow for the vulnerability of drought on the different socio-economic classes to be better evaluated. For example, if a moderate drought were to occur over an area, the poorer community's which rely heavily on subsistence farming for their livelihood may feel the impacts of drought at a greater extent than people living in more urbanized communities. Identifying the localized areas more vulnerable to drought, may assist with these areas being prioritized in the drought management and mitigation decisions.

The assessment conducted within the scope of this study looked at three selected drought indices (SPI, SPEI, and VHI). This was done in order to demonstrate the importance of understanding drought and how it may transitions from one type of drought to another. However, it is noted that there are a wide range of other indices available that could potentially be considered for future studies on drought propagation. It was noted that another potential limitation of the study was from the calculation of SPEI, whereby it was acknowledged from SPEI package manual that was known both PET and ETo calculations were considered to be equivalent, when deriving SPEI. Further to this another potential limitation to the study may have been through assuming SPEI to be considered as an agricultural drought index within the context of this study. This assumption was based owing to literature which indicates the potential that at various timescales SPEI is able to monitor the likely conditions associated with agricultural droughts

In this study the transition of meteorological drought to agricultural droughts were assessed. However it should be noted that studying the drought propagation process in terms of all the different drought types (i.e. meteorological, agricultural and hydrological), can provide a greater, and more integrated perspective on the impacts of drought faced in an area. Therefore, future studies on drought propagation should consider approaches and indices to assess all three drought types.

7. REFERENCES

Abdulrazzaq, ZT, Hasan, RH and Aziz, NA. 2019. Integrated TRMM data and standardized precipitation index to monitor the meteorological drought. Civil Engineering Journal 5 (7): 1590-1598.

Adisa, OM, Botai, JO, Adeola, AM, Botai, CM, Hassen, A, Darkey, D, Tesfamariam, E, Adisa, AT and Adisa, AF. 2019. Analysis of drought conditions over major maize producing provinces of South Africa. Journal of Agricultural Meteorology 75 (4): 173-182.

AghaKouchak, A, Farahmand, A, Melton, F, Teixeira, J, Anderson, M, Wardlow, BD and Hain, C. 2015. Remote sensing of drought: Progress, challenges and opportunities. Reviews of Geophysics 53 (2): 452-480.

Ahmadalipour, A, Moradkhani, H, Yan, H and Zarekarizi, M. 2017. Remote sensing of drought: vegetation, soil moisture, and data assimilation. In: Remote sensing of hydrological extremes. Springer.

Ambika, AK and Mishra, V. 2019. Observational evidence of irrigation influence on vegetation health and land surface temperature in India. *Geographical Research Letter* 46 (22): 13441-13451.

Bai, X, Shen, W, Wu, X and Wang, P. 2020. Applicability of long-term satellite-based precipitation products for drought indices considering global warming. Journal of Environmental Management 255 109846.

Baudoin, M-A, Vogel, C, Nortje, K and Naik, M. 2017. Living with drought in South Africa: lessons learnt from the recent El Niño drought period. International journal of Disaster Risk Reduction 23 128-137.

Bayissa, Y, Tadesse, T, Demisse, G and Shiferaw, A. 2017. Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. Journal of Remote Sensing 9 (7): 669.

Beguería, S, Vicente-Serrano and Angulo, M. 2010. A multi-scalar global drought data set: the SPEIbase:A new gridded product for the analysis of drought variability and impacts. Bulletin of the American Meteorological Society 91:1351-1354.

Beguería, S, Vicente-Serrano, SM, Reig, F and Latorre, B. 2014. Standardized precipitation evapotranspiration index (SPEI) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology 34 (10): 3001-3023.

Bento, VA, Gouveia, CM, DaCamara, CC and Trigo, IF. 2018. A climatological assessment of drought impact on vegetation health index. Journal of Agricultural and Forest Meteorology 259 286-295.f

Bhuiyan, C, Saha, A, Bandyopadhyay, N and Kogan, F. 2017. Analyzing the impact of thermal stress on vegetation health and agricultural drought–a case study from Gujarat, India. Journal of GIScience and Remote Sensing 54 (5): 678-699.

Bijaber, Noureddine, El Hadani, Driss, Saidi, Mariam, Svoboda, Mark D, Wardlow, Brian D, Hain, Christopher R, Rochdi, Atmane (2018). Developing a remotely sensed drought monitoring indicator for Morocco. Geosciences, 8(2), 55.

Blamey, R, Kolusu, S, Mahlalela, P, Todd, M and Reason, C. 2018. The role of regional circulation features in regulating El Niño climate impacts over southern Africa: A comparison of the 2015/2016 drought with previous events. International Journal of Climatology 38 (11): 4276-4295.

Bloomfield, J and Marchant, B. 2013. Analysis of groundwater drought building on the standardised precipitation index approach. Journal of Hydrology Earth System Sciences 17 4769-4787.

Botai, CM, Botai, JO, Dlamini, LC, Zwane, NS and Phaduli, E. 2016. Characteristics of droughts in South Africa: a case study of Free State and North West provinces. Journal of Water 8 (10): 439.

Bouaziz, M, Medhioub, E and Csaplovisc, E. 2021. A machine learning model for drought tracking and forecasting using remote precipitation data and a standardized precipitation index from arid regions. Journal of Arid Environments 189 104478.

Creamer Media's Engineering News. 2010, https://www.engineeringnews.co.za/article/kzn-drought-and-other-challenges-face-cane-growers-2010-07-02

Crétat, J, Richard, Y, Pohl, B, Rouault, M, Reason, C and Fauchereau, N. 2012. Recurrent daily rainfall patterns over South Africa and associated dynamics during the core of the austral summer. International Journal of Climatology 32 (2): 261-273.

Cruz-Roa, A, Olaya-Marín, E and Barrios, M. 2017. Ground and satellite based assessment of meteorological droughts: the Coello river basin case study. International Journal of Applied Earth Observation Geoinformation 62 114-121.

Cullis, JD, Rossouw, N, Du Toit, G, Petrie, D, Wolfaardt, G, De Clercq, W and Horn, A. 2018. Economic risks due to declining water quality in the Breede River catchment. Journal of Water SA, 44 (3): 464-473.

DEAP, WCIWR and Development Planning, SA. 2011. Management (IWRM) Action Plan: Status Quo Report Final Draft. Journal Provincial Government, Department of Environmental Affairs.

Department of Environmental Affairs, 2018. Overberg District Municipality Climate Change Adaptation Summary Report Version 2.

Ding, Y, Gong, X, Xing, Z, Cai, H, Zhou, Z, Zhang, D, Sun, P and Shi, H. 2021. Attribution of meteorological, hydrological and agricultural drought propagation in different climatic regions of China. Journal of Agricultural Water Management 255 106996.

Dube, L and Jury, M. 2000. The nature of climate variability and impacts of drought over KwaZulu-Natal, South Africa. South African Geographical Journal 82 (2): 44-53.

Ekundayo, O, Okogbue, E, Akinluyi, F, Kalumba, A and Orimoloye, I. 2020. Spatiotemporal drought assessment using vegetation health index and standardized precipitation index over Sudano-Sahelian region of Nigeria. Journal of African Geographical Review 1-13.

Fauchereau, N, Trzaska, S, fult, M and Richard, Y. 2003. Rainfall variability and changes in southern Africa during the 20th century in the global warming context. Journal of Natural Hazards 29 (2): 139-154.

Fensholt, R, Anyamba, A, Huber, S, Proud, SR, Tucker, CJ, Small, J, Pak, E, Rasmussen, MO, Sandholt, I and Shisanya, C. 2011. Analyzing the advantages of high temporal resolution geostationary MSG SEVIRI data compared to Polar Operational Environmental Satellite data for land surface monitoring in Africa. International Journal of Applied Earth Observation Geoinformation 13 (5): 721-729.

Gcanga, A, Horn, A, Kloppers, W and Africa, S. 2018. Supporting the Breede River Catchment. Journal of Water, 13 (2): 25-28.

Gevaert, A, Veldkamp, T and Ward, P. 2018. The effect of climate type on timescales of drought propagation in an ensemble of global hydrological models. Journal of Hydrology and Earth System Sciences 22 (9): 4649-4665west.

Gidey, E, Dikinya, O, Sebego, R, Segosebe, E and Zenebe, A. 2018. Analysis of the long-term agricultural drought onset, cessation, duration, frequency, severity and spatial extent using Vegetation Health Index (VHI) in Raya and its environs, Northern Ethiopia. Journal of Environmental Systems Research, 7 (1): 1-18.

Gorelick, N, Hancher, M, Dixon, M, Ilyushchenko, S, Thau, D and Moore, R. 2017. Google Earth Engine: Planetary-scale geospatial analysis for everyone. Journal of Remote Sensing of Environment 202 18-27.

Guo, H, Bao, A, Liu, T, Ndayisaba, F, He, D, Kurban, A and De Maeyer, P. 2017. Meteorological drought analysis in the Lower Mekong Basin using satellite-based long-term CHIRPS product. Journal of Sustainability 9 (6): 901.

Guo, M, Li, J, Wang, Y, Long, Q and Bai, P. 2019. Spatiotemporal variations of meteorological droughts and the assessments of agricultural drought risk in a typical agricultural province of China. *Journal of the Atmosphere* 10 (9): 542.

Han, Z, Huang, S, Huang, Q, Leng, G, Wang, H, Bai, Q, Zhao, J, Ma, L, Wang, L and Du, M. 2019. Propagation dynamics from meteorological to groundwater drought and their possible influence factors. Journal of Hydrology 578 124102.

Huang, S, Huang, Q, Chang, J, Leng, G and Xing, L. 2015. The response of agricultural drought to meteorological drought and the influencing factors: A case study in the Wei River Basin, China. Journal of Agricultural Water Management 159 45-54.

Huang, S, Li, P, Huang, Q, Leng, G, Hou, B and Ma, L. 2017. The propagation from meteorological to hydrological drought and its potential influence factors. Journal of Hydrology 547 184-195.

Hughes, C, De Winnaar, G, Schulze, R, Mander, M and Jewitt, G. 2018. Mapping of water-related ecosystem services in the uMngeni catchment using a daily time-step hydrological model for prioritization of ecological infrastructure investment–Part 1: Context and modelling approach. Journal of Water SA, 44 (4): 577-589.

Itsukushima, R. 2019. Characteristics and controlling factors of the drought runoff coefficient. Journal of Hydrology Earth System Sciences Discussions 1-24.

Jong, SM, Van der Meer, FD and Clevers, JG. 2004. Basics of remote sensing. In: Remote sensing image analysis: Including the spatial domain. Springer.

Kamali, B, Abbaspour, KC, Wehrli, B and Yang, H. 2018. Drought vulnerability assessment of maize in Sub-Saharan Africa: Insights from physical and social perspectives. *Jounal of Global Planetary Change* 162 266-274.

Keyantash, J and Dracup, JA. 2002. The quantification of drought: an evaluation of drought indices. Bulletin of the American Meteorological Society 83 (8): 1167-1180.

Khan, R and Gilani, H. 2021. Global drought monitoring with big geospatial datasets using Google Earth Engine. Journal of Environmental Science and Pollution Research 28 (14): 17244-17264.

Kogan, FN. 1995. Application of vegetation index and brightness temperature for drought detection. Journal of Agricultural and Forest Meteorology 15 (11): 91-100.

Kogan, FN. 2000. Contribution of remote sensing to drought early warning. Journal of Early warning systems for drought preparedness and drought management 75-87.

Kroese, N, Visser, P, Nhlapo, A, Mngadi, P, Terblanche, D and Banitz, L. 2006. Daily Rainfall mapping over South Africa (DARAM): Infrastructure and capacity building. WRC Report.

Kumar, L and Mutanga, O. 2018. Google Earth Engine applications since inception: Usage, trends, and potential. Journal of Remote Sensing 10 (10): 1509.

Kwon, M, Kwon, HH and Han, D. 2019. Spatio-temporal drought patterns of multiple drought indices based on precipitation and soil moisture: A case study in South Korea. International Journal of Climatology 39 (12): 4669-4687.

Labudová, L, Labuda, M and Takáč. 2017. Comparison of SPI and SPEI applicability for drought impact assessment on crop production in the Danubian Lowland and the East Slovakian Lowland. Journal of Theoretical and Applied Climatology 128 (1): 491-506.

Li, Y, Huang, S, Wang, H, Zheng, X, Huang, Q, Deng, M and Peng, J. 2022. High-resolution propagation time from meteorological to agricultural drought at multiple levels and spatiotemporal scales. Journal of Agricultural Water Management 262 107428.

Lynch, S. 2003. Development of a RASTER database of annual, monthly and daily rainfall for Southern Africa. WRC Rep.

Ma’rufah, U, Hidayat, R, & Prasasti, I. (2017). Analysis of relationship between meteorological and agricultural drought using standardized precipitation index and vegetation health index. IOP conference series: earth and environmental science, 54(1), 012008.

Masitoh, F and Rusydi, A.2019. Vegetation Health Index (VHI) analysis during drought season in Brantas Watershed. IOP Conference Series: Earth and Environmental Science, 012033. IOP Publishing.

McKee, TB, Doesken, NJ and Kleist, J.1993. The relationship of drought frequency and duration to time scales. Proceedings of the 8th Conference on Applied Climatology, 179-183. Boston.

Mdungela, NM, Bahta, YT and Jordaan, AJ. 2017. Indicators for economic vulnerability to drought in South Africa. *Journal of Development in Practice* 27 (8): 1050-1063.

Mendicino, G, Senatore, A and Versace, P. 2008. A Groundwater Resource Index (GRI) for drought monitoring and forecasting in a Mediterranean climate. Journal of Hydrology 357 (3-4): 282-302.

Mengistu, M, Olivier, C, Botai, JO, Adeola, AM and Daniel, S. 2021. Spatial and temporal analysis of the mid-summer dry spells for the summer rainfall region of South Africa. Journal of Water SA 47 (1): 76-87.

Meque, A and Abiodun, BJ. 2015. Simulating the link between ENSO and summer drought in Southern Africa using regional climate models. *Journal of Climate Dynamics* 44 (7): 1881-1900.

Meza, I, Rezaei, EE, Siebert, S, Ghazaryan, G, Nouri, H, Dubovyk, O, Gerdener, H, Herbert, C, Kusche, J and Popat, E. 2021. Drought risk for agricultural systems in South Africa: Drivers, spatial patterns, and implications for drought risk management. *Journal of Science*

Mishra, AK and Singh, VP. 2010. A review of drought concepts. Journal of Hydrology 391 (1-2): 202-216.bai

Moorhead, JE, Gowda, PH, Singh, VP, Porter, DO, Marek, TH, Howell, TA and Stewart, B. 2015. Identifying and evaluating a suitable index for agricultural drought monitoring in the Texas high plains. *Journal of the American Water Resources Association* 51 (3): 807-820.

Motlagh, MS, Ghasemieh, H, Talebi, A and Abdollahi, K. 2017. Identification and analysis of drought propagation of groundwater during past and future periods. Journal of Water resources management 31 (1): 109-125.

Mukherjee, S, Mishra, A and Trenberth, KE. 2018. Climate change and drought: a perspective on drought indices. Journal of Current Climate Change Reports 4 (2): 145-163.

Muthumanickam, D, Kannan, P, Kumaraperumal, R, Natarajan, S, Sivasamy, R and Poongodi, C. 2011. Drought assessment and monitoring through remote sensing and GIS in western tracts of Tamil Nadu, India. International journal of remote sensing 32 (18): 5157-5176.

Naik, M and Abiodun, BJ. 2020. Projected changes in drought characteristics over the Western Cape, South Africa. Journal of Meteorological Applications, 27 (1): e1802.

Namugize, JN, Jewitt, G and Graham, M. 2018. Effects of land use and land cover changes on water quality in the uMngeni river catchment, South Africa. Journal of Physics, Chemistry of the Earth, 105 247-264.

Ndlovu, MS and Demlie, M. 2020. Assessment of meteorological drought and wet conditions using two drought indices across KwaZulu-Natal Province, South Africa. Journal of Atmosphere, 11 (6): 623.

Nejadrekabi, M, Eslamian, S and Zareian, M. 2022. Spatial statistics techniques for SPEI and NDVI drought indices: a case study of Khuzestan Province. International Journal of Environmental Science 1-22.

News24. 2015. Drought hitting KwaZulu-Natal hard: Newspaper Article https://www.news24.com/news24/Green/News/Drought-hitting-KwaZulu-Natal-hard-20150618

Nkhonjera, GK and Policy. 2017. Understanding the impact of climate change on the dwindling water resources of South Africa, focusing mainly on Olifants River basin: A review. Journal of Environmental Science 71 19-29.

Ogunrinde, AT, Olasehinde, DA and Olotu, Y. 2020. Assessing the sensitivity of standardized precipitation evapotranspiration index to three potential evapotranspiration models in Nigeria. Journal of Scientific African 8 e00431.

Olanrewaju, CC and Reddy, M. 2022. Assessment and prediction of flood hazards using standardized precipitation index—a case study of eThekwini metropolitan area. Journal of Flood Risk Management 15 (2): e12788.

Omar, SA and Abiodun, BJ. 2020. Characteristics of cut-off lows during the 2015–2017 drought in the Western Cape, South Africa. Journal of Atmospheric Research, 235 104772.

Orimoloye, IR, Belle, JA, Orimoloye, YM, Olusola, AO and Ololade, OO. 2022. Drought: A common environmental disaster. *Journal of the Atmosphere* 13 (1): 111.

Patil Abhijit, S, Patil Akshay, A, Patil Somnath, P, Saundade Sushant, D, Chugule Kusum, A, Katavare Shital, B and Panhalkar Sachin, S. 2021. Analysis of the agriculture drought severity and spatial extent using Vegetation Health Index (VHI) in Manganga watershed of Maharashtra, India.

Pei, Z, Fang, S, Wang, L and Yang, W. 2020. Comparative analysis of drought indicated by the SPI and SPEI at various timescales in Inner Mongolia, China. Journal of Water 12 (7): 1925.

Pienaar, L and Boonzaaier, J. 2018. Drought policy brief Western Cape Agriculture. *Journal of the Western Cape Department of Agriculture, the Bureau for Food Agricultural Policy, Elsenburg*.

Potopová, V, Štěpánek, P, Možný, M, Türkott, L and Soukup, J. 2015. Performance of the standardized precipitation evapotranspiration index at various lags for agricultural drought risk assessment in the Czech Republic. Journal of Agricultural and Forest Meteorology 202 26-38.

Rensburg, L, De Clercq, W, Barnard, J and Du Preez, C. 2011. Salinity guidelines for irrigation: case studies from Water Research Commission projects along the lower Vaal, Riet, Berg and Breede rivers. Journal of Water SA 37 (5): 739-750.

Riebeek, H, & Simmon, R. (2009). Catalog of earth satellite orbits. NASA Earth Observatory. In.

Rouault, M and Richard, Y. 2005. Intensity and spatial extent of droughts in southern Africa. Journal of Geophysical Research Letters 32 (15).

Sherval, M, Askew, L and McGuirk, P. 2014. Manifestations of drought. Encyclopedia of Quality of Life Well-Being Research Springer Netherlands, Dordrecht 3756-3761.

Shi, H, Zhao, Y, Liu, S, Cai, H and Zhou, Z. 2022. A new perspective on drought propagation: Causality. Journal of Geophysical Research 49 (2): e2021GL096758.

Shin, JY, Chen, S, Lee, J-H and Kim, T-W. 2018. Investigation of drought propagation in South Korea using drought index and conditional probability. Journal of Terrestrial, Atmospheric Oceanic Sciences 29 (2).

Sifiso, N, Bonani, N, Simphiwe, N, Heidi, P and Moses, L. 2017. Economy-wide effects of drought on South African Agriculture: A computable general equilibrium (CGE) analysis. *Journal of Development Agricultural Economics* 9 (3): 46-56.

South African Weather Services, (2019), Seasonal forecast for summer 2019/20 and the current state of drought in South Africa. Document Reference: Medrel4 Nov 2019. https://www.weathersa.co.za/Documents/Corporate/Medrel4Nov2019

Stagge, JH, Tallaksen, LM, Gudmundsson, L, Van Loon, AF and Stahl, K. 2015. Candidate distributions for climatological drought indices (SPI and SPEI). International Journal of Climatology 35 (13): 4027-4040.

Strydom, S, Jewitt, G, Savage, M and Clulow, A. 2020. Long-term trends and variability in the microclimates of the uMngeni Catchment, KwaZulu-Natal, South Africa and potential impacts on water resources. Journal of Theoretical Applied Climatology 140 (3): 1171-1184.

Suleman, S, Chetty, K, Clark, D and Kapangaziwiri, E. 2020. Assessment of satellite-derived rainfall and its use in the ACRU agro-hydrological model. Journal of Water SA 46 (4): 547-557.

Tamiminia, H, Salehi, B, Mahdianpari, M, Quackenbush, L, Adeli, S and Brisco, B. 2020. Google Earth Engine for geo-big data applications: A meta-analysis and systematic review. Journal of Photogrammetry and Remote Sensing 164 152-170.

Theron, S, Archer, E, Midgley, S and Walker, S. 2021. Agricultural perspectives on the 2015-2018 Western Cape drought, South Africa: Characteristics and spatial variability in the core wheat growing regions. Journal of Agricultural and Forest Meteorology 304 108405.

The Witness. 2015. https://www.citizen.co.za/witness/news/kzn-farmers-battle-to-keep-their-livestock-alive -as-drought-worsens-20151103

Tian, L, Yuan, S and Quiring, SM. 2018. Evaluation of six indices for monitoring agricultural drought in the south-central United States. *Journal of Agricultural Forest Meteorology* 249 107-119.

Tirivarombo, S, Osupile, D and Eliasson, P. 2018. Drought monitoring and analysis: standardised precipitation evapotranspiration index (SPEI) and standardised precipitation index (SPI). Journal of Physics and Chemistry of the Earth, 106 1-10.

Umiati, T.2019. Spatial analysis and monitoring of drought using Standardized Precipitation Index in East Java. Journal of Physics: Conference Series, 012088. IOP Publishing.

Van Loon, A and Laaha, G. 2015. Hydrological drought severity explained by climate and catchment characteristics. Journal of Hydrology 526 3-14.

Van Loon, A. 2013. On the propagation of drought: how climate and catchment characteristics influence hydrological drought development and recovery. University of Birmingham.cret

Van Loon, AF, Gleeson, T, Clark, J, Van Dijk, AI, Stahl, K, Hannaford, J, Di Baldassarre, G, Teuling, AJ, Tallaksen, LM and Uijlenhoet, R. 2016. Drought in the Anthropocene. Journal of Nature Geoscience 9 (2): 89.

Van Loon, AF, Rangecroft, S, Coxon, G, Breña Naranjo, JA, Ogtrop, FV, Van Lanen and Henny, A. 2019. Using paired catchments to quantify the human influence on hydrological droughts. Journal of Hydrology Earth System Sciences 23 (3): 1725-1739.

Vetter, S. 2009. Drought, change and resilience in South Africa's arid and semi-arid rangelands. South African Journal of Science 105 (1): 29-33.

Vicente-Serrano, SM, Beguería, S and López-Moreno, JI. 2010. A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. Journal of Climate 23 (7): 1696-1718.

Vicente-Serrano, SM, Begueria, S, Lorenzo-Lacruz, J, Camarero, JJ, López-Moreno, JI, Azorin-Molina, C, Revuelto, J, Morán-Tejeda, E and Sanchez-Lorenzo, A. 2012a. Performance of drought indices for ecological, agricultural, and hydrological applications. Earth Interactions 16(10):1-27.

Vicente-Serrano, SM, Zouber, A, Lasanta, T and Pueyo, Y. 2012b. Dryness is accelerating degradation of vulnerable shrublands in semi-arid Mediterranean environments. Ecological Monographs 82:407-428.

Vicente-Serrano, SM, Lopez-Moreno, JI, Bengueria, S, Lorenzo-Lacruz, J, Sanchez-Lorenzo, A, Garcia-Ruiz, JM, Azorin-Molina, C, Moran-Tejeda, EM, Revuelto, J, Trigo, R, Coelha, F and Espejo, F. 2014. Evidence of increasing drought severity caused by temperature rise in southern Europe. Environmental Research Letters 9(4):1-9.

Vicente-Serrano, SM, Van der Schrier, G, Beguería, S, Azorin-Molina, C and Lopez-Moreno, JI. 2015. Contribution of precipitation and reference evapotranspiration to drought indices under different climates. Journal of Hydrology 526:42-54.

Vather, T, Everson, C, Mengistu, M and Franz, T. 2018. Cosmic ray neutrons provide an innovative technique for estimating intermediate scale soil moisture. South African Journal of Science 114 (7-8): 79-87.

Wang, Wen, Ertsen, Maurits W, Svoboda, Mark D, & Hafeez, Mohsin. (2016). Propagation of drought: from meteorological drought to agricultural and hydrological drought. In: Hindawi.

West, H, Quinn, N and Horswell, M. 2019. Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. Journal of Remote Sensing of Environment 232 111291.

WMO and (GWP), GWP. 2016. Handbook of Drought Indicators and Indices (Svoboda, M and Fuchs, B. A). Integrated Drought Management Programme (IDMP), Integrated Drought Management Tools and Guideline Series 2.

Yao, N, Zhao, H, Li, Y, Biswas, A, Feng, H, Liu, F and Pulatov, B. 2020. National-scale variation and propagation characteristics of meteorological, agricultural, and hydrological droughts in China. Journal of Remote Sensing 12 (20): 3407.

Zargar, A, Sadiq, R, Naser, B and Khan, FI. 2011. A review of drought indices. Environmental Reviews 19 (NA): 333-349.

Zhang, X, Obringer, R, Wei, C, Chen, N and Niyogi, D. 2017. Droughts in India from 1981 to 2013 and Implications to Wheat Production. Journal of Scientific Reports 7 44552.

Zhong, R, Chen, X, Lai, C, Wang, Z, Lian, Y, Yu, H and Wu, X. 2019. Drought monitoring utility of satellite-based precipitation products across mainland China. Journal of hydrology 568 343-359.