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SCHOOL OF GEOGRAPHY, ARCHAEOLOGY AND ENVIRONMENTAL
STUDIES



MODELLING TO DETERMINE OPTIMAL WATER– AVAILABILITY SCENARIOS
UNDER DROUGHT CONDITIONS IN AGRICULTURAL ENVIRONMENTS: A STUDY
OF THE WESTERN CAPE, SOUTH AFRICA

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PhD Thesis

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the Witwatersrand, Johannesburg, in fulfilment of the requirements for the Degree of Doctor
of Philosophy.

DECLARATION

I, **Mthulisi Ngwenya**, declare that this thesis, including the data, figures, tables, and any other information, is my original work. I have, where necessary, acknowledged the source(s) of the material that has been used. Furthermore, this thesis is being submitted for the award of the degree of Doctor of Philosophy to the Faculty of Science at the University of the Witwatersrand in Johannesburg, Republic of South Africa. This is the first time I am submitting this thesis for examination and the award of the degree thereafter. It has never been submitted to any other university before for a similar purpose. Sections of this work have been published or submitted for publication to the following peer reviewed journals.

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EXECUTIVE SUMMARY

Prolonged drought events have created persistent water shortages, and this has led to fierce competition amongst water users and a decline in agricultural production in agroecological zones (AEZs) of the Western Cape (WC) Province in South Africa. A common strategy to manage drought and the associated water shortages is based on crisis management (ex-ante). However, a risk-based approach seems to be in line with proactive and optimal water resources management. Therefore, considering the challenges and opportunities in the context of sub-Saharan Africa's policies and frameworks, how can drought risk management be most effectively and sustainably implemented through monitoring and vulnerability risk assessment considering the case study of the agricultural environments in semi-arid areas. In this regard, the overarching aim of this study was to quantify and analyse the impacts of meteorological drought on sustainable water availability in the AEZs of the WC during the between from 1980 and 2050. This study used two forms of datasets: observational data and model simulations. Observed precipitation data (1980–2020) were gathered from the University of East Anglia's Climate Research Unit gridded Time Series (CRU TS Version 4.07) <https://www.cru.uea.ac.uk/cru/data/hrg> database using Google Earth engine interface, while future precipitation datasets (2021–2050) under SSP5–8.5, SSP2–4.5 and SSP1–2.6 climate scenarios were generated by the sixth version of Model for Interdisciplinary Research on Climate, (MIROC6) <https://esgf-node.llnl.gov/search/cmip6/> database. These datasets were processed using the Standardized Precipitation Index (SPI), Reliance (R_{el}), Resilience (R_{es}) and Vulnerability (V_{ul}) indicators and Sustainability Index (SI). The Mann-Kendall (M-K) test was used for trend analysis at a significance level of $p < 0.05$. The results revealed that under the influence of climate change there will be a decrease in expected precipitation between 2021 and 2050 across all districts, with the greatest decrease expected in sub-tropical cool sub humid zone (STCSH). The average R_{el} index across the study area in observed data was calculated to be 0.53, which changed to 0.49 in the SSP2–4.5 scenario, a decrease of 1.43%. There was no change in average R_{es} index across the study area for both base period and under climate change scenario, calculated to be 0.42. The average V_{ul} index across the study area in the base period was calculated to be 0.47, which changed to 0.51 under the influence of climate change, an increase of 7.08%. The study findings indicated a progressive reduction in water availability across climate change scenarios with SSP5–8.5 indicating statistically significant negative trends while both the SSP2–4.5 and SSP1–2.6 indicated mostly positive insignificant precipitation trends in the near term (2021–2050). The results further indicate that in

arid climates, future SI, exhibited moderate water shortage ($0.60 < SI < 0.80$), while in semiarid climates future SI values, exhibited mild water shortages ($0.62 < SI < 0.71$); while in the humid climates future SI values projected normal to above normal water availability condition ($0.52 < SI < 0.58$). Trend analysis results indicated non-insignificant positive vulnerability trends and significant negative trends for both reliability and resilience indicator. Overall, the results suggest that between 2021 and 2050 drought conditions will aggravate water scarcity in AEZs compared to observed drought condition (1980-2020). The results of this study can aid policymakers in mitigating drought related water scarcity and foster drought resilient communities.

Key words: Drought, climate change, water availability, climate models, reliance, vulnerability, resilience

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ABBREVIATIONS

AEZ	Agroecological Zones
CMHYD	Climate Change for Water Modeling
CMIP6	Coupled Model Intercomparison Projects
CRED	Centre For Research on the Epidemiology of Disaster
CRU TS	Climate Research Unit Time Series
DEWS	Drought Early Warning System
DMP	Drought Management Plans
DRMM	Drought Readiness Mitigation Mechanisms
DSI	Drought Severity Index
DVRA	Drought Vulnerability and Risk Assessment
DWAF	Department Of Water Affairs and Forestry
ENSO	El Nino Southern Oscillation
FEWS NET	Famine Early Warning System Network
GCM	Global Climate Model
GHA	Great Horn of Africa
GIEWS	Global Information Early Warning System
GLEAM	Global Land Evaporation Amsterdam Model
GPM	Global Precipitation Mission
GRACE	Gravity Recovery and Climate Experiment
GWP	Global Water Partnership
HMNDP	High Level Meeting on National Drought Planning
IPCC	Intergovernmental Panel on Climate Change
LST	Land Surface Temperature
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percent Error
MENA	Middle East North Africa
METRIC	Mapping Evapotranspiration at High Resolution Internalized Calibration
MIROC	Model for Interdisciplinary Research on Climate
M-K	Mann-Kendall
MODIS	Moderate Resolution Imaging Spectrometer
NASA	National Aeronautics and Space Administration

NCFD	National Consultative Forum on Drought
NDVI	Normalized Difference Vegetation Index
PDO	Pacific Decadal Oscillation
PDSI	Palmer Drought Severity Index
RCP	Representative Concentration Pathway
SAWS	South Africa Weather Service
SDI	Synthesized Drought Index
SPI	Standard Precipitation Index
SSA	Sub- Saharan Africa
SSP	Shared Socioeconomic Pathways
STCA	Subtropical Cool Arid
STCSA	Subtropical Cool Semi-Arid
STCSH	Subtropical Sub Humid
STWA	Sub-Tropical Warm Arid
STWSA	Subtropical Warm Semi-Arid
STWSH	Subtropical Warm Sub Humid
TCI	Temperature Condition Index
TRMM	Tropical Rainfall Measuring Mission
UNDP	United Nation Development Program
UNFCC	United Nation Framework on Climate Change
UNISDR	United Nations International Strategy for Disaster Reduction
UNOCHA	United Nations Office for The Coordination of Humanitarian Affairs
VCi	Vegetation Condition Index
WFD	Water Framework Directive
WMO	World Meteorological Organisation

CHAPTER ONE

FRAMES OF REFERENCE

1.1. Introduction

In recent decades, there has been growing evidence that the impact of climate change on hydrological systems has increased the frequency and severity of drought conditions in certain regions (Abel et al., 2019; Simatele et al., 2023). Drought affects many facets of life and society (e.g., agriculture, energy, food security, health, water resources, migration, and resource conflict) (Diffenbaugh et al., 2015). Hanel et al. (2018) reported that as droughts affect more economic sectors, there are more conflicts among water users and increased societal vulnerability. Meissner et al. (2013) argued that drought is one example of an extreme weather event that will become more common and intense due to climate change. Tadesse et al. (2008) and Wilhite (2019) contended that drought is a complex natural hazard that affects millions of people every year, particularly exacerbating water scarcity and causing significant harm to infrastructure, the environment, and has the potential to weaken economies. Schmidtlein et al. (2008); Wilhite (2019) suggested that the risk of drought in any given region is determined by the region's exposure to the event (i.e., the probability of drought occurrence at different severity levels) as well as the vulnerability of society to drought. Numerous scholars, such as Maponya & Mpandeli (2012); Nyam et al. (2020), reported that because of drought, chronic water shortages will become the single most significant danger to alleviating poverty and promoting global prosperity. Dai (2013) reported that it is predicted that climate change will most certainly increase the frequency and severity of droughts across the globe, particularly in countries that are classified as arid and semi-arid. Pamla et al. (2021) suggested that unprecedented water shortages because of recurrent drought pose one of the most significant environmental concerns in water resources and agriculture. Musyimi et al. (2018) agreed with this view. They argued that compared to other sectors, the agricultural sector is the largest user of water since it is responsible for the consumption of nearly 80% of the world's freshwater reserves.

Pereira (2017) argued that drought risk management in agricultural environments is essential in practical discussions on effective, equitable and sustainable water resources planning. Drought risk management includes creating strategies for mitigating the impacts of droughts (Ngcamu & Chari, 2020). Because of this, there is a growing concern in society regarding the socio-economic

repercussions of droughts and potential strategies for avoiding or mitigating their impacts (Cook et al., 2018). Wilhite (2019) argued that droughts would continue to increase in frequency, severity, and duration because climatic conditions are changing, and there have been proven increases in extreme climate phenomena. According to Wilhite & Pulwarty (2017), a reduction in the gap between the availability of water and the demand for it will significantly increase the severity of the effects of drought. Although agricultural water availability is typically the first and most drought-affected sector (Lottering et al., 2021; Nyam et al., 2020; Ojara et al., 2022), many other sectors, including energy production, tourism and recreation, transportation, urban water supply, public health, and the environment (Kristensen et al., 2018; Makaya et al., 2020), have experienced substantial impacts, and these will increase at an accelerating rate as a result of further warming and growing competition for finite water resources.

1.2. Background of the study

In light of the above, Bayissa et al. (2017) contended that human practices that are not sustainable and the detrimental impacts of climate change are contributing to increasing frequency of droughts and substantial alterations in natural water flow mechanisms. Similarly, Okal et al. (2020) argued recurrent droughts have a greater impact on the global community compared to other natural hazards. As a result, droughts are considered the most expensive and complex challenge of the 21st century. Additionally, it is hypothesized that increased occurrences of droughts may lead to several issues, such as a disruption in the water budget model (Chen et al., 2013), alterations in evapotranspiration processes (Buttafuoco et al., 2018), and reduced water availability in the soil (Zhang & Li, 2020). These issues will result in a scarcity of water and food. Chandrasekara et al. (2021) contended that an increase in the incidence of meteorological droughts will result in substantial difficulties in food production, especially in rainfed agro-ecological zones. This poses a substantial risk to the global community's endeavours to eradicate poverty and address climate change by 2030 (Masih et al., 2014). While scholars like Kam et al. (2021) have confirmed that more frequent droughts will greatly change the availability of key aspects in sustainable agriculture, such as surface and groundwater, there is still limited consensus on the specific statistics regarding the effects of recurring droughts on a global, regional, and local scale.

The sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2021) has confirmed that climate change-induced droughts, occurring at current levels of global warming, have led to an increase in food insecurity and human mortality rates. These threats have escalated from low levels in the fifth assessment to moderate levels in the sixth assessment (Ziervogel et al., 2014). According to Mohleji & Pielke (2014), the ongoing drought has caused the death of over one million people and resulted in economic losses over sixty billion US dollars since 1974. Gidey et al. (2018) asserted that the population dwelling in regions experiencing high water stress, due to repeated droughts, is expected to rise considerably from 300 million to over 5 billion by 2025. In 2020, a report from the European Commission indicated that developed countries in the European Union and the United Kingdom experienced substantial annual economic losses of approximately €9 billion due to recurring droughts. Spain incurred the highest losses, amounting to €1.5 billion per year. In March 2021, substantial dust storms occurred in the northern parts of China, which were strongly linked to prolonged drought conditions caused by the long-term effects of global warming that the country has been experiencing in the past few decades (Li et al., 2021).

Similarly, research conducted in regions of the world located below the equator reveals that more than 500,000 individuals in sub-Saharan Africa are presently vulnerable to the gradual consequences of repeated drought. The resulting financial damages are estimated to exceed \$30 billion USD (Okal et al., 2020). Ayugi et al. (2022) argued that any changes in the timing and distribution of rainfall in sub-Saharan Africa, caused by human-induced global warming, will lead to food insecurity in the affected region. Liverman (2008) contended that the reason for this is the high susceptibility of agriculture in sub-Saharan Africa to climate change. According to Downing et al. (1997), the majority of countries in Sub-Saharan Africa do not possess the necessary abilities and resilience to mitigate the effects of repeated droughts. Raji et al. (2021) argued that a rise in the occurrence of drought events caused by climate change will have an impact on ecosystem services (ES), leading to water scarcity and food insecurity. Nhamo et al. (2019) asserted that the food security situation in South Africa heavily relies on rainfed agriculture. Fitchett et al. (2016) and Habiyaemye (2020) contended that the consequences of drought will be notably conspicuous and calamitous in developing nations located in the southern regions of the globe, such as South Africa. Recurrent drought episodes in South Africa will have a substantial impact on agricultural production and worsen food poverty in the region (Baudoin et al., 2017).

According to Botai et al. (2017), South Africa is highly susceptible to long-lasting droughts and is expected to experience a shortage of water by 2025. Savenije (2000) argued that southern Africa, namely South Africa, will experience a decline in water availability from 1700 m³ per person to below 1000 m³ per person. This statement implies that if there is a slight increase in the frequency of extreme drought events, South Africa's water security and food security will be substantially affected. This is because South Africa has a mean annual precipitation of 500mm/year, which is considerably lower than the global average of 860mm/year (Otieno & Ochieng, 2007). Ziervogel et al. (2022) take a geographically projected perspective and caution that in South Africa, the Eastern Cape and other inland areas encounter more severe flood episodes, while the western sections of the country are more susceptible to recurring drought occurrences. Ziervogel et al. (2014) proposed that this could be attributed to an increase in the occurrence of drought episodes. The Department of Water and Sanitation, previously called the Department of Water Affairs and Forestry in 2004, officially identified the Western Cape as one of the arid regions in South Africa, experiencing inconsistent levels of rainfall. Some regions in the Western Cape see an annual precipitation of less than 350mm, substantially lower than the national average of 500mm per year (Kam et al., 2021).

Sebastian (2015) stated that the Western Cape (WC) contains six agro-ecological zones (AEZs) in South Africa. These zones are the subtropical warm/arid (STWA), subtropical cool arid (STCA), subtropical warm semi-arid (STWSA), subtropical cool/semi-arid (STCSA), subtropical warm sub humid (STWSH), and subtropical cool sub humid (STCSH). The Western Cape (WC) region, with its predominantly agricultural economy focused on exporting fruits and reliance on a water supply system built on catchment areas, exemplifies a region highly vulnerable to the devastating effects of recurring droughts (Kam et al., 2021). The Western Cape's reputation as a province prone to drought is supported by the recent 2015-2017 period of severe drought (Ndebele et al., 2020). Throughout this time frame, the WC province had severe inter-annual drought conditions, resulting in a water supply crisis that posed a threat to cease water supplies to around four million persons (Vogt et al., 2018). Throughout the drought period, the water supply decreased substantially to only 20% capacity in January 2018 (Lange et al., 2020). Additionally, in 2019, there were more dry conditions, which led to a substantial 25% decrease in crop yield (Raude et al., 2018). Baudoin et al. (2017) emphasized that the severe drought experienced from 2015 to 2017 had a substantial negative effect on the agricultural sector, leading to a substantial decrease in employment opportunities. Additionally,

communities dependent on aquatic ecosystem services, such as ecotourism and fisheries, suffered the loss of sustainable livelihoods. Furthermore, the drought resulted in an increase in food prices.

The increasing occurrence of recurring droughts at the global, regional, and national levels presents a substantial risk to the fair, effective, and long-lasting distribution of water resources. It has the potential to cause a substantial decrease in water levels and the consequent desiccation of water bodies (Wambua, 2018). This has the potential to create severe obstacles for agricultural productivity and greatly impact the use and distribution of water for home consumption. According to Bayissa et al. (2017), it is essential to monitor and simulate the historical characteristics of drought in order to assess the impact of risks, make forecasts, and predict future drought events. According to Ongoma et al. (2018), examining the spatial and temporal characteristics of previous droughts might assist individuals in making informed choices and perhaps bring about substantial alterations in how farmers manage and distribute water. This can also assist individuals in formulating proactive planning plans for an impending future characterized by climate change. Nevertheless, accurately assessing drought attributes in agro-ecological zones necessitates a methodology that utilizes dependable and easily accessible data to ascertain the occurrence of drought (Okal et al., 2020).

Araujo et al. (2021) observed that scientific research in recent decades has facilitated the development and implementation of unique multidisciplinary methods for evaluating the dynamic and evolutionary aspects of drought occurrences. Thus far, these novel techniques have facilitated the categorization of droughts into four primary classifications: meteorological, agricultural, hydrological, and socio-economic. One approach is to utilize historical climatic time series data to construct drought-monitoring indices that illustrate the occurrence and progression of droughts (Ayugi et al., 2022). The drought monitoring indices utilize historical climatic data at intervals of 1, 3, 6, 12, 18, and 24 months to determine the time it takes for drought to manifest in social, economic, and environmental domains (Nhamo et al., 2019). Tozier de la Poterie et al. (2018) asserted that they examined the occurrence of agricultural drought by measuring the availability of soil moisture in the vadose zone across short to medium-term periods (1-, 3-, 6-month). Alternatively, a categorization of drought based on a 12- and 18-month duration is better suited for assessing the availability of surface and subterranean water over an extended period. Das et al. (2019) suggested incorporating long-term timescales, like the 12-month timeline, into the historical modelling of meteorological and hydrological droughts. Conversely, Citakoglu & Coşkun (2022) stated that socioeconomic droughts occur when the demand

for an economic resource exceeds its availability due to a deficiency caused by climatic conditions. In this study, it was deemed more suitable to focus on meteorological droughts, which are the most prevalent and are defined by a departure from the usual rainfall patterns, resulting in below-average precipitation levels time periods (Gidey et al., 2018).

There are several drought indices used worldwide, each utilizing specific datasets to accurately capture the spatial and temporal characteristics of droughts (Nhamo et al., 2019). Commonly used indices for evaluating meteorological droughts include the Palmer Drought Severity Index (Sheffield et al., 2012), the Surface Water Supply Index (Mishra & Singh, 2010), the Standardized Precipitation Index (McKee et al., 1993), the Rainfall Anomaly Index (Raziei, 2021), and the Standardized Precipitation Evapotranspiration Index (Memon & Shah, 2019). Kchouk et al. (2022) proposed that the monitoring indices vary depending on the area because of the ever-changing and developing nature of drought conditions. For instance, the Palmer Drought Severity Index is commonly used in North American countries, but the Reconnaissance Drought Index is more suited for Australia (Jiao et al., 2019). Although there are various indices available, Su et al. (2017) suggested that using a single drought monitoring index would suffice in evaluating the multiple aspects of droughts. Meanwhile, Nam et al. (2017) emphasized that the World Meteorological Organization suggested in 2009 that the Standardized Precipitation Index should be universally employed to characterize and analyse meteorological drought conditions in any catchment.

Contemporary literature by scholars like Botai et al. (2016); Das et al. (2019); Gidey et al. (2018); Kao & Govindaraju (2010); Zhang & Li (2020) and Kao & Govindaraju (2010), has shown that recurring drought consequences are constantly changing, widespread, and among the most expensive natural disasters. However, natural dangers continue to be the most intricate and unpredictable phenomena. Alam et al. (2023) and Das et al. (2019) employed several methodological frameworks to investigate the spatial and temporal attributes of repeating drought episodes. Simultaneously, Ayugi et al. (2022) and Orimoloye et al. (2019) emphasized the influence of external factors, such as a shifting climate, insufficient drought monitoring systems, and conflicting water demands from different users, which complicate the comprehension of recurring drought occurrences. The conflicting demands for water may lead to lethal clashes. The convergence of several problems and the increasing occurrence of repeated droughts pose numerous difficulties in agro-ecological zones

(AEZs) that water managers and farmers must confront to understand meteorological droughts and devise proactive, adaptable management approaches.

The sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2021) has highlighted substantial evidence of the detrimental impact of severe drought occurrences on both human and ecological systems. In their study, Reason & Rouault (2005) examined the severity and geographical scope of droughts in South Africa. They determined that there has been a notable increase in the extent of areas impacted by drought during the 1970s due to the heightened influence of the El Nino Southern Oscillation. Otto et al. (2018) examined the human factors that led to the 2015-2017 drought in the Western Cape. They found that activities like deforestation and intensified agriculture were worsening the effects of droughts caused by human-induced climate change. The study emphasized the need for scientific research on strategies to enhance the ability of the Western Cape community to adapt to these challenges. Johnston (2018) conducted an evaluation of the influence of a recurring drought on agricultural productivity on Western Cape farms. The study determined that the drought was severely reducing farmers' output. He suggested implementing a system of responsible water distribution and usage to address the conflicting demands of water consumers. Botai et al. (2017) utilized the Standardized Precipitation Index (SPI) with historical data from weather stations to evaluate the geographical and temporal features of drought in different water management regions of South Africa. Their research revealed that droughts in the Western Cape had a detrimental impact on water availability. The water storage levels in dams had dropped to less than 30% capacity, suggesting that the socio-economic difficulties faced by the Western Cape community would persist even after the drought had ceased. Baudoin et al. (2017) conducted socio-economic assessment studies to comprehend the experiences and findings from the recent drought season of 2015-2017. Their research revealed that human-induced climate change resulted in a threefold increase in the occurrence of droughts. The studies conducted by Otto et al. (2018); Johnston (2018); Baudoin et al. (2017) and Botai et al. (2016) suggest that the severe effects of human-caused climate change, such as frequent drought in the Western Cape, have prompted further research to understand the connection between the drought's spatial and temporal features and the availability of water in agro-ecological zones.

To this end, the increasing frequency and severity of droughts at a global, regional, and national scale present a substantial threat to the fair, effective, and sustainable distribution of water resources (Vogt

et al., 2018). This situation can significantly reduce water levels and the consequent desiccation of water bodies (Wambua, 2018). Consequently, drought poses substantial challenges for agricultural output and greatly affects the availability of water for household needs in susceptible populations. Bayissa et al. (2017) argued that understanding the trade-offs and synergies of spatiotemporal characteristics of drought on physical water scarcity is essential for managing the risks associated with drought, making accurate projections, and anticipating future water availability scenarios. et al. (2018) proposed that assessing the impacts of drought on water resources could aid decision-makers in making educated choices and perhaps lead to significant alterations in how farmers distribute water for crops.

1.3. Thematic considerations

Numerous scholars, such as Lange et al. (2020); Tapiador et al. (2020); Wang et al. (2004) have suggested that monitoring and evaluating future characteristics of hydro climatic variability together with shared socioeconomic pathways– representative concentration pathways (RCP–SSPs) is vital for modelling future drought characteristics and their impacts on water security. However, recent advancements in climate projections and drought prediction have remained sophisticated and largely limited (Hao et al., 2014), partly due to uncertainties in climate data simulations (Basak et al., 2022). Poornima & Pushpalatha (2019) argued that the only scientifically acceptable technique for modelling future drought characteristics has been using Global Climate Model (GCM) projections developed under the Coupled Model Intercomparison Projects (CMIP). The Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC, 2020) recently unveiled the Coupled Model Intercomparison Project Phase 6 (CMIP6) to investigate and compare climate projections made from coupled ocean–atmosphere–cryosphere–land GCMs (Meehl et al., 2000). The CMIP6 framework couples plausible future representative concentration pathways (RCPs) with alternative shared socioeconomic pathways (SSPs) in order to research climate change impacts, adaptation, and mitigation (Eyring et al., 2019). Rogelj et al. (2012) noted that the CMIP6 framework applies a combination of four plausible climate change scenarios, namely SSP1–2.6, SSP2–4.5, SSP3–7.0 and SSP5–8.5 to monitor future drought characteristics.

O'Neill et al. (2017) suggested that plausible climate change scenarios constitute an essential component of climate change impact as they aid researchers and decision-makers in understanding

the consequences of near-and long-term climate changes. The SSP1–2.6 model describes the low extreme limit of the range of projected scenarios and appraises the RCP2.6 scenario (Tebaldi et al., 2021). The SSP2–4.5 model describes the intermediate portion of the range of projected scenarios and revises the RCP4.5 scenario (Peng et al., 2023). The SP3–7.0 scenario is in the upper-middle part of the full range of scenarios. It was newly introduced after the RCP scenarios, closing the gap between RCP6.0 and RCP8.5 (Tan & Duan, 2017). The SSP5–8.5 model characterises the high extreme limit of the range of projected scenarios (Zelinka et al., 2020). Mirgol et al. (2021) argued that climate change alternative scenarios, together with GCMs, enable water resource managers to predict the impacts of drought in the face of future global climate uncertainties. Vicente-Serrano et al. (2022) noted that the SSP–RCP climate change scenarios from CMIP6 permit for risk impact assessment of potential mitigation and adaptation strategies in natural resources climate management and societal transformation consistently.

Although GCM simulations underpinned by the CMIP6 framework present an excellent methodology to model the climate change impacts, it is widely accepted that GCM output has a very coarse resolution compared to that at which anthropological activities in a region of interest occur (Zelinka et al., 2020). Gupta et al. (2020) argued that GCM simulated datasets have a coarse spatial resolution (usually 500 kilometres grid cell), which is more significant than necessary for use in the more regional and local-based basins that require up to a minimum of 20-kilometres (km) grid cells. Scholars such as Huo-Po et al. (2013) and Tebaldi et al. (2021)) have suggested that GCM simulations require downscaling to obtain output that can be used at regional and local scales. Downscaling bridges the gap between global yet coarse predictions and practical needs such as precipitation projection for hydrologic operations in local basins under climate change (Tapiador et al., 2020). Mirgol et al. (2021) highlighted that downscaling procedures have evolved to be an effective way of linking GCM simulations (frequently atmospheric circulation data) to local scale surface variables (such as precipitation). Christensen et al. (2007) reported that two types of downscaling techniques are available: dynamic downscaling (DD) and statistical downscaling (SD).

Wang et al. (2004) noted that DD involves the use of high-resolution regional climate model (RCM) simulations to extrapolate the impacts of large-scale climate processes to regions or local scales of interest. The resolution in most RCMs ranges from 20 km to 60 km (Stefanidis et al., 2020). Due to its high computing cost, DD has minimal application in impact studies and is only helpful for local

scale simulations (Burke et al., 2006). Salvi et al. (2011) argued that DD is complicated and demands the same computing power as GCM simulations. Rashid et al. (2017) noted that DD is difficult to execute accurately and is primarily used to process GCM projection to better resolution RCM output. On the other hand, SD techniques are more efficient than DD techniques and are widely used due to their structural simplicity (Iizumi et al., 2011). One of the many benefits of using SD techniques is that compared to the DD technique, they require less computations and may be applied to downscale many GCM climate simulations (Sachindra et al., 2014). Fowler et al. (2007) noted that SD techniques offer local-scale climate information from GCM climate projections. Broadly, SD approaches can be further categorised into three classes: transfer function method (Ding et al., 2019), weather typing (Richardson, 1981) and weather pattern schemes (Qin et al., 2021). The Bias Correction (BC) underpinned by the transfer function method has been primarily adopted and widely applied in climate change studies for downscaling purposes (Payus et al., 2020; Wood et al., 2015).

Zhang & Guo (2016) noted that to predict drought characteristics credibly, a suitable drought index should be selected. While numerous drought monitoring indices are applied for drought characterisation, contradictory findings on their characteristics have been published, partly due to embedded constraints in the numerous drought monitoring indices (Park et al., 2015). The use of these indices is location-specific due to the dynamic and evolutionary characteristics of drought environments. Amongst these numerous drought monitoring indices, the most widely used ones include the Palmer Drought Severity Index (PDSI) (Palmer, 1965), Soil Moisture Index (SMI) (Wetherald & Manabe, 2002), and the Standardised Precipitation Index (SPI) (McKee et al., 1993). The Palmer Drought Severity Index (PDSI) is widely used in North America to measure the accumulated spatio-temporal deviation of moisture supply. It applies that the Thornwaite's method of estimating potential evapotranspiration. However, the PDSI has restricted precision due to PET estimation's existential complexity and uncertainty, mostly in extreme climate conditions and mountainous regions. On the other hand, the SMI was developed to evaluate the quantity of water accessible by crops in the soil (Wetherald & Manabe, 2002). The SMI index needs an assortment of climate data such as precipitation, temperature, potential evapotranspiration, and plant data such as vegetation type, leaf area, and management practices (Wetherald & Manabe, 2002). The Standardized Precipitation Index (SPI) is a widely used drought index that relies solely on precipitation data and is based on a probabilistic methodology. It has gained popularity over other indices due to its ability to

be calculated at different timescales ranging from 1 to 24 months. Moreover, it can differentiate between various types of droughts, such as agricultural, meteorological, and hydrological droughts (Hayes et al., 2011).

1.4. Rationale

To this end, various scholars such as Engelbrecht & Monteiro (2021); Kelley et al. (2015); Ndebele et al. (2020), concur that the pervasive and costly nature of drought remains the single greatest threat to water resources and agricultural production particularly in drought-prone regions such as the WC province of South Africa that rely on rainfed agriculture. Whilst several studies have investigated the probable impacts of climate change-induced drought on water resources, their investigations have been aimed at the catchment level (Kusangaya et al., 2014). For example, research conducted by Park et al. (2015) has revealed that the impact of climate change in humid tropical zones of southern Africa caused some changes in the spatio-temporal distribution of observed precipitation. However, the study applied large-scale hydrological models that were underpinned by an RCM to examine the influence of climate change on hydrological elements such as evapotranspiration (ET) and surface runoff until 2029. Similarly, Graham et al. (2022) investigated the hydrological feedback to future climate change over the Thukela River Basin, South Africa. Their study revealed that future temperatures were predicted to increase in all scenarios, while there was no agreement on the impacts on water availability. The above studies underscored the necessity for supplementary, reliable drought modelling studies in South Africa that seek to understand the future characteristics of drought better to manage the associated risk. More recently, using multi-model regional climate simulations from the Co-ordinated Regional Climate Downscaling Experiment (CORDEX), Abiodun et al. (2019) investigated the probable effects of climate change on droughts over four major basins in southern Africa. While the study investigated drought throughout southern Africa, it did not investigate climate change scenarios using the CMIP6 framework and was not localised in the Western Cape region in particular. Moreover, decisions on drought monitoring are usually undertaken at the provincial level, so there is an exigent requirement for new research at the provincial scale (Kusangaya et al., 2014).

Ngaka (2012) further noted that amongst all the nine provinces of South Africa, the Western Cape (WC) Province is particularly prone to the impacts of drought. This assertion is concretised by the severe drought that occurred in the Western Cape Province during the 2015 to 2017 hydrological

years. During this time, Baudoin et al. (2017) reported that the WC Province experienced a severe inter-annual drought that led to unprecedented water shortage since 1904 and was subsequently declared by the national government as a disaster region. Vogel et al. (2019) contended that the inter-annual drought in 2015–2017 resulted in water scarcity that endangered nearly seven million residents of the Western Cape Province. During the inter-annual drought epoch, there was a massive decline in water storage levels in the province, ultimately reaching a meagre 20% of its total storage capacity in January 2018 (Watson et al., 2021). The Theewaterskloof Dam, which is responsible for 41% of the province's water storage capacity, underwent a significant decrease to around 11% of its total storage capacity of 480 million cubic meters in early 2018 (Otto et al., 2018). In addition, in 2019, dry conditions resulted in a 25% decrease in crop yield (Raude et al., 2018). Baudoin et al. (2017) concluded that in the last three decades the WC province has been experiencing more frequent and severe drought events, projecting that they will lead to more devastating consequences on water resource availability, negatively impact agricultural production and cause a significant decrease in employment prospects. Raude et al. (2018) further argued that coastal communities in the WC Province that rely on aquatic ecosystem services, such as ecotourism and fisheries, were projected to suffer significant losses in terms of sustainable livelihoods.

In light of the above, various scholars such as Engelbrecht et al. (2017) have contended that predicting and quantifying the impact of drought is critical to diminish the both primary and secondary impacts such as declining water availability and agricultural production. Botterill & Cockfield (2013) argued that due to the complexities of assessing the spatiotemporal dynamics of drought at various scales, there is a need for an integrated approach to managing water resources under drought conditions, with a view to maintain a balance between water demand and supply in any water resource system. Chamani et al. (2023) contended that due to the difficulty of identifying all the perturbations caused by drought events and the associated impacts on water availability under drought conditions, it is necessary to employ an integrated approach using indicators to assess the response to drought of ecosystems. Several approaches have been proposed to assess the drought response of ecosystems based on different indicators. These approaches include Bayesian Network approach (Croke et al., 2007), Driving Force-Pressure-State-Impact-Welfare Response (DPSIWR) model (Pires de Souza Araujo et al., 2021) and the Reliability ($R_{el.}$)–Resilience ($R_{es.}$)–Vulnerability ($V_{ul.}$) framework (Hazbavi et al., 2018). The DPSIWR, initially proposed by Cooper (2013) and improved by de Andrés

et al. (2018), who incorporated the human welfare component to the framework, has its limitation as it does not explore the cause-effect linkages between global change, impacts on ecosystem services and the potential impacts on human welfare. The Reliability–Resilience –Vulnerability ($R_{el} \cdot R_{es} \cdot V_{ul}$) framework, initially proposed by Hashimoto et al. (1982), has been widely adopted and is largely recommended by scholars such as Chamani et al. (2023); Sadeghi et al. (2020) to assess different responses of ecosystems to satisfactory and unsatisfactory states, such as drought episodes. (Fooladi et al., 2021) contended that different aspects of water resource availability can be derived from a joint distribution analysis using both $R_{el} \cdot R_{es} \cdot V_{ul}$ framework and drought monitoring techniques. Reliability refers to how often the system is in a satisfactory state during a given period (Hoque et al., 2020). Resilience measures how quickly, on average, a system can recover to a satisfactory state after experiencing an unsatisfactory state (Rahman et al., 2017). Vulnerability indicates the potential damage to the system caused by an unsatisfactory state (Araujo et al., 2021). Asefa et al. 2014) argued that using an integrated approach to analysing water scarcity under drought conditions can provide insight into ecosystem response under changing and undesirable climatic conditions such as drought.

Despite the WC province's high-water vulnerability to drought impacts, only a limited number of climate projections studies have been made for the region (Abiodun et al., 2019; Diallo et al., 2014; Engelbrecht et al., 2013). Hence, the primary purpose of the study was to examine the potential impacts of meteorological drought on water resource availability in the WC province, an area especially vulnerable to climate change.

1.5. Research questions

In view of the above considerations, the following key research questions guided the research process:

- i. What are the historical patterns (1980-2020) of precipitation and drought characteristics in the WC Province and how do they impact the availability of water resources?
- ii. How will the future (2021-2050) precipitation and drought characteristics in the WC Province under different climate change scenarios affect future water availability?
- iii. Which climate change scenario will enable sustainable water availability between 2021 and 2050?
- iv. What will be the implications of the findings of this study in a wider context, particularly in water stressed regions of sub-Saharan Africa?

1.6. Research aims and objectives.

The aim of this study was to quantify how meteorological drought are affecting water availability and agricultural productivity over agroecological zones of the Western Cape Province using historical and future datasets during the period between 1980 and 2050. Given this, therefore, the specific objectives of this study were to:

- i. Analyse the observed (1980-2020) variations in severity, intensity, and frequency of meteorological drought across different AEZs in the Western Cape Province.
- ii. To downscale and use bias correction techniques to the three-climate change scenario (SSP5–8.5, SSP2–4.5 and SSP1–2.6) datasets projected from the sixth version of Model for Interdisciplinary Research on Climate (MIROC6),
- iii. Evaluate the spatio–temporal dynamics of meteorological drought in the near–term period (2021–2050) under three projected scenarios (SSP5–8.5, SSP2–4.5 and SSP1–2.6) in the Western Cape Province of South Africa,
- iv. Assess the changeability of the water resource system reliability, resilience, and vulnerability in AEZs of the Western Cape and consequently map the water availability sustainability index characteristics in the WC province.
- v. To provide a strategic recommendation for enhancing drought management and mitigation strategies in agricultural production systems in South Africa.

1.7. Theoretical considerations

Although theories linking water resources management and drought risk assessment have been limited, drought characterization is a complex issue influenced by time and space (Calverley & Walther, 2022; Quiring, 2009; Ramos et al., 2021). Regardless of which drought and water resource management strategy policy makers adopts, society expects decision-makers to optimize the availability and distribution of water resources (Pedro-Monzonís et al., 2015). Weng et al. (2015) argued that using indexes to assess water resources during drought events, can aid in proactive management decision-making. Indexes are collections of weighted variables or indicators that reflect societal requirements and are used to formulate water policies (Weng et al., 2015). Godfrey & Chalmers (2012) noted that indicators are intended to convey environmental information about a water resources system by accumulating variables as an index as shown in Figure 1.1 below.

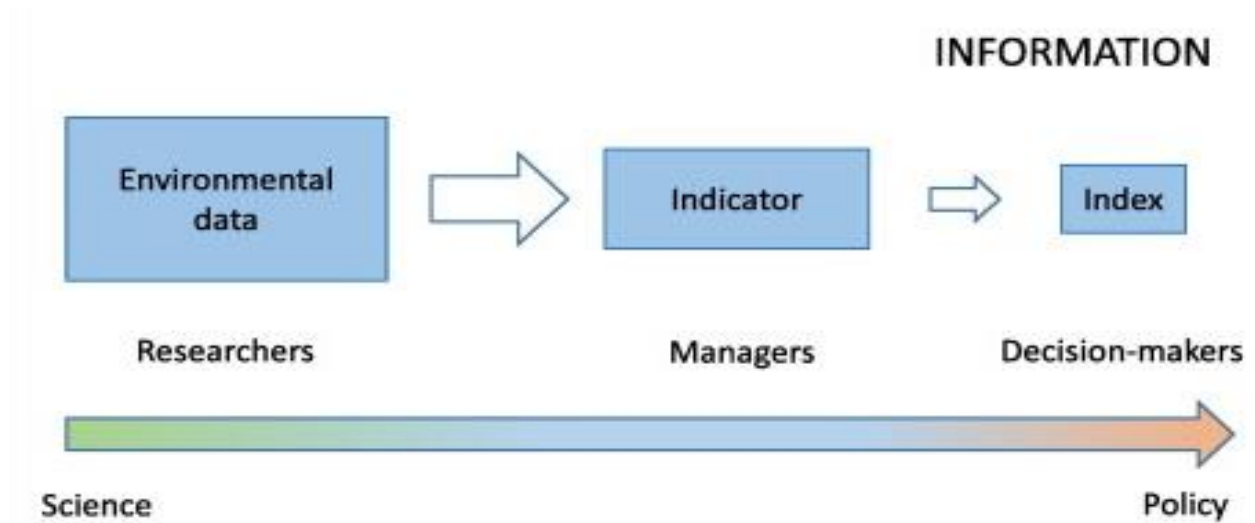


Figure 1.1 Information flow in water resources management (Source: Pedro–Monzonís et al., 2015)

Pedro–Monzonís et al. (2015) contended that effective management of water resources during drought situations requires a comprehensive understanding of the various elements of drought risk and exploration of different options for drought management. Botterill & Cockfield (2013) added that water resource planning is a critical process that affects all areas of society, necessitating the creation of comprehensive water resource management strategies that involve all levels of decision-making. Wilhite (2019) observed that water resource planning encompasses all aspects of planning, including developing prompt responses to drought situations to minimize the risks and consequences of water scarcity. Meanwhile, Tsakiris & Vangelis (2004) water resources management comprises the complete body of science and administrative policies and operational activities relating to various stages of drought. Tadesse et al. (2008) identified the implementation of Drought Early Warning Systems (DEWS), conducting Drought Vulnerability and Risk Assessments (DVRA), and the establishment of Drought Response and Mitigation Mechanisms (DRMM) as the three vital components of water resources management under drought conditions (Figure 1.2).

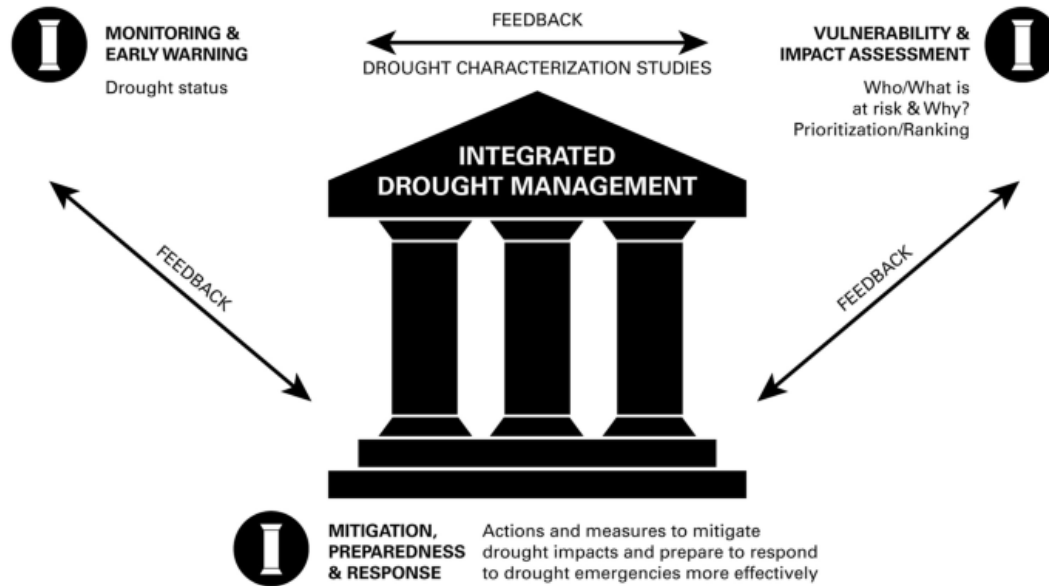


Figure 1.2 Drought risk management (Source: Integrated drought management programme (IDMP, 2016))

Svoboda et al. (2017) reported that DEWS involves tracking drought indicators and indices using various climate and biophysical factors, such as precipitation, temperature, soil moisture, vegetation condition, stream flow, and groundwater. On the other hand, Quiring (2009) argued that DVRA involves evaluating the system/societal vulnerability caused by environmental and socioeconomic elements or processes that make a system more prone to the effects of drought. Nam et al. (2015) argued that DRMM involves structural and non-structural measures enacted by water governance institutions to minimise the adverse effects of drought. Structural measures include the implementation of suitable crops, the construction of dams, and engineering projects (Ramos et al., 2021). Non-structural measures involve adopting policies, raising awareness, developing knowledge, fostering public commitment, establishing legal frameworks, and improving operating practices (Calverley & Walther, 2022). The response to drought involves providing aid, intervention during, or shortly following a drought catastrophe with a comprehensive long-term drought strategy (de Brito, 2021). Hsiang & Burke (2014) argued that DRMM aims to improve the ability to minimise or mitigate the consequences of drought by implementing suitable measures and actions.

Meanwhile, Tsakiris et al. (2013) proposed a drought characterisation framework that considers different types of droughts depending on the variable being considered, namely meteorological,

agricultural, and hydrological droughts (Figure 1.3). According to the framework, meteorological droughts are identified as the persistent absence of precipitation and an increase in evapotranspiration over short to long-term time scales (Van Loon et al., 2016). Nam et al. (2017) reported that meteorological drought often serves as a precursor to other types of droughts, frequently affecting large spatial areas. Kchouk et al. (2022) contended that agricultural drought could be understood as a deficiency of moisture in the soil root zone necessary to meet the water requirements of crops, thereby causing crops to reach a state of permanent wilting. On the other hand Singh & Xiaosheng (2019) reported that hydrological drought could be described as a period of reduced streamflow and below-average water levels in lakes and groundwater. Mishra & Singh (2011) argued that hydrological droughts are associated with decreased surface and subsurface water flow within a catchment management system. The cumulative impacts of meteorological, agricultural, and hydrological droughts lead to socio-economic drought (Basak et al., 2022).

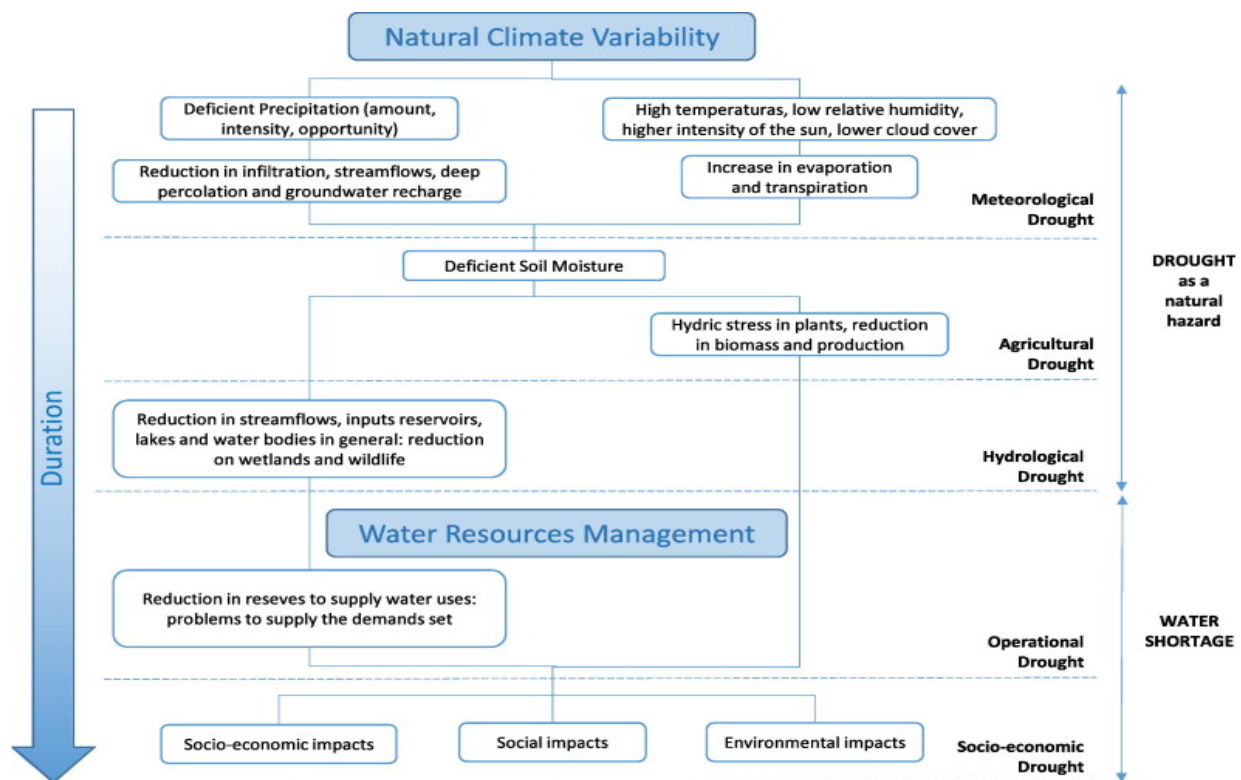


Figure 1.3 Drought characterisation framework (Source: Tsakiris et al., 2013)

To this end, De Brito (2021), Estrela et al. (2012), Hayes et al. (2012), Svoboda et al. (2017), and Tsakiris et al. (2013) agreed that quantifying the impacts of drought on water resource availability is

a first step in mitigating the associated primary and secondary impacts in a water-scarce region. Furthermore, Mishra & Nagarajan (2011) proposed that socioeconomic drought, as proposed by Tsakiris et al. (2013), cannot be regarded as a natural hazard, as it results in a water deficiency to meet societal and environmental needs. This scarcity arises from the impacts of climate change and the overuse of water resources for various human activities, such as agriculture (Van Loon et al., 2016).

Despite the existence of many theories and methodologies for investigating water availability under drought conditions, there has been incongruous findings, due to embedded limitations in the numerous drought monitoring indices (Chen et al., 2013; Mostafazadeh & Zabihi, 2016). Over the years, contemporary literature has indicated that drought risk, i.e., the likelihood of negative consequences such as water shortages, is not driven only by natural hazards (droughts, floods, etc.) but rather emanates from the interactions between natural hazards, exposure, and vulnerability (Sharma & Ravindranath, 2019). According to the IPCC (2014), exposure in this context implies the ‘presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected’ by such hazards (O’Neill et al., 2017). Meanwhile, Nasrollahi et al. (2018) argued that vulnerability is the predisposition to be adversely impacted, resulting from the sensitivity of territory to harm coupled with a lack of coping and adaptive capacity. Due to its complexity and multi-dimensional nature, drought risk can, therefore, not be adequately represented solely by a single factor or variable, such as poverty (González Tánago et al., 2016). Instead, it is often driven by various context and impact-specific factors, including environmental, social, economic, cultural, physical, and governance-related aspects (Birkmann et al., 2013; Hagenlocher et al., 2019).

Birkmann et al. (2013), González Tánago et al. (2016) and Hagenlocher et al. (2019) argued that the need to monitor the impacts of drought risk on water security is highlighted by global agreements and charters such as the Sendai Framework for Disaster Risk Reduction 2015–2030 (van Niekerk et al., 2020) or the 2018/19 UNCCD Drought Initiative (Právělie, 2021). According to Rajeev (2022), various methods are available for describing drought vulnerability and risk in the context of climate change and natural hazards such as droughts. These include quantitative, qualitative, and increasingly mixed methods approaches that combine both (Schneiderbauer et al., 2017). Hagenlocher et al. (2018) argued that adopting and applying a plurality of methods can yield complementary evidence to

elucidate better the intricacy of processes that facilitate drought vulnerability and risk. The selection of the method employed depends not only on the scope of the assessment (local to global) but also on the consideration of the drivers, classifying spatiotemporal patterns and hotspots of risk (Frischen et al., 2020). Qualitative vulnerability and risk assessment regularly apply extensive data collection methods such as interviews, focus group discussions (FGDs), or narratives to divulge context-specific drivers of risk (Frischen et al., 2020). However, Schneiderbauer et al. (2017) argued that quantitative assessments tend to employ criteria and indicators/indices to evaluate vulnerability and risk, often in a spatially overt manner.

Moreover, to evaluate drought risk hotspots, the characterisation of historical trends and dynamics and the development of future scenarios in vulnerability and risk have sparked increasing interest and attention in recent years for several reasons (Birkmann et al., 2013). Hagenlocher et al. (2018) argued that characterising historical trends or risk dynamics could aid in monitoring and evaluating risk reduction and adaptation strategies. Birkmann et al. (2015); Garschagen & Kraas (2010) argued that future climate risk scenarios can offer valuable deterrent and adaptive planning contributions. Jurgilevich et al. (2017) argued that while the number of studies that include spatiotemporal characterisation of drought is increasing, the bulk of future scenario-related studies do not consider scenarios of vulnerability but rather focus on the hazard component of the risk concept. Feizizadeh and Kienberger (2017), Fekete (2009), Hagenlocher and Castro (2015), and Schmidlein et al. (2008) have pointed out that several stages involved in quantitative drought risk studies, such as data imputation, outlier data handling, standardization, and weighting of indicators, introduce uncertainty into the modelling results. However, statistical validation techniques have demonstrated the ability to provide appropriate evidence on the reliability, resilience, and methodological robustness of risk assessments. In addition, Birkmann et al. (2015) argued that the application of quantitative techniques in the field of drought and water security assessment remains largely underdeveloped.

1.8. Overview of research methodology

Figure 1.4 illustrates the methodological approach that was applied to model drought hazards. In the present study the quantification drought risk involved understanding historical and future threats and how those threats may be reduced through disaster risk reduction (DRR) efforts. A detailed understanding of drought risk was crucial for detecting regions most vulnerable to water scarcity because of drought. The current study assumed that climate change modified precipitation patterns; therefore, climate variable projections were used to integrate drought characteristics with water availability risk assessments. Information on climate scenarios was combined with global climate models (GCM) output that were then statistically downscaled to finer resolution for hazard analysis in the region of interest. GCMs are the main tool used for climate projections, and comprehensively capture dynamics of the atmosphere-ocean system as well as other physical phenomena. Examples of commonly used GCMs include the HadCM3 (Hadley Centre Coupled Model version 3; (Gordon et al., 2000) and the HadGEM2-ES (Hadley Centre Global Environment Model version 2 - Earth-System, e.g.,(Campbell et al., 2018) which were developed by the UK Met Office.

Although GCM simulations underpinned by the CMIP6 framework presented an excellent methodology to model the climate change impacts, the present study assumed that GCM output has a very coarse resolution compared to that at which anthropological activities in a region of interest occur (Zelinka et al., 2020). Gupta et al. (2020) argued that GCM simulated datasets have a coarse spatial resolution (usually 500 kilometres grid cell), which is more significant than necessary for use in the more regional and local-based basins that require up to a minimum of 20-kilometres (km) grid cells. Scholars such as Huo-Po et al. (2013) and Tebaldi et al. (2021) have suggested that GCM simulations require downscaling to obtain output that can be used at regional and local scales. Downscaling bridges the gap between global yet coarse predictions and practical needs such as precipitation projection for hydrologic operations in local basins under climate change (Tapiador et al., 2020). Mirgol et al. (2021) highlighted that downscaling procedures have evolved to be an effective way of linking GCM simulations (frequently atmospheric circulation data) to local scale surface variables (such as precipitation). Christensen et al. (2007) reported that two types of downscaling techniques are available: dynamic downscaling (DD) and statistical downscaling (SD).

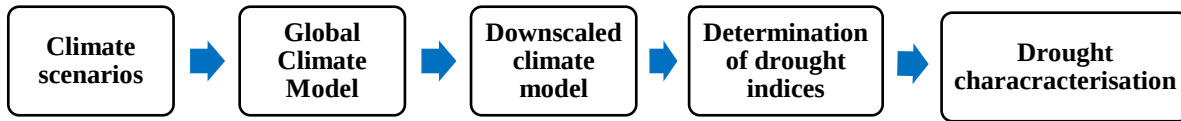


Figure 1.4 An overview of methodological approach (Source: Tadesse, 2008)

There are several drought indices used worldwide, each utilizing specific datasets to accurately capture the spatial and temporal characteristics of droughts (Nhamo et al., 2019). Commonly used indices for evaluating meteorological droughts include the Palmer Drought Severity Index (Sheffield et al., 2012), the Surface Water Supply Index (Mishra & Singh, 2010), the Standardized Precipitation Index (McKee et al., 1993), the Rainfall Anomaly Index (Raziei, 2021), and the Standardized Precipitation Evapotranspiration Index (Memon & Shah, 2019). Kchouk et al. (2022) proposed that the monitoring indices vary depending on the area because of the ever-changing and developing nature of drought conditions. The Palmer Drought Severity Index is commonly used in North American countries, but the Reconnaissance Drought Index is more suited for Australia (Jiao et al., 2019). Although there are various indices available, Su et al. (2017) suggested that using a single drought monitoring index would suffice in evaluating the multiple aspects of droughts. Nam et al. (2017) emphasized that the World Meteorological Organization suggested in 2009 that the Standardized Precipitation Index should be universally employed to characterize and analyse meteorological drought conditions in any catchment.

Botterill & Cockfield (2013) argued that due to the complexities of drought characterisation at various scales, there is a need for an integrated approach to managing water resources under drought conditions, with a view to maintain a balance between water demand and supply in any water resource system. Chamani et al. (2023) contended that due to the difficulty of identifying all the perturbations caused by drought events and the associated impacts on water availability under drought conditions, it is necessary to employ an integrated approach using indicators to assess the response to drought of ecosystems. Several approaches have been proposed to characterise drought based on different indicators. These approaches include Bayesian Network approach (Croke et al., 2007), Driving Force-Pressure-State-Impact-Welfare Response (DPSIWR) model (Pires de Souza Araujo et al., 2021) and the Reliability ($R_{el.}$)–Resilience ($R_{es.}$)–Vulnerability ($V_{ul.}$) framework (Hazbavi et al., 2018). The DPSIWR, initially proposed by (Cooper, 2013) and improved by de Andrés et al. (2018), who

incorporated the human welfare component to the framework, has its limitation as it does not explore the cause-effect linkages between global change, impacts on ecosystem services and the potential impacts on human welfare. The Reliability–Resilience–Vulnerability ($R_{el.}R_{es.}V_{ul.}$) framework, initially proposed by Hashimoto et al. (1982), has been widely adopted and is largely recommended by scholars such as (Chamani et al., 2023; Sadeghi et al., 2020) to assess different responses of water resource system to satisfactory and unsatisfactory states, such as drought episodes. Fooladi et al., (2021) contended that different aspects of water resource availability can be derived from a joint distribution analysis using both $R_{el.}R_{es.}V_{ul.}$ framework and drought monitoring techniques. Reliability refers to how often or likely the system is to be in a satisfactory state throughout the entire assessment period (Hoque et al., 2020). Resilience, on the other hand, measures how quickly, on average, a system bounces back to a satisfactory state after experiencing an unsatisfactory state (Rahman et al., 2017). Meanwhile, vulnerability pertains to the potential damage that a system may suffer as a consequence of being in an unsatisfactory state (Araujo et al., 2021). Asefa et al. (2014) argued that using an integrated approach to analysing water scarcity under drought conditions can provide insight into ecosystem response under changing and undesirable climatic conditions such as drought.

1.9. Scope of study

In sustainable water resources management, numerous challenges can be investigated, like water–use licensing rights, fragmentation within water governance institutions, modelling the impacts of land use land cover changes on surface water processes, floodplain management, wastewater treatment and many other aspects that are relevant to the water sector. However, the present research was focused on adapting drought quantification methods to assess and analyse the impact historical and future precipitation records on water availability. The research focused on determining drought evaluation indicators, such as severity, intensity, and frequency, and characterisation of reliance, resilience, and vulnerability in the Western Cape Province and the intersectionality thereof with water availability. Limiting the present study to the Western Cape Province was vital since it hosts all the different agro-climatic zones of South Africa. The Western Cape province was chosen as the study area as it hosts all six agroecological zones, namely, sub–tropical warm arid (STWA), sub–tropical cool arid (STCA), sub–tropical warm semi–arid (STWSA), sub– tropical cool semi–arid (STCSA), sub–tropical warm sub-humid (STWSH) and subtropical remarkable sub-humid (STCSH) of South

Africa (Sebastian, 2015). Furthermore, the study area was chosen because of the limited adaptive capacity to drought impacts of nearly 7 million of its residents. Districts found in STWSH and STCSH were chosen due to their high levels of water pollution, overconsumption of water resources, and severe constraints on water infrastructure, affecting the water supply to the population. At the same time, districts found in STWA, STCA, STWSA, and STCSA were chosen due to the social and economic status of the people, inadequate planning and increasing urbanisation. Other considerations to the selection of the study stations included the high levels of inequalities in the provision of water, the prolonged drought experienced in the study area, and the challenges of providing safe water to the population.

Despite the existence of many theories and methodologies for characterising the impacts of drought water resources, the study focused on using climate datasets and drought monitoring indices. The study assumed that drought-monitoring indices are location-specific due to the changing nature of drought episodes. Among the different drought monitoring indices, that could have been used are the Palmer Drought Severity Index (PDSI) (Palmer, 1965), Reconnaissance Drought Index (RDI) (Tsakiris & Vangelis, 2004), and the Standardised Precipitation Evapotranspiration Index (SPEI) and the Standardised Precipitation Index (SPI) (McKee et al., 1993). The Palmer Drought Severity Index (PDSI) is extensively used in North America to measure the combined spatiotemporal deviation of moisture supply. It uses the Thorn Waite's method of estimating potential evapotranspiration but has limited accuracy due to constraints in determining potential evapotranspiration (PET) in mountainous regions. On the other hand, RDI is used to monitor the impacts of drought and climate change on water resources and is evaluated as a ratio between received precipitation and PET (Ahmadi et al., 2021). However, the RDI does not have the capability to assess the drought dynamics using changes in temperature (Vicente-Serrano et al., 2010). The SPEI offers a comparatively flexible method that assesses the collective impact of precipitation and temperature deficit (Beguería et al., 2014). However, the SPEI has limitations when comparing drought events between different agro climatic zones. For instance, in semi-arid zones, the SPEI is more sensitive to temperature changes, while in humid zones, it is more sensitive to precipitation (Vicente-Serrano et al., 2020). Furthermore, in contrast to the PDSI, the SPEI does not consider the water balance equation and does not incorporate soil moisture conditions in categorizing agricultural droughts. On the other hand, the SPI is one of the most widely used indices to quantify drought and is based on a probabilistic methodology that

uses precipitation as the only input. The present study was limited to the use of SPI which is widely recommended by the World Meteorological Organization (WMO) as the drought index of choice over other indices due to its ability to be computed at multiple timescales (3-, 6-, 12-, 18-, and 24-month's) and capacity to differentiate between agricultural, meteorological and hydrological drought types (Hayes et al., 2011).

1.10. Ethical considerations

Research involving human subjects requires informed consent from human participants. Haraguchi & Lall (2015) suggest that ethical issues are a crucial part of any study and that a full risk assessment for any proposed study in terms of safety is mandatory not only because it is required by the Faculty/School of the academic institution, but because ethical issues that may arise, have huge impacts on the entire research design and consequently on the quality of the research results. However, this was an entirely quantitative research study and only involved collection of remotely sensed data and ethical approval was not required as per the University of the Witwatersrand regulations.

1.11. Thesis structure

Chapter one provides the frames of reference to the study. In this chapter, the background of the study, thematic considerations, rationale, research questions, aims and objective, theoretical and methodological considerations, the scope of the study, ethical considerations and lastly, the thesis structure is presented.

Chapter Two consists of the literature review and theoretical perspectives from a global, sub-Saharan Africa and South Africa lens on the impacts of drought on water resource availability. It provides a subsection on the “hydro-illogical” approach to drought and water resource management, followed by a subsection on the three-pillar drought management approach, which adopts a more risk, based integrated drought management approach. This is followed by a section that highlights the importance of pursuing drought monitoring and early warning systems (DEWS), drought vulnerability and risk assessment (DVRA) and drought readiness, mitigation mechanisms (DRMM) by national government structures to ensure sustainable management of water resources. This is followed by subsections dedicated to meteorological, agricultural, hydrological drought monitoring

for fostering sustainable water resources. Lastly, integrated approaches to drought monitoring and research gaps from previous research are presented.

Chapter Three presents the methodological considerations adopted in the fieldwork. This chapter includes the philosophical underpinnings, the research design which included the description of the study site, the data instrumentation, collection, and analysis. This was followed by the methodological reflections of the research.

Chapter Four is based on empirical findings that were used to develop three research manuscripts that sought to address the research questions. This chapter characterises, assesses, and explores empirical evidence on historical and future drought trends and the associated impacts on water availability. The chapter provides an analysis of historical precipitation and drought trends in the Western Cape Province using observed data obtained from the Climate Research Unit of the University of East Anglia in the United Kingdom and future precipitation datasets (2021–2050) under SSP5–8.5, SSP2–4.5 and SSP1–2.6 climate scenarios generated by the sixth version of Model for Interdisciplinary Research on Climate, (MIROC6). Lastly, the chapter adopts a reliance, resilience, and vulnerability framework to explore optimal water resources management scenarios.

Chapter Five The chapter interprets and discusses the implications of the findings in relation to drought incidence and the associated impacts on water availability, while elucidating on any new insights in research. The chapter is structured and organised into three sections that draw on the overarching aim and objectives of the study. The first section discusses and identifies the appropriate historical hydro climatic variability trends derived in the six-agroecological zones of the WC Province and applies them to relate drought incidence with previous water shortages. The next section discusses the empirical findings from future climate scenarios and analyses according to water availability scenarios. The last section provides evidence of increasing water scarcity caused by frequent drought under SSP2-4.5 climate change scenario in the study area.

Chapter Six concludes the research by synthesizing the findings of the research and proposing recommendations for future research on the subject area. It comprises four main subsections drawn from the study. The first section summarises the key findings of the historical observed trends and how they align with or diverge from the research questions that framed the research. The second

section summarises the findings of future drought and water availability trends and explores the implication thereof to water availability. The third section summarises the optimal water management scenarios envisioned under the SSP5-8.5 climate scenarios. The chapter also presents future recommendations to aid in decision-making processes on proactive water resource management.

CHAPTER TWO

THEORETICAL CONSIDERATIONS AND LITERATURE REVIEW

2.1. Introduction

This chapter analyses previous research studies that have been conducted on water scarcity because of drought and the techniques that have been used to quantify the impacts of drought, with a particular emphasis on global, regional, and South African perspectives. At the beginning of the chapter, a description of the essential concepts utilized in the research is provided. The chapter also provides an overview of drought characteristics and forecasts from a global, sub-Saharan Africa and South African perspective, as well as the implications these characteristics have for water resources availability and agricultural production. A sub-section on the intersectionality of the hydro-illogical and the three-pillar drought management approach in South Africa is presented to offer insights on the connections between climate change, water, and integrated water resources management in the South African context. The chapter then reviews drought monitoring and early warning systems (DEWS), drought vulnerability and risk assessment (DVRA) and drought readiness and mitigation measures (DRMM). It continues by establishing a connection between the different types of drought monitoring techniques applied for each type and then draws knowledge gaps on drought management and integrated water resources management and sustainable livelihoods. This is done within the context of South Africa.

2.2 Definition of key concepts

Several key terms relating to climate change, drought and water resources management were used in the study. These terms are defined below according to how they are used in the thesis:

a) Climate change — is defined as “the significant variation of average weather conditions causing warmer, wetter, or drier conditions over several decades or longer” by the United Nations Framework Convention on Climate Change (UNFCCC), (UN, 2020). The World Bank (2020) defined climate change as the long– term trend that differentiates climate change from natural weather variability. In this study, climate change will be used to mean a long– term change in global or regional climate patterns.

b) Drought — the term drought may refer to persistent lack of precipitation (meteorological drought), low soil moisture (agricultural drought), low river flows and low water levels in rivers, lakes, and groundwater (hydrological drought) and combination of the above (socioeconomic drought) (Kao & Govindaraju, 2010). In this study, meteorological droughts are considered.

c) Water scarcity — refers to a condition of imbalance between freshwater availability and demand where freshwater demand exceeds availability (Vogt et al., 2018). FAO (2020) defined water scarcity as a state of human deprivation characterized by lack of access to affordable and safe water to satisfy societal needs or a condition in which these needs are met at the expense of the environment. In this study, water scarcity is considered from both the perspective offered by FAO (2020) as a state of human deprivation characterized by lack of access to affordable and safe water to satisfy societal needs or a condition in which these needs are met at the expenses of the environment.

d) Global climate models — also called General Circulation Models, Global Climate Models, or GCMs. Teutschbein & Seibert (2012) climate models are used to make predictions about future climate and the knowledge gained can contribute to policy decisions regarding climate change. (Meehl et al., 2012) noted that climate models use many different factors such as water vapor, carbon dioxide, heat, and the Earth's rotation as inputs to calculate how these factors interact with the ocean, air, and land. In this study GCMs will be used to predict future precipitation variables.

e) Resilience— according to Rahman et al. (2017), resilience measures how quickly, on average, a system rebounds to a satisfactory state after reaching an unsatisfactory state. Hazbavi et al. (2018) argued that it is the ability of a system to adapt to the impacts of climate change without excessive harm. It is determined by the degree to which the social system can organize itself to increase its capacity for learning from past disasters for better future protection and to improve risk reduction measures (IPCC, 2020). In the present resilience assessed how quickly, on average, a system rebounds to a satisfactory state after reaching an unsatisfactory state.

f) Reliance — according to Hoque et al. (2020) reliance refers to the frequency or probability of the system being in a satisfactory state during the total assessment period. Dost & Kasiviswanathan (2023) defined reliance as a system's capacity to maintain consistent water availability. A reliability value closer to unity indicates consistent water availability, whereas a value below unity suggests increased

variations in water availability. The present study defined reliability as the frequency or probability of the watershed being in a satisfactory state during the total data period.

g) Vulnerability — is the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude and rate of climate change and variation to which a system is exposed, its sensitivity and its adaptive capacity (IPCC, 2007). This is the definition adopted by the study.

h) Sustainability — according to the Brundtland Report it refers to meeting the needs of the present generation without compromising the ability of future generations to meet their own needs. In the present study sustainable development is defined as water availability to meet economic, environmental and ecosystem service delivery, and social goals, including character and subjectively defined values (Arowoshegbe, Uniamikogbo and Gina, 2018).

2.3 A Global perspective on drought and water scarcity

Vicente-Serrano et al. (2022) reported that over the years, there has been a rising trend in drought incidences with devastating consequences on water security in most regions of the world (Figure 2.1). Brunner et al. (2019) noted that global drought episodes experienced between 1976 and 2006 have led to a twofold increase in both the geographical coverage and population impacted, while Sabater et al. (2018) reported a fourfold rise in average annual living costs. Although water is generally plentiful in Europe (EU), a significant portion of the continent is nonetheless affected by droughts and water scarcity (Gergis & Henley, 2017). According to Garrote et al. (2018), water scarcity due to drought affects at least 11% of the European population and 17% of the EU territory. Oki & Kanae (2006) contended that the EU experienced one of its most severe droughts in 2003, affecting more than 100 million people and covering one-third of the EU area. Carvalho et al. (2019) found that water scarcity is prevalent in the southern regions of EU due to an increasing frequency and severity of drought episodes coupled with high water demand. Kristensen et al. (2018) argued that climate change-driven droughts are expected to exacerbate European water scarcity. The southern and southeastern regions of the EU, already afflicted by water scarcity, are anticipated to be more severely affected by the drought impacts (Voulvoulis et al., 2017). Shepherd et al. (2016) argued that these regions will experience decreased water availability due to drought episodes' increasing frequency

and severity. Although water availability is typically expected to improve in northern regions, water availability may decline during summer seasons, which might result in drought spells (Ungureanu et al., 2020). Vogt et al. (2018) highlighted that repeated drought episodes in the European Union have aggravated the complexities of managing water scarcity. Another important example is the inter-annual drought in California, United States of America (USA) between 2012 and 2016, which led to water restrictions in urban areas and caused severe losses in crop yields

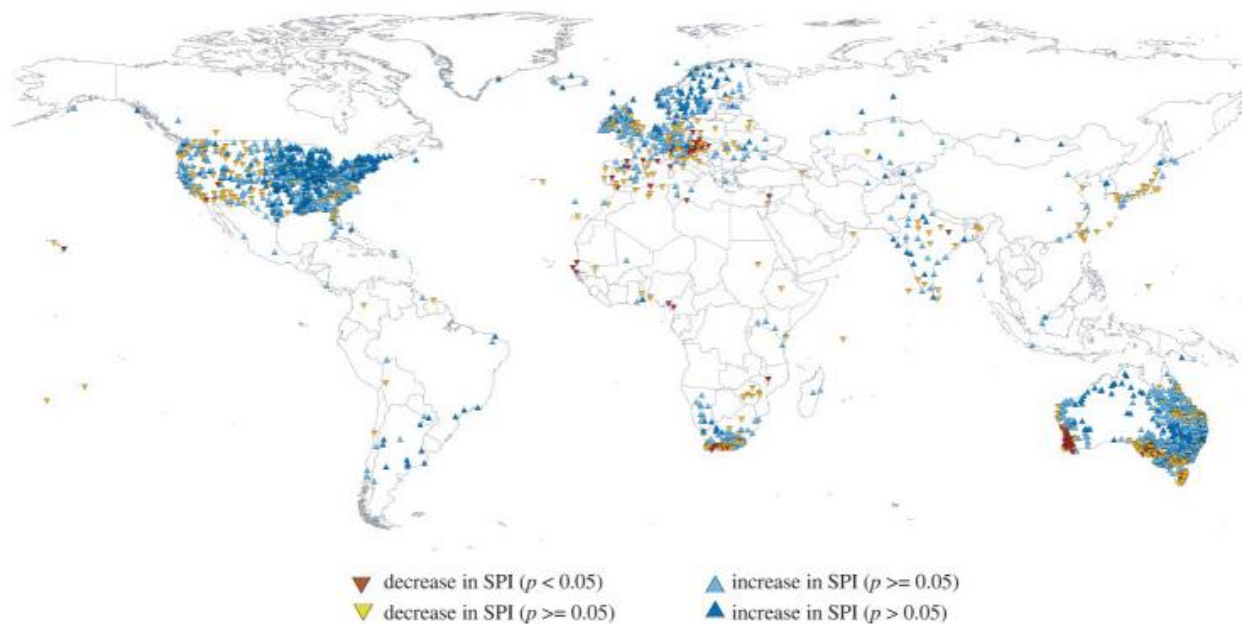


Figure 2.1 Global Drought Trends (Source: Vicente– Serrano et al., 2022)

Similarly, Iglesias et al. (2011) conducted comparative studies on the impacts of drought in the EU and the USA. They concluded that the economic impact of drought in the EU has been almost five times higher than that in the entire USA during the past two decades. Ungureanu et al. (2020) argued that the drought in Spain during the mid-2003s significantly affected over six million individuals and had devastating consequences on the agricultural sector. Santos et al. (2021) reported that the EU implemented the Water Framework Directive (WFD) to attain the 'good status' of all European water bodies in response to the recurring drought. The primary objective of the WFD is to attain and sustain a "good status" for all bodies of water within a predetermined timeframe, utilizing an integrated approach to implement river basin management plans (RBMPs) (Reyjol et al., 2014). The RBMPs are the primary tools for achieving the environmental objectives outlined in the Water Framework

Directive (WFD), such as safeguarding drinking water, preserving aquatic ecosystems, and managing drought (Carvalho et al., 2019). Martínez et al. (2020) argued that addressing these drought impacts using the WFD is crucial for achieving environmental objectives and maintaining the excellent status of water bodies.

In Asia, droughts and associated impacts of water scarcity have grown increasingly persistent, frequent, and severe in various places (van der Schrier et al., 2011), particularly in the hotspot regions of South Asia (Ullah et al., 2022). Miyan (2015) argued that climate change in South Asia has resulted in severe droughts, impacting water supplies, energy generation, and agricultural production. Masson-Delmotte et al. (2021) argued that droughts in Asia have significantly disrupted the livelihoods of almost 1.6 billion individuals, while Miyan (2015) documented that over the years, Western India, Southern India, and Central Pakistan have experienced significant droughts. Anik et al. (2023) reported that Afghanistan, India, Pakistan, and Sri Lanka have encountered droughts with a frequency of at least once every three-year period over the previous five decades, whereas Bangladesh and Nepal are frequently plagued by inter-annual droughts. In 2012, Pakistan declared an emergency in Tharparkar and Mirpur Khas districts because of a severe drought, leading to the resettlement of numerous individuals (Saha et al., 2021). Aadhar & Mishra (2020) found that the South Asian summer monsoon (SASM) is the dominant mode of climate variability on interannual timescale and can wield significant impacts on the global climate, including the El Niño– Southern Oscillation (ENSO).

Consequently, Fan et al. (2017) argued that the SASM substantially affects drought occurrences in Asia. Hina et al. (2021) and Ullah et al. (2022) further argued that the interannual and decadal fluctuations in SASM precipitation are connected to the broader patterns of oceanic and atmospheric circulation in the area, specifically the multivariate El Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), and Indian Ocean Dipole (IOD). The sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) has acknowledged that South Asia is a region prone to drought, where the increasing temperatures have heightened the likelihood of extreme climatic events. Piao et al. (2022) asserted that it is imperative to acknowledge the role of human activities in causing droughts and their severity in a changing climate. This recognition is crucial for preparing for the impacts of droughts and implementing sustainable water resource management practices (Piao & Wang, 2023).

Meanwhile, the Middle East and North African (MENA) region is classified as the world's most water-stressed (Zekri & Al-Maamari, 2020). The region is home to 6.3% of the global population. However, it has a mere 1.4 percent share of the world's renewable freshwater resources (Hejazi et al., 2023). Evidence from throughout the subcontinent indicates that recent years have been amongst the driest (Cook et al., 2018; Touchan et al., 2011), and the magnitude of the experienced droughts can partially be attributed to anthropogenic climate change. Namdar et al. (2021) found that the global average water availability per capita is approximately 7 000m³ per year, whereas in the MENA region, it is only 1 200m³ per year. Zekri & Al-Mamari (2020) argued that the MENA region has the second highest per capita rate of freshwater extraction globally, up to 804 m³ per year after the United States of America. Furthermore, the MENA region utilizes more than 75 percent of its renewable water resources (İrfan & Hatice, 2023). Tomaszekiewicz (2021) argued that as the population in MENA countries grows and the economy rapidly expands, the amount of water available per person would decrease significantly in the next few decades.

Diawoł-Sitko (2020) projected that by 2050, many MENA nations may experience a decline in water resources to fewer than 200m³ per capita per year with approximately 85 percent of the water in the MENA region allocated for agricultural purposes. Scholars such as Cook et al. (2018) and van Ruijven et al. (2014) have argued that drought in the MENA region affects several aspects of food, energy, and water security, which can sometimes result in political unrest, increasing social inequality, and disease outbreaks (Rajsekhar & Gorelick, 2017; Stanke et al., 2013; Woodhouse & Muller, 2017). The region does not yet have operational drought early warning systems connected to strategic drought risk management, despite efforts being made to deal with these catastrophic events through multi-sectoral and interdisciplinary collaborations among communities and across scales (S. Pulwarty & Sivakumar, 2014; Verner et al., 2018). The presence of periodic droughts in MENA nations indicates that despite substantial investment in the water sector, effective water management remains a critical economic and environmental challenge (Loudyi & Kantoush, 2020). Asaad & Suleiman (2023) contend that the over-extraction of groundwater coupled with more severe and frequent drought incidents adversely impacts public health, agricultural production, and the environment.

2.5 A sub-Saharan African (SSA) perspective on drought and water scarcity

In the sub-Saharan African context, the historical impacts of drought on SSA countries are shown in Table 2.1, while the severity is shown in Figure 2.2. Ayugi et al. (2022) reported that drought in SSA has claimed the lives of millions of people and seriously damaged the continent's social, environmental, and economic well-being. The figures from Table 2.1 indicate only the reported total deaths; the actual total could even be higher. For example, the recent 2015–17 drought figures for South Africa show the number of people affected, but the fatalities have not yet been recorded on the Emergency Events Database (EM– DAT). EM–DAT is monitored by the Centre for Research on the Epidemiology of Disaster (CRED) and is responsible for recording all the natural catastrophes, i.e., geophysical, meteorological, hydrological, climatological, and biological – each of which further contains one or more types of specific natural disasters (Shen & Hwang, 2019). Mugiyo et al. (2023) argued that water scarcity challenges in SSA in the second half of the 20th century were caused by multiple factors, but severe droughts preceded all. According to Dosio et al. (2020); Grasham et al. (2019); Gupta et al. (2020); Klutse et al. (2018) and Matchaya (2020) projections suggest that most parts of SSA will experience prolonged droughts and increased rainfall variability by 2025 and water available for agriculture and domestic use will likely experience increasing constraints. Niang et al. (2019); Williams et al. (2018) reported that water scarcity due to drought in SSA severely affects food security and human vulnerability across the subcontinent. Busico et al. (2021); Cuthbert et al. (2019) and Taylor et al. (2019) contended that the most persistent water scarcity challenges in SSA in the last 40 years were preceded by severe drought episodes like in the hydrological years 2015 – 17 that nearly led to the pronouncement of Day– Zero by water authorities in countries such as South Africa, Zimbabwe, Malawi, and Lesotho.

Table 2.1 Reported historical drought impacts from 1900 to 2015 (Source: Tadesse et al., 2016)

Country	Year	Total deaths	Total Affected
South Africa	2015	N/A	2 800 000
Somalia	2010	20 000	4 000 000
Sudan	1983	150 000	8 400 000
Ethiopia	1983	300 000	7 750 000
Chad	1981	3 000	1 500 000
Mozambique	1981	100 000	4 750 000
Somalia	1974	19 000	230 000

Ethiopia	1973	100 000	3 000 000
Ethiopia	1965	2000	1 500 000
Cape Verde	1946	30 000	N/A
Cape Verde	1940	20 000	N/A
Cape Verde	1920	24 000	N/A
Niger	1910	85 000	32 000
Cape Verde	1900	11 000	N/A

Kharraz et al. (2012) noted drought and water scarcity challenges are exacerbated by the fact that almost 80 per cent of the SSA region's landmass is comprised of deserts, arid areas, and semi-arid regions. The World Water Assessment Program (2019) reported that the bulk of the population residing in SSA depends on constrained water resources, and agricultural activities in the region depend on natural rainfall. Moreover, the UNDP (2022) reported that nearly half of the SSA population lives in severe poverty, where climate change's impacts can potentially enhance future drought episodes' frequency, severity, length, and spatial extent. Kapangaziwiri et al. (2012) reported that water scarcity due to droughts also jeopardises decades of development progress by reducing a community's capacity to absorb and adjust to a changing climate. Tadesse (2016) argued that there is a consistent decline in precipitation and runoff patterns across significant rivers in SSA and that most countries in the region have rapidly growing populations threatened by the social, economic, and environmental impacts of drought. Busby et al. (2014) and Kharraz et al. (2012) argued that ensuring water availability to 1.5 billion people by 2030 and 2.4 billion by 2050 is a daunting challenge that water authorities in SSA will be expected to meet. Trenberth (2020) noted that precipitation deficits have impacted East Africa, West Africa, and southern Africa in different ways, as shown in Figure 2.2.

Quenum et al. (2019) reported that countries in the West African Sahel (WAS), such as Burkina Faso, Niger, Nigeria, Cameroun, Mali, Chad, Central African Republic, Mauritania, and Senegal region (), are part of a transitional region with a semi-arid climate, situated between the Sahara Desert and the humid tropical areas of Africa. The area is distinguished by a pronounced annual north-south rainfall difference and significant fluctuation in rainfall amounts (Ayugi et al., 2022). The mean annual precipitation (MAP) differs based on latitudes, ranging from the moist Guinea coast to the northernmost regions (Ebi & Bowen, 2016), significantly affecting water availability. The fluctuation in rainfall in the region and, consequently, water availability is mainly linked to the West African

monsoon, which involves the movement of moisture from the Gulf of Guinea (Kasei et al., 2010). This phenomenon occurs throughout the summer (July to September) due to the northward shift of the Intertropical Convergence Zone (Nicholson, 2018). Ogou et al. (2019) revealed that in the years 1961, 1970, 1983, 1992 and 2001, there has been an increase in the frequency and severity of drought with an average return duration of nine years.

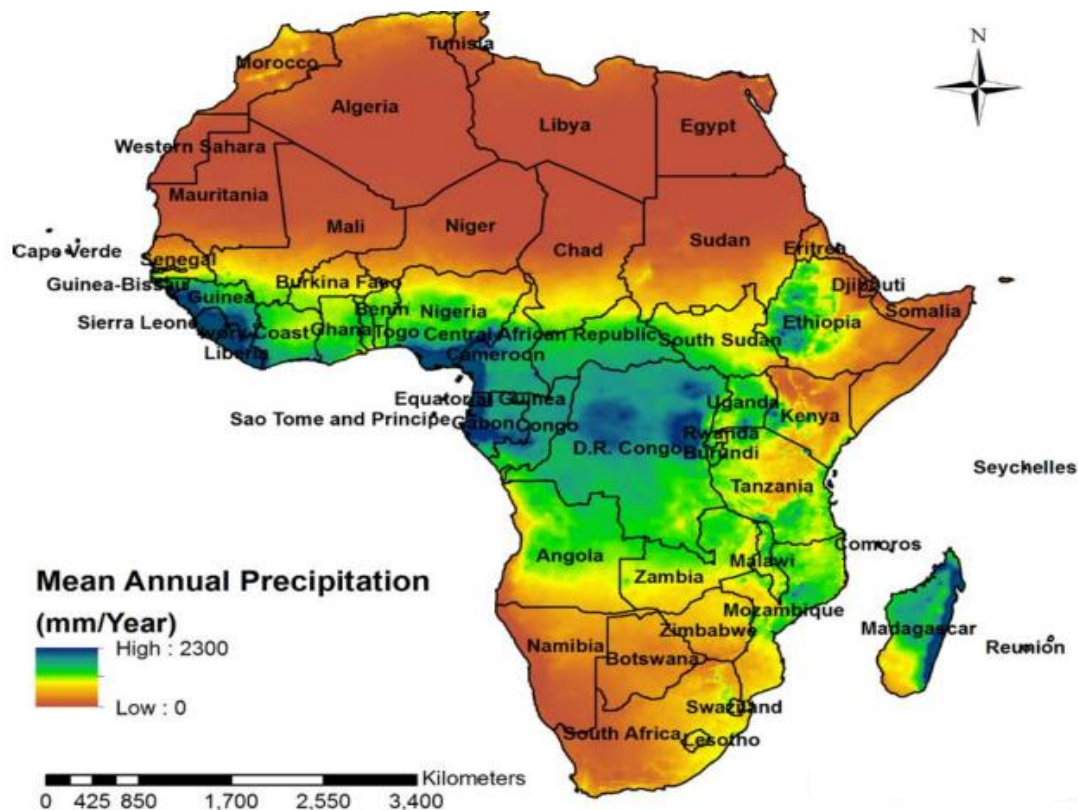


Figure 2.2 Mean annual rainfall (1981– 2014) patterns of the African continent (Source: Tadesse et al., 2016)

West Africa's drought can have direct and indirect impacts (Kasei et al., 2010). For example, in 2011, Mauritania experienced a drought due to insufficient precipitation, resulting in low harvests, livestock losses, and food costs (Calow et al., 2010). Dibi-Anoh et al. (2023) noted that in 2015, Mali experienced severe water scarcity challenges that affected nearly 300,000 people, while in 2018, in Cote d'Ivoire 70% of the dams that supply cities to dry up. Because of below-average precipitation rates in 2018, the drought affected about 3.7 million people in Burkina Faso. Adaawen (2021) reported that at the close of 2019, a drought that affected over 2.6 million in Niger caused severe food shortages and ultimately resulted in famine in Senegal. It is projected that over 30% of Nigerians will

suffer from severe food insecurity in 2030 because of the country's prolonged drought, putting almost 500,000 people at risk of starvation (Adaawen, 2021). Quenum et al. (2019) reviewed a range of literary sources and concluded that droughts in WAS can be attributed to multiple variables.

However, subsequent studies conducted by Biasutti et al. (2008); Caminade & Terray (2010) and Rowell (2001) explored the relationship between changes in Sahel drought patterns over both short-term (inter-annual) and long-term (decadal scale) periods and changes in sea surface temperatures (SST). Hoerling et al. (2006) reported a significant correlation between interhemispheric (north-south) temperature gradients in the tropical Atlantic and sea surface temperatures (SST) in the tropical Pacific and Indian oceans. The relationship between the temperature difference in sea surface temperatures (SST) between the northern and southern regions (where the seas experienced warming and cooling after 1970) on a worldwide scale is believed to have caused the Sahel drought over ten years (Hoerling et al., 2006). Ilori & Ajayi (2020) proposed that the Atlantic's cross-equatorial sea surface temperature (SST) gradients play a significant role in the location of the Intertropical Convergence Zone (ITCZ).

Meanwhile, the situation is no different in Somalia, Ethiopia, Eritrea, Djibouti, Kenya, Sudan, and South Sudan, collectively known as the countries of the Great Horn of Africa (GHA) (Figure 2– 2). Despite being in the tropics, several countries in the GHA region are considered desert and semi-arid territories (Gidey et al., 2018). Lyon (2014) and Shilenje et al. (2019) argued that previous studies in GHA indicate a decline in average rainfall from March to May (MAM) in recent decades. Similarly, Nicholson (2018) highlighted a notable rainfall deficiency over the years 1998, 2000, 2005/2006, 2007, 2008, 2009, and 2011, affecting both the long and short rain seasons. Tofa et al. (2021) contended that this tendency is particularly concerning, given that, the population heavily relies on rain-fed agriculture for food production and the industry continues to have a significant portion of employment. According to Thomas et al. (2020), drought periods have a discernible effect on the economy of the GHA region, present dangers to human life, and result in substantial deterioration of the natural environment. The drought periods in 2010/2011 and 2016 resulted in a food scarcity that affected more than 10 million individuals, resulting in fatalities and the disruption of livelihoods (Ojara et al., 2022). Haile et al. (2020) examined the effects of climate on drought patterns in GHA and found that Eritrea, parts of Ethiopia, South Sudan, Sudan, and Tanzania experienced more

droughts that are frequent. In contrast, Rwanda, Burundi, and parts of Uganda experienced more minor droughts during the latter half of the twentieth century (Ojara et al., 2022).

In the context of southern African biomes, which includes South Africa, Zimbabwe, Zambia, Mozambique, Angola, Lesotho, Swaziland, Botswana, and Malawi, the distribution of rainfall undergoes substantial changes that are associated with the El Niño– Southern Oscillation (ENSO) (Reason & Rouault, 2005). In southern African biomes, there have been severe and extensive droughts in the years 1982– 1984, 1991– 1992, and most recently, between 2015 and 2017 (Reason & Rouault, 2005). The drought between 2015 and 2017 was the most severe since the early 1980s and had significant adverse impacts on water and food security (Archer et al., 2018). Engelbrecht & Monteiro (2021) reported that climate change would exacerbate severe weather phenomena such as droughts in southern Africa. However, the exact extent of these impacts remains uncertain. Kusangaya et al. (2014) noted that the recent drought events between 2015 and 2017 resulted in significant crop and ecosystem failure in the southern African region. Turyasingura et al. (2023) emphasized that southern African countries with mean annual precipitation of less than 500mm typically experience severe socioeconomic repercussions from drought. Ujeneza & Abiodun (2015) contended that like in other regions in sub-Saharan Africa, understanding the impacts and spatiotemporal characteristics of droughts in southern Africa is crucial since agriculture serves as the fundamental economic endeavor for most of the populace in these nations.

The United Nations Office for the Coordination of Humanitarian Affairs (UNOCHA) has reported that about 16 million people in Southern African countries like Malawi, Zambia, Zimbabwe, Mozambique, Swaziland, and Lesotho were at risk of starvation in 2016 (WFP, 2016). Moreover, in 2020, more than a third of Namibia's population - 780,000 people - were considered water insecure. This led the Namibian government to declare a state of emergency on May 17, 2013 (WFP, 2020). Meanwhile in 2016, the World Food Program (WFP) reported that the 2016 El Niño– induced drought had severely affected the southern African region. According to WFP, roughly 1.5 million people, or 16% of South Africa's rural populace, were impacted by the drought in 2015– 2016, while a severe drought in South Africa decreased the water availability and agricultural output (Ujeneza & Abiodun, 2015). Mishra and Singh (2010) argued that the ENSO primarily influences drought occurrence in southern Africa. However, Blamey & Reason (2007) contended that contrasting findings suggest no association between winter rainfall in southern Africa and ENSO. Several additional studies have

demonstrated that various other atmospheric patterns can significantly influence southern Africa's rainfall patterns. For example, the IOD or Zonal Mode is believed to have a robust association with seasonal rainfall during the southern African summer (Manatsa et al., 2017). The study conducted by Ujeneza and Abiodun (2015) revealed that the quasi-biennial oscillation (QBO) significantly impacts the summer rainfall in Malawi. Reason and Rouault (2005) discovered a significant correlation between winter rainfall in western South Africa and the Antarctic Oscillation (AAO) as well as sea surface temperature (SST) in the central South Atlantic. Rouault and Richard (2005) argued that the ENSO could significantly affect determining the occurrence of drought in southern Africa. Furthermore, Ujeneza & Abiodun (2015) suggested that the most intense droughts in southern Africa between 1901 and 2004 were linked to ENSO episodes. Nevertheless, the absence of consensus among prior research on the origin of droughts in southern Africa necessitates further investigations to comprehend the atmospheric dynamics that influence the frequency and intensity of droughts in this area (Manatsa et al., 2017). Comprehending this information is crucial for effectively monitoring, predicting, and alleviating drought in the region (Kusangaya et al., 2021).

2.6 A South African perspective on drought and water scarcity

Vigaud et al. (2009) argued that most of the rainfall in South Africa occurs from November to March, coinciding with the movement of the tropical trough towards the pole. Driver & Reason (2017) reported that drought occurrence in South Africa is influenced by a subtropical anticyclone that prevents moisture from entering the region from the Congo Basin. Blamey & Reason (2007) reported that during drought periods, the anticyclone directs westward movement of air along its northern side towards troughs located near Madagascar, and this causes a southward movement of dry air that descends over southern Africa. Driver & Reason (2017) further argued that northwest cloud bands that connect tropical convection in Angola to mid-latitude westerly Rossby waves across the Agulhas Gyre produce approximately 50% of South Africa's rainfall. During drought events in South Africa, the cloud bands in the northwest region move towards the east of Madagascar due to the warming of the local ocean, which is linked to a positive Indian Ocean Dipole (IOD) and Pacific (Driver & Reason, 2017). The different stages of the ENSO exhibit a significant correlation with the fluctuations in circulation, rainfall, and temperature in southern Africa over specific seasons (Dieppois et al., 2015). The occurrence of mega-drought episodes in southern Africa is generally associated with intense El Niño occurrences (Spinoni et al., 2019).

Botai et al. (2017) reported that it is widely acknowledged that prolonged droughts in South Africa are exacerbating the water scarcity, while Savenije (2000) contended that South Africa would undergo a decline in water availability from 1700 m³ per capita to less than 1000 m³ per capita due to the increasing frequency and severity of droughts. This assertion suggests that even a tiny increase in severe drought episodes would substantially affect South Africa's water and food security (Otieno & Ochieng, 2007). Chami & Moujabber (2016) suggested that the reason for this is that South Africa experiences a mean annual precipitation of 500 mm per year, which is significantly below the global average of 860 mm per year. Ziervogel et al. (2014) adopted a regionally projected viewpoint. They warned that in South Africa, the Eastern Cape Province and other inland regions experience more intense flood events, whilst the western parts of the country, such as the Western Cape Province are more prone to drought incidents. The South African Department of Water and Sanitation (DWS) 2004, then known as the Department of Water Affairs and Forestry (DWAF), officially designated the Western Cape as one of the most drought-prone regions in South Africa, characterized by irregular rainfall patterns. Kam et al. (2021) reported that certain districts in the Western Cape Province observe a mean annual precipitation of less than 350mm, which is notably lower than the national average of 500mm per year (Kam et al., 2021).

Kanyoka et al. (2008) contended that water scarcity challenges in South Africa are further aggravated by the historical problem of unequal access to water and substandard water services, which were deliberately promulgated by the previous apartheid government's policies of racial segregation known as 'separate development'. Booysen et al. (2019) argued that the mean water use in South Africa continues to exceed the suggested threshold required to maintain a sustainable water supply and that persistent droughts in South Africa have primarily affected water resources in various provinces, including the Western Cape (WC). Kam et al. (2021); Kapangaziwiri et al. (2012) and Weaver et al., (2017) argued that the WC province, known for its primarily agrarian economy centered around fruit exports and dependence on a water supply infrastructure based on catchment areas, serves as a prime example of a province that is highly susceptible to the severe impacts of climate change-induced droughts. The WC's susceptibility to drought is substantiated by the current 2015–2017 period of acute drought, as evidenced by Ndebele et al. (2020). Vogt et al. (2018) noted that during this period,

the WC had significant inter-annual drought conditions, leading to a water supply crisis that endangered the provision of water to around four million individuals.

On the other hand, Lange et al. (2020) reported that during the drought period, the WC Province experienced a substantial decline in its water storage capacity reaching a mere 20% in January 2018. Furthermore, in 2019, there was a notable increase in arid conditions, resulting in a significant decline of 25% in agricultural output (Raude et al., 2018). Baudoin et al. (2017) highlighted that the prolonged drought between 2015 and 2017 also had a pronounced adverse impact on the agriculture industry, significantly reducing job prospects. Moreover, Kam et al. (2021) reported that communities reliant on aquatic ecosystem services, such as ecotourism and fisheries, experienced the deprivation of viable means of subsistence. Considering the above challenges, Baudoin et al. (2017), Tadesse (2016), Vogt et al. (2018), and Weaver et al. (2017) argued that South Africa has invested a great deal of time and effort into developing a proactive drought and water resources management strategies. Wilhite (2017) argued that these efforts were accelerated by developing the National Consultative Forum on Drought in the early 1990s. This brought more stakeholders to the planning table and allowed more sectors to be included in drought planning efforts. Tamarin-Brodsky et al. (2020) noted that these efforts resulted in new drought policies that strove to encourage risk management, assist farmers financially, protect natural resources, and promote the best use of water resources for individual farmers. However, a challenge remains for the South African government to maintain a policy balance between encouraging a risk management approach for large agricultural enterprises and providing a safety net for the resource-limited sectors of the population (Williams et al., 2018). Despite some evidence of a paradigm shift from emergency response to more holistic drought risk management and disaster risk reduction approaches, the focus across various governance levels remains rooted in technical and financial relief solutions in southern Africa (Vogel et al., 2019). Consequently, Cullis et al. (2011); Dallas & Rivers-Moore (2014) and Nkhonjera (2017) conceded that it is expected that climate change and a multi-year drought will aggravate existing pressures on water availability for agriculture, affecting public health and food and water security in South Africa unless robust and proactive drought risk management approaches are pursued.

2.7 The ‘Hydro– illogical’ drought and water resources management approach

In the past, numerous scholars such as Nhemachena et al. (2020); Safari et al. (2022) and Tsakiris et al. (2013) have argued that drought management systems by governments and other water governance

institutions throughout the world have been reactive— poorly coordinated, ineffective, and followed a 'hydro– illogical crisis management' approach (Figure 2.3). Estrela et al. (2012) noted that the 'hydro–illogical' crisis management approach presented in Figure 2.3 is often associated with the provision of post–drought relief or assistance to those most affected in response to a drought event. Wilhite (2019) argued that this approach commonly depicts the post–impact response wherein, during the beginning phases of drought formation, there is an initial recognition of the imminent drought impacts, which is then succeeded by a sense of worry and alarm as the severity of the drought intensifies. However, after regular rainfall, the government's intention to establish a proactive drought management policy for enhanced preparedness in future droughts is frequently abandoned, resulting in a regression to the state of indifference in the cycle (Fragaszy et al., 2020). Hayes et al. (2011) suggested that the 'hydro– -illogical' crisis management approach has been linked to a failure to acknowledge that drought is a regular occurrence within the climate and that it primarily focuses on addressing the impact without giving due emphasis to the root causes of vulnerabilities within drought occurrences. Hence, Bokal et al. (2014) and Grobicki et al. (2015) reported that water governance institutions must adopt proactive and more risk–based drought and water resources management approaches.

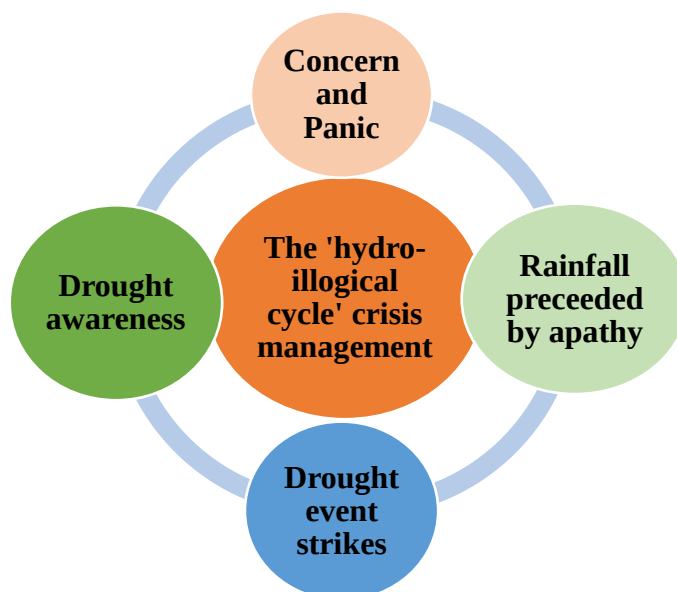


Figure 2.3 The 'hydro– illogical' crisis management approach (Source: Wilhite, 2017)

2.8 The ‘Three Pillar’ drought and water resources management approach

Until recently, various scholars such as Bokal et al. (2014); Manatsa et al. (2017); Wilhite (2019) have begun to agitate for developing nations to adopt the three-pillar approach to drought water resources management (Figure 2.9). They argued that it is a coordinated drought management plans (DMPs) that include comprehensive drought monitoring, early warning systems, drought vulnerability and risk assessments, the identification and adoption of appropriate local– level drought readiness, mitigation, and response measures. Daksiya et al. (2021) and Fonseca et al. (2019) argued that adopting the three-pillar approach could potentially mitigate and reduce future drought impacts on water resources availability. Bressers et al. (2016) asserted that it is crucial for all drought–prone countries, especially those in arid and semi–arid regions, to embrace a new DMP paradigm for managing drought that focuses on minimizing risks. However, Tsakiris et al. (2013) observed that there has been a lack of global initiative to start a discussion on developing and implementing national drought management policies that focus on proactive and risk–based approaches. Similarly, Bokal et al. (2014) contended that in the absence of a well–coordinated national DMP encompassing comprehensive monitoring, timely warning systems, effective information dissemination, thorough vulnerability and risk assessments, and the implementation of suitable local–level measures to mitigate and respond to risks, drought-prone countries will persist in their historical pattern of reacting to drought events.

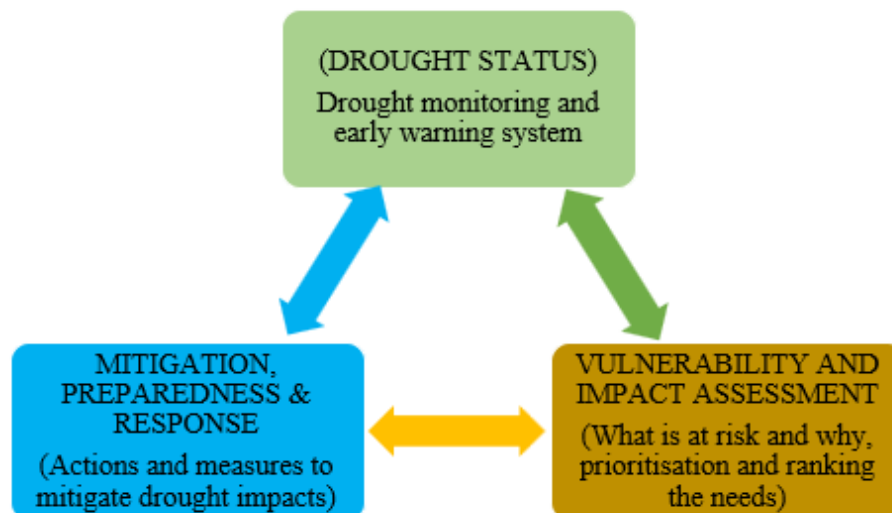


Figure 2.4 The three-pillar approach to drought impact assessment (Source: IDMP, WMO, GWP, 2015)

According to Schewe et al. (2014), the three-pillar drought and water resources management plan represents a key DMP that seeks to support sustainable water resources management and build resilience to drought extremes. DMPs should outline pertinent drought and water scarcity indicators and their thresholds, provide comprehensive early warning systems, and establish priorities and pathways to be followed by decision-makers during a drought episode (Marzi et al., 2021). Masson-Delmotte et al. (2021) argued that for effectiveness, DMPs should foster simple, pragmatic, and scientifically proven approaches based on technical evidence and adopt experiences from past drought events. Hervás-Gómez & Delgado-Ramos (2019) argued that while the institutional arrangements of each country vary, three drought and water resources management levels should be established: Strategic, Operational, and Contingency (or Emergency). They argued that at the strategic level, reliable and accurate drought early warning systems are vital to formulating proactive drought-risk management policies. However, Urquijo-Reguera et al. (2022) argued that predicting the drought characteristics (onset, end, thresholds, drought phases, affected area and users, direct drought impact, is a considerably complex task).

It is with this background that Wilhite (2019) reported on a High-level Meeting on National Drought Policy (HMNDP) that was held in Geneva, Switzerland, in March 2013 (HMNDP 2013). He argued that the principal sponsors of this meeting were the World Meteorological Organization (WMO), the Secretariat of the United Nations Convention to Combat Desertification (UNCCD), and the Food and Agriculture Organization of the United Nations (FAO), in collaboration with several other partners, such as the Global Water Partnership (GWP). The meeting resolved and recommended the adoption of an integrated drought management plan (IDMP), which emphasized the pursuit of a three-pillar approach to drought management (Figure 2.4) and argued that the approach's plan foresees actions prior to and during the event, including measures for mitigation, preparation, monitoring, early warning, response, and recovery (Tigkas et al., 2019). As illustrated in Figure 2.4, Funk & Shukla, (2020) argued that to create a successful DMP aimed at water scarcity risk reduction, policies and strategies must emphasize the three pillars: monitoring and early warning system, vulnerability and impact assessment and mitigation and response.

To this end, it is evident that droughts are a natural phenomenon caused by a deficit in precipitation, and they characterise a certain statistical irregularity concerning the long-term mean across spatial and temporal scales (Hervaz-Gomez and Delgado-Ramos, 2019). A drought event might trigger

water scarcity (depending on the duration and magnitude) (Ortega-Gaucin et al., 2021). However, Zeybekoğlu & Aktürk (2021) argued that during a drought episode, not only is the water availability likely to be, but also the water quality is seriously affected because of less dilution and higher concentration of contaminants. Mortoja & Yigitcanlar (2022) contended that this would further lower the volume of water that is fit for human consumption while making its management more expensive and challenging. Hurtado et al. (2023) noted that depending on the reliance and resilience of the water resource system, water scarcity because of drought incidence commonly results in water restrictions (irrigated crops, industrial and touristic activity, environmental flows, urban and household water uses) and increased competition and conflicts among water users. Therefore, the socio-economic and environmental impacts of water scarcity because of drought can be considerable and will vary according to the drought management strategies in place (Rossi & Cancelliere, 2013). Estrela (2016) argued that impacts would be more severe in water-scarce basins, regions lacking water storage infrastructures, and the absence of integrated drought and water management plans.

2.9 Drought monitoring and early warning systems (DEWS)

The DEWS component in drought risk management involves tracking drought indicators and indices at varying spatiotemporal scales using climate and biophysical variables such as precipitation, temperature, soil moisture, vegetation condition, stream flow, and groundwater (Hao et al., 2014). However, Funk and Shukla (2020) argued that early detection of droughts can pose significant challenges, primarily due to the difficulty of accurately determining the occurrence of past drought events. Hao et al. (2014) contended that drought monitoring is further complicated by the fact that the shortage of available water can arise in various ways, and its severity can be measured based on several factors such as water scarcity levels, the vulnerability to the impacts of drought, coping capacity, and exposure of the human environment system. Similarly, Wilhite (2017) noted that the manifestation of drought impacts is often gradual and slow, and this presents an excellent opportunity for developing efficient drought monitoring and early warning systems using climate variables. Hao et al. (2014) noted that over the past few years, numerous drought-monitoring models have been used for research purposes and as operational decision-making tools. Grasso (2023) argued that drought monitoring and prediction systems still lag in development compared to other natural disasters, such as thunderstorms, mainly due to the intricate mechanisms associated with the initiation and progression of droughts. Kundzewicz et al. (2019) noted that the complexity of drought monitoring

in various developing countries, such as South Africa, is evident through the lack of progress in establishing effective national drought policy.

Waha et al. (2017) suggested that as the impacts of climate change become more severe, nations must progress towards increased readiness, using drought monitoring and early warning systems, as these systems offer the required knowledge to make prompt decisions about managing water and other natural resources. DEWS consolidates and articulates information from several fields of study and data origins, including diverse physical and social realms (Funk & Shukla, 2020). For effective DEWS, a bottom-up approach— that involves station data to grids, then to basin or provincial/district level, and even national analyses— is typically recommended (Hannaford et al., 2019). However, a top-down approach is used in many countries or regions due to resource constraints (Senay et al., 2015). Predictions and warnings about droughts should also give users vital information to make decisions (Pulwarty & Sivakumar, 2014). Incorporating traditional knowledge can also enhance early warning systems and drought monitoring. Drought-prone countries can also use the publicly available worldwide drought data while creating or enhancing their drought monitoring instruments (triggers) and early warning systems (Hao et al., 2014). Dong & Liu (2014) reported that the Global Information and Early Warning System (GIEWS), the Climate Prediction Center (CPC) of the National Oceanic and Atmospheric Administration (NOAA), and the Famine Early Warning Systems Network (FEWS NET) drought information and other products are some of the operational global programs that national early warning systems in Africa may be able to leverage. Linking correlations between these groups of questions might be intimidating. However, DEWS integrates the skills of interdisciplinary specialists in a manner that considers the historical background and circumstances of drought evaluation (Grasso, 2023). Climate models and satellite-enhanced weather monitoring systems can forecast and track precipitation and temperature in several locations with a satisfactory degree of precision (Rodrigues et al., 2020), which can be used to improve the effectiveness of drought early warning systems.

Traditionally, methods for assessing and characterising drought have primarily relied on measurements taken at specific locations and using certain climate variables to monitor meteorological, agricultural, and hydrological drought (West et al., 2019). However, there has been a significant change in the way drought assessment and characterisation are done due to

improvements in remote sensing and earth observation technology, such as the introduction of the Landsat series in 1972 by the National Aeronautics and Space Administration (NASA) (Mishra & Singh, 2011). Sur et al. (2020) suggested that remote sensing-based systems provide meteorological data and assess conditions at the Earth's surface, including vegetation and water levels. Choi et al. (2013) noted that remote sensing techniques have transformed drought assessment and characterisation using climate-related factors on a grander scale and over more extended periods than was previously achievable using traditional approaches. Sheffield et al. (2014) noted that remote sensing technologies enhance drought monitoring and management, especially in places with limited data availability.

Svoboda et al. (2012) contended that drought characterisation entails assessing the inherent indicators of drought severity, spatial extent, and frequency. Nam et al. (2017) argued that the components of drought assessment include the timely availability of data, the analysis, synthesis, and distribution of data that can be utilised in decision support tools, communication strategies, educational initiatives, and occasionally a forecasting aspect if it is accessible. Núñez et al. (2014) reported that multiple data sources from climate models have been utilised to characterise drought for monitoring purposes in different places worldwide (Mishra & Singh, 2011). Dong et al. (2021) argued that drought assessments often rely on climatic and hydrological data, with drought indices serving as widely accepted methodologies. Many drought assessment techniques have concentrated on climate and hydrologic-oriented indicators and indices that monitor variations in components of the hydrologic cycle, such as temperature, streamflow, and soil moisture (Mishra & Singh, 2011). These observations are primarily derived from the point-based data collected in the field using precipitation, temperature, streamflow, and soil moisture conditions as the input variables (Fragaszy et al., 2020). Wardlow et al. (2015) argued that the science community has been able to access unprecedented new remote sensing data sets for precipitation, snow, soil moisture, land surface temperature, evaporation, total water storage, vegetation, and land cover. Rhee et al. (2020) contended that satellite observations have opened new avenues in global drought monitoring from meteorological, agricultural, hydrological, and ecological perspectives. Heumann (2011) noted that satellite-based sensors' advantages relative to traditional ground-based observations include global, near-real-time observations, consistent data records, and improved spatial resolution.

2.9.1 Meteorological drought monitoring

Meteorological drought can be defined as a persistent absence of precipitation and an increase in evapotranspiration over short to long-term time scales (Li et al., 2021). Meteorological drought often serves as a precursor to agricultural and hydrological drought and frequently affects large spatial areas (Nam et al., 2017). According to Du et al. (2013), measuring precipitation using remote sensing products has improved the accuracy and extent of meteorological drought monitoring. West et al. (2019) reported that the initial efforts to measure precipitation using remote sensing were through the TRMM (Tropical Rainfall Measuring Mission), a cooperative venture between NASA and the Japan Aerospace Exploration Agency (JAXA). Rodrigues et al. (2020) reported that TRMM was notable for being the first satellite to include a dedicated microwave precipitation radar and collected precipitation datasets in tropical and subtropical regions between 35°S and 35°N between 1997 and 2015. TRMM had a limited orbital cycle, conducted 16 cycles per day, with a measurement swath of 878 km and a spatial resolution of 0.25° when decommissioned (Igri et al., 2022). The 17-year legacy precipitation dataset is a crucial reference point for measuring worldwide rainfall. It continues to be regularly employed in evaluating global precipitation patterns and the climatic factors contributing to drought (Yan et al., 2021). The Global Precipitation Measurement (GPM) mission, as described by (Hou et al., 2018), was the successor of TRMM. Ramonet et al. (2020) argued that evaluating GPM retrievals at different levels indicated a significant correlation between in-situ gauged and TRMM data. Therefore, the GPM and linked TRMM/GPM datasets have emerged as significant resources in drought monitoring research (Alizadeh & Nikoo, 2018).

Using TRMM/GPM datasets, various analytical techniques have been utilised in drought assessments that incorporate remotely sensed precipitation for drought characterisation. These methods include calculating long-term rainfall anomalies (Bayissa et al., 2017; Cattani et al., 2021) using indices such as the Precipitation Condition Index (PCI) (Xu et al., 2024). The Standardised Precipitation Index (SPI), developed by McKee et al. (1993), is another frequently utilised index computed based only on precipitation data. This characteristic made it significantly more efficient regarding data usage compared to the Palmer Drought Severity Index (PDSI) for various applications. According to West et al. (2019), the SPI has a crucial benefit in that its values have an equal likelihood of occurring regardless of the period, region, or size. This allows it to reflect wet and dry events across various conditions equally. The availability of long-term records allow for the computation of SPI, and this

enables the identification of meteorological droughts across extensive geographical areas (Winkler et al., 2017).

Kchouk et al. (2022) noted that the commencement of meteorological drought is frequently a crucial indicator of agricultural or hydrological drought. Memon and Shah (2019) thus argued that it is crucial for DEWS to strive to incorporate meteorological variables to evaluate different types of droughts. Morid et al. (2006) reported that an essential element in meteorological and agricultural droughts is the augmentation of evapotranspiration rates. Ficklin et al. (2015) noted that accurate evapotranspiration assessment is crucial for efficient drought assessment. The determination of evapotranspiration necessitates the inclusion of remotely sensed supplementary variables such as the state of vegetation, its type, and soil characteristics (Palanisamy et al., 2023). Currently, there are several remote sensing data products available for evapotranspiration, which are obtained from observations made by different satellite families, including the Global Land Evaporation Amsterdam Model (GLEAM), MODIS (Moderate Resolution Imaging Spectroradiometer) and Landsat satellites (Cattani et al., 2021).

Peng et al. (2020) noted that GLEAM is a process–based semi–empirical model aiming at estimating land evaporation and its separate components. The technique underwent revision in 2014 and is presently in its third version (Martens et al., 2020). The present GLEAM product comprises a sequence of microwave (C– and L– band) data about vegetation, soil moisture, precipitation, and thermal observations of land surface temperature (LST) obtained from sensors like MODIS and the SMOS (Soil Moisture Ocean Salinity) mission (Martens et al., 2020). Zhao et al. (2022) argued that GLEAM employs data from sensors with extensive operational experience, allowing for the availability of Version 3.3 of the product from 1980 to 2018 (West et al., 2019). A significant number of droughts–related research studies have utilised remotely sensed precipitation or evapotranspiration data, primarily on a global or continental level (Zhao et al., 2022). However, due to the nature of these datasets, the spatial resolution of these studies has been relatively low (Martens et al., 2020). This could be because previous earth observation satellites placed a higher emphasis on temporal resolution than spatial resolution (Tortini et al., 2020). Nevertheless, significant efforts have been undertaken to enhance the spatial resolution of meteorological remotely sensed data. van Dijk et al. (2018) employed MODIS observations of surface water extent, vegetation, and LST, which were integrated into a landscape hydrological model.

Passive sensor-derived datasets have been reanalysed to depict evaporation and evapotranspiration accurately. Wulder et al. (2019) argued that using Landsat satellites has contributed to the advancement of novel monitoring methods that offer improved resolution (Wulder et al., 2019). The inclusion of the thermal band on Landsat 3 (released in 1978) and its subsequent improvement on Landsat 4 (1982) and later versions enabled the retrieval of high-resolution (30 m visible) land classifications and land surface temperature (LST). The observations have resulted in acquiring evapotranspiration estimates with a relatively high level of detail (Sadeghi et al., 2020). A recent study utilised the Google Earth Engine to compute essential meteorological and hydrological parameters by leveraging the thermal capabilities of satellite sensors (Sadeghi et al., 2020). EEFlux, which stands for Earth Engine Evapotranspiration Flux, was created by building upon the METRIC model (Mapping Evapotranspiration at High Resolution with Internalized Calibration) developed by Allen et al. in 2000. This tool utilises a set of algorithms to generate estimates of evapotranspiration by analysing imagery from Landsat 5 TM (1984–2013), Landsat 7 ETM+ (1999–Present), and Landsat 8 OLI–TIRS (2013–Present) (Oroud & Balling, 2021).

2.9.2 Agricultural drought monitoring

Agricultural drought can be understood as a deficiency of moisture in the soil root zone necessary to meet the water requirements of crops, thereby causing crops to reach a state of permanent wilting (Kchouk et al., 2022). While soil moisture can be used as a direct indicator of drought, the land surface temperature (LST) and vegetation status are indirectly related to soil moisture, and consequently, affect the agricultural drought (Amani et al., 2017). Furthermore, Amani et al. (2017) argued that a combination of the LST and vegetation information has also been applied for drought assessment through the Normalized Difference Vegetation Index (NDVI). Long-lasting meteorological droughts in a certain area will start to affect the local water systems and farming practices and ultimately result in agricultural droughts (Mwangi et al., 2014). Liu et al. (2022) defined "agricultural drought" as a reduction in the accessible soil moisture for vegetation caused by insufficient rainfall. It is sometimes referred to as "soil moisture drought". Agricultural droughts typically manifest over extended periods, ranging from medium to long-term (Sun et al., 2017). These droughts have significant consequences such as diminished crop yields or complete failures, ultimately leading to imbalances in food demand and supply (Mwangi et al., 2014). Assessing agricultural dryness by satellite observation involves

quantifying soil moisture levels using active microwave radar and passive radiometers such as SMOS or SMAP (Soil Moisture Active Passive) (Aadhar & Mishra, 2020; Zhang et al., 2021). An alternative method involves utilizing passive multispectral sensors such as Landsat or the more current Sentinel-3 to examine vegetation (Um et al., 2022).

2.9.3 Hydrological drought monitoring

The progress in utilizing remote sensing techniques for hydrological drought analysis has been somewhat restricted (West et al., 2019) as there are not enough sensors and satellites specifically designed for this purpose (Mwangi et al., 2014). Currently, more research is needed to apply this concept specifically to hydrological drought (Isaak et al., 2012). Remote sensing technologies have enabled monitoring changes in Earth's overall water storage in relation to hydrological and groundwater droughts (Sadeghi et al., 2020). NASA and the German Aerospace jointly conducted the Gravity Recovery and Climate Experiment (GRACE) mission, initiated in 2002 (Tapley et al., 2004). The mission was initially planned to last for 5 years. However, owing to its achievements, the mission was prolonged until 2017. The GRACE project comprised a pair of satellites in a synchronized orbit (Kornfeld et al., 2019). The distance between the satellites was measured by on-board instrumentation, and it varied by around 200 km due to the fluctuations in Earth's gravitational field (Tapley et al., 2004). The provided observations were utilised to generate monthly depictions of variations in the Earth's gravitational field. GRACE monitored fluctuations in terrestrial water storage (TWS) throughout all water storage compartments, including soil moisture, surface water, and groundwater (Buitink et al., 2020). GRACE possessed the distinctive characteristic of not relying on surface conditions and being able to obtain data at depths greater than five centimetres below the surface (Odongo et al., 2023).

Datasets from GRACE has been effectively utilized in various hydrological drought monitoring research, such as analysing the characteristics of drought events, investigating variations in drought severity across regions, and tracking groundwater depletion (Ma et al., 2017). GRACE has also been utilized to compute indices suitable for extensive hydrological drought monitoring, including the Drought Severity Index (DSI), the Total Storage Deficit Index (TSDI), and the Multivariate Standardized Drought Index (MSDI) (Ferreira et al., 2016). These indices primarily demonstrate

spatial and temporal variations in drought severity. In the USDM, GRACE was utilized to observe hydrological and groundwater droughts (Um et al., 2022).

2.9.4 Integrated approaches to drought monitoring

Remote sensing data products have been utilised to compute novel integrated monitoring indices developed explicitly to monitor different types of droughts. For instance, Du et al. (2013). introduced the Synthesized Drought Index (SDI), which is a composite measure that combines the Vegetation Condition Index (VCI) (Kogan, 1997), the Temperature Condition Index (TCI) (Kogan, 1995), and the PCI. The SDI stands out because it incorporates remote sensing data products obtained from MODIS and TRMM. This enables a comprehensive evaluation of drought progression by considering precipitation deficit, soil moisture depletion, and vegetation stress in an integrated manner, (Du et al., 2013). Incorporating indices and various remote sensing–derived data products is a significant advancement in efficiently monitoring droughts across several drought categories. Zhang et al. (2017) have emphasised that agricultural or hydrological drought indices are more suitable for monitoring longer–term droughts and may not adequately capture shorter–term dry occurrences. Hence, it is imperative to incorporate a meteorological index in conjunction with these metrics to comprehensively analyse the spread of drought and short–term meteorological droughts (Shah & Mishra, 2020).

Zhang et al. (2017) further emphasise the significance of employing a multi–or integrated index strategy for monitoring drought. Other research studies utilised diverse remote sensing products to investigate numerous types of droughts concurrently. Nicolai-Shaw et al. (2017) included GLEAM data into their agricultural drought monitoring approach by leveraging the relationship between evaporation and vegetation status. The scientists were particularly interested in the delay in vegetation reaction to maxima in evapotranspiration and they related this delay to a potential shortcoming of GLEAM data, namely the underestimating water availability in deeper soil strata necessary for supporting plant development (Arun Kumar et al., 2021). Orth & Destouni (2018) conducted a study utilising different remote sensing data products to evaluate the imbalance in water balance during droughts across continental Europe. Specifically, they focused on examining the correlation between several stages of the hydrological cycle, including precipitation, evapotranspiration (GLEAM), vegetation status (measured using vegetation index), and runoff. Gebrechorkos et al. (2023) argued

that the GLEAM dataset was utilised to illustrate the patterns in evapotranspiration, which exhibited a significantly slower rate of change compared to the variations in runoff following the onset of the drought in southern Europe. Martens et al. (2020) suggested these findings indicate that agricultural drought has a more pronounced effect on reducing runoff compared to its impact on evapotranspiration.

Hao et al. (2015) emphasised the significance of using diverse datasets from various sensor types, even when monitoring a limited number of droughts-related indicators. Zhang et al. (2017) demonstrate the correlation between various soil moisture datasets and indices and varied accumulation durations of SPI data, indicating varying drought severity levels. Chakraborty et al. (2023) the passive microwave data obtained from AMSR–E, specifically the Soil Moisture Condition Index (SMCI) developed by Zhang & Jia (2013), strongly correlated with short-term Standardised Precipitation Index (SPI) in areas with sparse vegetation. On the other hand, multispectral indices such as the Vegetation Condition Index (VCI) and Temperature Condition Index (TCI) demonstrated a stronger correlation with a 3- to 3-month SPI. Employing numerous remotely sensed soil moisture products is advantageous in agricultural drought monitoring since various indices and sensors possess distinct merits and limitations (Zhao et al., 2022). Nevertheless, the nature of the relationship will heavily rely on the specific attributes of the monitored land surface variables. For instance, specific vegetation parameters may exhibit a slower response to the onset of drought compared to soil moisture levels in the same area, owing to the resilient biophysical characteristics of the vegetation (Zhao et al., 2022). Additional local land surface attributes, such as terrain and land cover, will also influence this correlation (Zhang et al., 2017).

Brown et al. (2008) developed VegDRI (Vegetation Drought Response Index) is one of the earliest and most extensively used integrated drought monitoring indicators. The development of VegDRI aimed to harness the advantages of both remote sensing and climate-based drought monitoring methods (Nam et al., 2015). The remote sensing component offers spatial data derived from NDVI data regarding vegetation distribution and overall state (Bushra et al., 2019). VegDRI generates vegetative stress and condition data associated with drought, with a spatial resolution of 1 km. This data is updated every week (Brown et al., 2008). Initially, VegDRI was compared to the USDM model, and the findings indicated that VegDRI provided notable improvements. In 2015, VegDRI was incorporated into the new USDM model to improve the spatial precision of simulated drought

patterns (Hao & Singh, 2015). VegDRI has been utilised in creating novel models (Tadesse et al., 2010) and has also played a role in evaluating drought conditions on a national level (Wu et al., 2018). With the introduction of additional sensors and the creation of datasets, remotely sensed data will probably be integrated into national-scale models and early warning systems in a comparable manner (Ramonet et al., 2020). Although the advantages of combining field measurements and classical meteorological indices with remote sensing techniques are evident, many studies.

As such the growing interest in water resources and drought management research on the creation of integrated indices that combine standard meteorological datasets with remote sensing methodologies (Liu et al., 2016), utilising local field measurements, such as those obtained from soil moisture sensors, can greatly enhance the accuracy of data analysis compared to relying solely on remotely sensed data (van Dijk et al., 2018). Despite recent progress in remote sensing, the measurement of soil moisture content is now limited to the surface material (1–5 cm). This presents a challenge because crop roots typically extend to a depth of 10–20 cm, making it difficult to measure soil moisture deficiencies in the root zone directly (Nam et al., 2017). To address this issue, it is advisable to include in-situ data taken at greater depths into drought monitoring methodologies in conjunction with satellite observations. Funk and Shukla (2020) stated that these approaches have the advantage of preserving the spatial and temporal benefits of remote sensing methods and integrating localised data on soil moisture, precipitation, and other variables.

2.10 Drought vulnerability and water scarcity risk assessment (DVRA)

According to Singh et al. (2014), the concept of ‘vulnerability’ has its roots in geography, however, and research on natural hazards applies the term as a fundamental idea in a variety of other research contexts such as ecology, public health, poverty and development, sustainability science, climate impacts and adaptation. Nazari et al. (2015); Paavola (2008) and Shahid & Behrawan (2008) defined vulnerability as the characteristics of a watershed system or group of people in terms of capacity to withstand, cope with, and recover from the impact of natural or man-made hazards. According to IPCC (2020), vulnerability is defined as the extent to which a natural or social system is prone to sustaining damage from the impacts of climate change. Zarafshani et al. (2016) reported that vulnerability is a function of the sensitivity of a system to changes in: (i) climate (the degree to which a system will respond to a given change in climate, including beneficial and harmful effects); (ii)

adaptive capacity (the degree to which adjustments in practices, processes, or structures can moderate or offset the potential for damage or take advantage of opportunities created by a given change in climate); and (iii) the degree of exposure of the system to climate hazards. Perkins et al. (2010) categorized drought vulnerability based on exposure, stress, and argued that most systems in developing countries are most sensitive to perturbations or stress and possess weak coping strategies. Phelps & Kelly (2019) stated that vulnerability is a condition in which individuals face water insecurity, job insecurity (unemployment), social insecurity, and health insecurity. Meanwhile, the United Nations International Strategy for Disaster Reduction (UN/ISDR) (2004) identified four vulnerability factors that are germane in the context of DMP: (i) physical factors, which describe the reliance and resilience of a region; (ii) socio-economic factors, which describe the level of education, good governance, financial resources of individuals, populations groups, and communities; and (iii) environmental factors, which describe the state of the environment within a region (Savari et al., 2022). Sharafi et al. (2020) contended that despite limitations on data availability, information on regional drought vulnerability and risk assessment could aid water managers in being proactive and instituting appropriate mitigation actions before the drought's occurrence. Pittman et al. (2011) suggested that vulnerability refers to how individuals and society experience the risk and threats of environmental hazards like drought. They consider farmers and pastoralists to be the most vulnerable groups to drought. Wilhelmi & Wilhite (2002) argued that in developing countries, vulnerability might be doubled in times of drought, particularly when water governance institutions fail to provide effective drought monitoring and early warning systems to support water supply systems. According to Sonmez et al. (2005), water scarcity challenges across the world have significantly increased in line with the increased number or severity of droughts, and the costly nature of drought vulnerability has led to increasing attention to the drought vulnerability in recent years.

According to Brooks et al. (2005), the characteristics that make water resource systems in a developing country vulnerable to drought could be different from those of a developed country. Smit & Wandel (2006) stated that hazardous weather differs from average weather by its potential to damage and not by its physical or statistical properties. For a water resource system, vulnerability is unlikely to be the same for low and high frequent droughts (Paavola, 2008). Drought and water security risk is a function of hazard and vulnerability, and therefore, the level of risk that the hazard poses to people is directly related to societal vulnerability. To mitigate against the impacts of drought

on water scarcity, vulnerability must be lessened (Chandrasekara et al., 2021). However, more effort has been spent on drought monitoring and prediction than identifying system vulnerabilities. Mohammed et al. (2018) emphasized that drought vulnerability risk assessment, drought monitoring, and early warning systems are more closely linked to water security rather than climatological events that contribute to water scarcity. Wilhelmi and Wilhite (2002) reported that efforts to address water scarcity challenges more effectively under drought conditions would fall short unless vulnerability and risk assessment are conducted and adopted as a vital consideration in the overall planning effort.

2.10.1 Vulnerability assessment models

Numerous vulnerability assessment models have been created to comprehend the impact of climate change on communities and how they adapt to changing circumstances (Bedeke, 2023). These models analyse human interactions with their physical and social environment, enabling researchers to identify the most vulnerable locations, sectors, and social groups. Three widely used methods to assess climate change vulnerability are model-based, stakeholder-oriented, and indicator (Hagenlocher & Castro, 2015). By determining the characteristics of the vulnerable system, the type of stress it is under and the effect it has on that system, effective coping strategies can be developed to enhance resilience in these vulnerable areas.

2.10.2 Simulation-based methods

Simulation techniques using model-based methods predict the impact of climate change (Bedeke, 2023). Biophysical models simulate the correlation between climate, soil, and crops. Water scarcity models assess drought impact. In Sub-Saharan Africa, yields will decrease by over 10% due to climate change risks. Nitrous oxide concentrations will increase due to improper fertilizer use. Intra-seasonal rainfall variability will threaten crop productivity. However, socio-economic factors like access to seeds, fertilizers, and land size are not considered in these methods. Economic models can aid in quantifying and predicting vulnerability to socio-economic risks and climate change. Hoddinott & Quisumbing (2010) identified three models to evaluate vulnerability: vulnerability to expected poverty, vulnerability as low expected utility, and vulnerability to uninsured risk exposure. These models provide valuable insights that can help policymakers develop effective strategies to mitigate the adverse effects of climate change on society.

2.10.3 Participant-based methods

Participant-based methods effectively determine people's vulnerability to climate change at different stages of analysis. Climate vulnerability and capacity analysis is a commonly used stakeholder-based method to assess farmers' vulnerability to climate change. It evaluates the impact of social and environmental stresses, such as droughts, lack of access to water, and deforestation, on climate change vulnerability. Gentle & Maraseni (2012) used this method to evaluate the impact of climate change on local communities in Nepal. Their findings revealed that climate change is an additional burden for impoverished people living in mountain communities already experiencing land degradation, food scarcity, a lack of water supply services, and increasing social inequality. The method can help stakeholders identify social and physical factors that drive climate change vulnerability and develop coping strategies. However, it has limitations. The results may only be applicable to a small population due to the limited number of participants involved. Additionally, group discussions could be influenced by power asymmetry and gender bias in decision-making processes, exacerbating existing inequality and perpetuating poverty and climate change vulnerability.

2.10.4 Index-based assessment methods

Index-based methods use proxy indicators to evaluate a system's vulnerability to climate change. These indicators can be combined to form indices that reflect the biophysical and socio-economic attributes of a particular system. The primary objective is to characterize the sources and drivers of climate change vulnerability. Indicators help quantify social and biophysical drivers of climate change vulnerability, enabling policymakers to develop coping strategies. At the local scale, indicators help assess and understand the nature of climate change vulnerability among individuals and households. The goal is not to rank the levels of vulnerability to climate change but to identify the most vulnerable families, communities, or sectors to climate change.

2.11 Research gaps

The increasing frequency of droughts on a global, regional, and national scale poses a massive threat to the availability of water resources. Raphael Muli Wambua et al. (2018) argued that frequent and severe droughts could introduce a substantial reduction in water levels, subsequently leading to the

drying out of waterbodies. They further argued that this has the potential to pose significant challenges to the agricultural production system and profoundly affect the utilization and allocation of water for domestic consumption. The World Bank (2018) reported that severe droughts are causing water scarcity to become a more urgent issue and that world leaders acknowledge that water scarcity, with drought being a contributing factor, is the most significant issue for which they are ill equipped. According to Fragaszy et al. (2020), the Global Risk Report ranks drought as one of the extreme weather occurrences with the highest likelihood and second-highest impact. They reported that empirical data from several global locations indicates that droughts rank among the most financially and socially burdensome natural disasters. Studies from numerous scholars, such as Bergaoui et al., (2015), have shown that droughts substantially affect the national budgets, export revenues, and imports of southern African countries. Drought also adds to social inequalities, adverse health effects, rural emigration, and broader political upheaval (Garschagen & Kraas, 2010). While previous studies on drought in southern Africa have focused on catchments and river basins, a limited number of studies appear to have focused on localized perturbations within the provincial scale.

A review of literature from scholars such as Nam et al. (2017) suggested that due to the natural precipitation variability and the significant and devastating impacts of drought on water resources, it is crucial to conduct drought risk management studies. Wilhite (2017) argued that integrated drought management studies should be adopted and supported by efficient monitoring and early warning systems that seek to reduce drought risks, such as chronic water shortages. Tsakiris et al. (2013) proposed that researching the impacts of climate change on water resources is necessary to address the impending difficulties of water shortage. Cosgrove & Loucks (2015) argued that the impacts of drought on water scarcity are intricate and multifaceted concepts influenced by a range of biophysical connections within the climate system. Kron et al. (2019) and Seibert et al. (2021) argued that given the global water resources vulnerability to climate change, understanding, and addressing the occurrence of drought in a changing climate requires insights from climate modelling of both historical and future periods. Mirza (2003) proposed that obtaining quantitative data on the impacts of drought on water scarcity, along with information about anticipated climate system changes, could enhance our comprehension of potential future hazards associated with water scarcity and agricultural output.

Birkmann et al. (2015) argued that drought monitoring and planning with the objective of mitigating drought risks associated with water availability requires a forward-looking perspective, and ideally should be based on different future climate scenarios for a given region and societal development— a need that has been increasingly emphasized over the past years. In addition, the monitoring of drought trends and changes in risk components and indicators over time can contribute to the development of adaptive measures, particularly in sub-Saharan Africa (Hagenlocher et al., 2019). The above literature indicates that existing drought risk assessments still focus primarily on the social dimension and do not necessarily apply a specific drought monitoring approach when characterizing the impact of drought hazards on water availability. While context is crucial, operational definitions of drought are more appropriate depending on region and purpose (Wilhite, 2000). This creates not only terminological and taxonomic confusion when operationalized in assessments but also complicates the comparability of assessments and their outcomes – a gap that has also been emphasized in previous studies (Bacon et al., 2017; Wu et al., 2018). Similarly, the reviewed literature indicates that there is increasing recognition that the impacts of drought on water resources and factors that dictate severity are complex, interact with each other, and are often features that determine a nation's ability to attain water security (Van Loon et al., 2016). Hagenlocher et al. (2019) reported that when assessing drought risk in the context of water resource management systems, a DEWS perspective could help understand and evaluate the role of drought propagation as a driver of water scarcity. Furthermore, literature indicates that the future water availability under projected climate change-induced drought conditions is unclear. In this regard, proactive drought modeling promises to support the role of early drought warning, vulnerability assessment as well as drought risk mitigation.

CHAPTER THREE

METHODOLOGICAL CONSIDERATIONS

3.1 Introduction

This chapter is organized into two primary sections the philosophical underpinnings and the research design. An overview of the philosophical underpinnings adopted in the study will be discussed first in section 3.2. The research design which gives a description of the study site, data instrumentation and data collection methods. As the research focused on the WC Province, section 3.3.1 describes the study site; the different AEZs of the province; and the prospective sources of precipitation data that could have been used. Section 3.3.2 discusses the data instrumentation techniques that were employed in modelling the impacts of drought on water resource, while section 3.3.3 provides a discussion of data collection and highlights how the techniques used to collect the datasets. Section 3.4 discusses the techniques used to analyse the data such as the trend free pre-whitening, trend analysis, drought characterisation, downscaling, and reliability, resilience, and vulnerability indicator determination. Finally, section 3.5 provides the methodological reflections in the current study.

3.2 Philosophical underpinnings/research approach

According Rajasekar & Verma (2019) research methodology is a branch of epistemology, and as such, research concepts are better investigated with specific approaches than with others. Laher (2007); Patton (2002) noted that any research process is rooted in philosophical principles about approaches, theories, and models. Eichler (1997) argued that considering the philosophical underpinning is crucial to understanding research. Greenwood & Levin (1998) argued that the three significant philosophies of science that bear on quantitative methodological considerations are empiricism, constructionism, and scientific realism. Solomon (2007) argued that empiricism is the philosophy of scientific research that recognises evidence and acknowledges it as being discovered in experiments. Bealer & Strawson (1992) noted that empiricism is a fundamental part of quantitative research and posits that all hypotheses and theories must be tested against observations of the natural world rather than resting solely on a priori reasoning, intuition, or revelation. On the other hand, Omodan (2022) argued that constructionism strives to understand how humans create knowledge – anything that society holds, accurate and meaningful. Ardiansyah & Ujihanti (2017) argued that

constructionist knowledge is a consequence of social processes. Therefore, social constructionists reject essentialist explanations that certain phenomena are natural, inevitable, and universally determined. Meanwhile, Rossi & Sleat (2014) suggested that scientific realism is the view that well-confirmed scientific theories are approximately true, the entities they postulate do exist, and we have a good reason to believe the theories. They argue that scientific realism comes in many forms; however, most versions of scientific realism display a commitment to at least two doctrines: (i) that there is a real world of which we are part and (ii) that both the observable and unobservable features of the world can be known by the proper use of scientific methods. Some versions of scientific realism incorporate additional theses (e.g., the claims that truth is the primary aim of science and that successive theories more closely approximate the truth), and some will nominate optional doctrines that may but do not need to be used by scientific realists. Realist researchers recognise that there are two distinct ways in which knowledge claims must be justified (Baderin, 2014). These are known as coherentism and reliabilism in philosophy. Reliability refers to the degree to which dependable procedures support a belief (Rossi Enzo, 2018). The countless techniques that aid in identifying empirical phenomena primarily focus on reliabilist reasoning.

In the present study, the scientific realism approach was adopted. A scientific realist approach to this type of research can help illuminate the conceptual foundations of the methods used. According to Bhaskar (2013), scientific realism has a rich conception of methodologies, which aids in understanding and guiding research. The methodologies of the realist approach have three major tasks: to describe how methods work, to critically evaluate methods against other techniques, and to recommend how to use specific techniques to pursue chosen research goals (Williams et al., 2017). Patton (2002) argued that the realist methodology is fundamentally goal oriented. It advocates the pursuit of valuable truth, explanatory understanding, and effective control of primary research goals. At a more specific level, the realist approach attempts to give due recognition to the research objectives. The realist methodology is naturalistic, meaning it is a substantive domain that studies phenomena and trends using the methods of various sciences (Chrisman, 2019).

3.3 Research design

Numerous modelling frameworks exist in contemporary literature to investigate the impacts of natural hazards (Cremen et al., 2022; McCuen et al., 2006). These approaches include the disaster

risk framework (Bründl et al., 2009), political ecology framework (Collins, 2008), pressure and release framework (Awal, 2015; Aziz, 2018), hazard of place framework (Eriksen et al., 2011); and vulnerability/sustainability framework (Skondras et al., 2020). This disaster risk framework is designed to enhance our understanding of the impacts of many natural hazards (Beck & Kropp, 2011). The perception of disaster risk has evolved from solely natural hazards to a compound event, encompassing hazards, exposure, and vulnerability. The disaster risk framework normally begins with assessing a regions past hazards and impacts and involves risk assessment to detect the nature of hazards and characterise their historical impressions at several spatiotemporal scales (Greenberg et al., 2012; Murphy & Gardoni, 2006). Lesk et al. (2016) applied the disaster risk framework to explore how drought incidence influences global crop production and analysed how future global river flood risk can be calculated using climate change impacts. Awal (2015) applied the pressure and release framework to adapt climate change shocks and stresses between ecological and social systems. The vulnerability/sustainability technique has been employed for quantitative and vulnerability studies (Tyler, 2016) while Shen & Hwang (2019) developed the spatial impact model for tornadoes.

However, in this research, the disaster risk and water resources management framework (Figure 3.1) was adapted to assess the impacts of droughts on water availability under different climate change scenarios and assist water resource managers in developing optimal water resource management strategies in the Western Cape Province of South Africa. The adapted disaster risk framework considered that climate change and environmental decline due to drought impacts gradually become part of the disaster risk equation. In the disaster risk management framework, disasters were considered as natural global environmental change processes (Lesk et al., 2016). Climate change and environmental degradation are all global change and disaster risk components. It was argued that not only is the drought risk more complex, but with development, climate change, and environmental changes, the risk is also dynamic, requiring regular reassessment. According to Figure 3.1, the element of drought risk, along with exacerbating factors from global change such as climate change, increased the frequency and severity of drought hazards, the spatial extent of the area exposed to drought and several people exposed, and vulnerability is reduced by improvement in technology, disaster risk management. The framework argues that regions are not equally exposed to natural hazards, and differences in geophysical factors, slopes, elevation, and proximity from the shore and inter-tropical location are parameters that influence a higher occurrence and severity of hazards.

Therefore, extracting resilience, reliance and vulnerability indicators requires extensive standardisation.

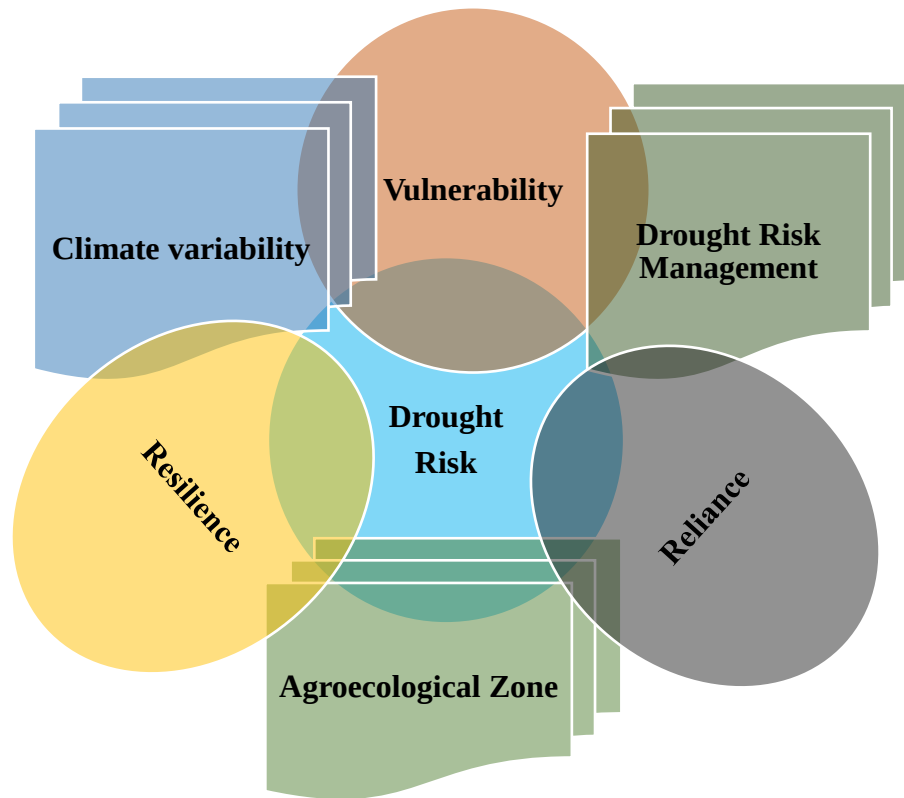


Figure 3.1 Disaster risk and water resource management framework (Adapted from Lesk et al., 2016)

The principal methodology employed in the research is shown in Figure 3.2. The methodology involved assessing the historical (1980-2020) and future (2021-2050) spatio-temporal characteristics of precipitation and drought trends and identifying climate anomalies. Secondly, drought vulnerability risk assessment (DRVA) was done using Reliability-Resilience-Vulnerability indicators. The approach integrated aspects of Rusk et al. (2022) modelling approaches, which involves the use of an impacts model to validate the simulated climate variable to reanalysis observed datasets (1980-2020) and downscaling a selected global climate model GCM to obtain finer-scale features (at a scale less than 100km). A more detailed discussion on the methodology is presented in section 3.4.

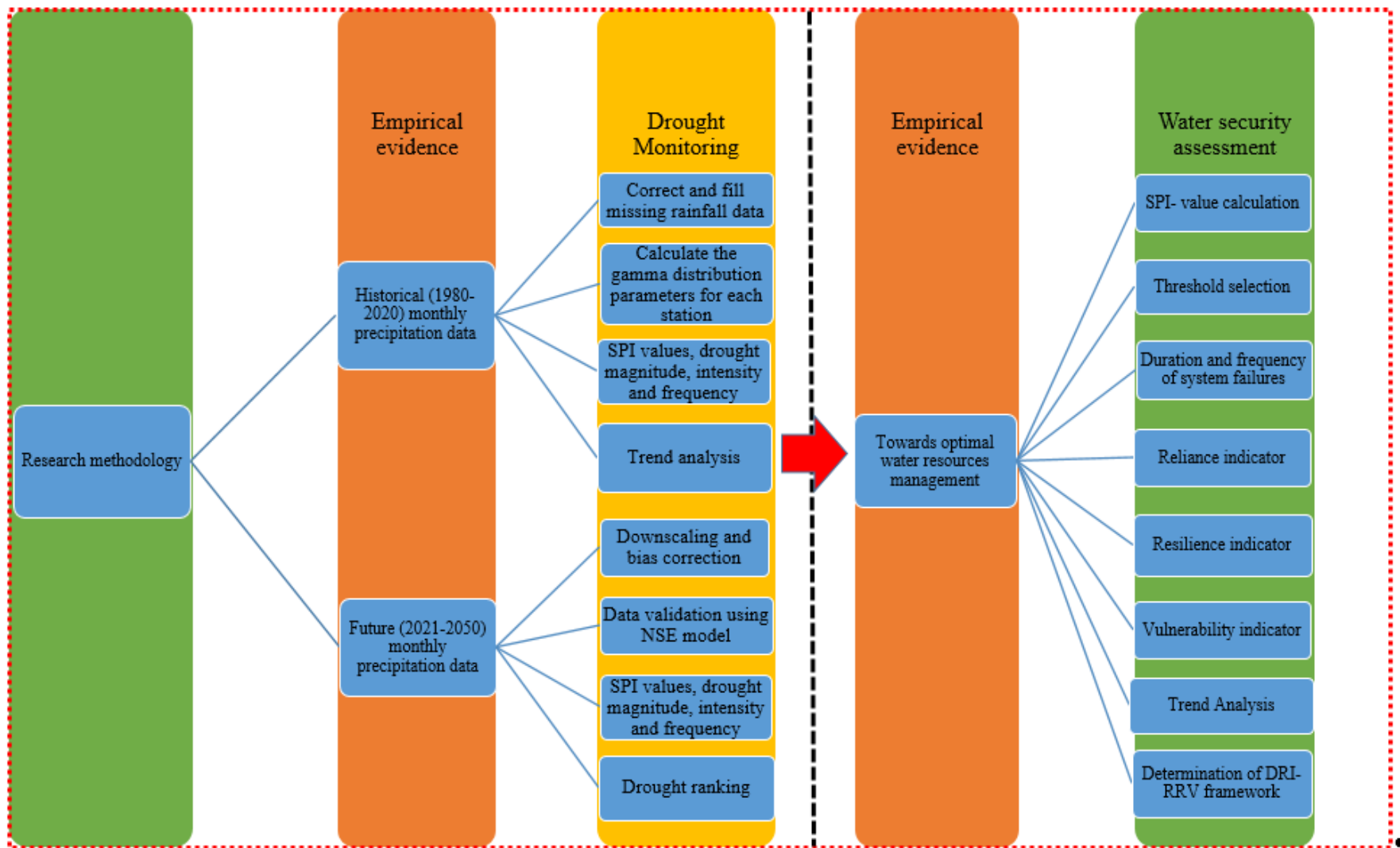


Figure 3.2 A schematic diagram of the research steps (Source: Based on field observation)

3.3.1 Description of study site

The Western Cape (WC) Province in South Africa is located at the southern tip of South Africa (Figure 3.3). The province shares borders with the Eastern and Northern Capes, the Atlantic Ocean to the west, and the Indian Ocean to the south. Due to its temperate Mediterranean climate, the province experiences mild, wet winters, and warm, dry summers. The average summer temperatures vary between 15°C and 27°C, and the average winter temperatures vary between 5°C and 22°C (Orimoloye et al., 2019). With only about 350 mm of mean annual precipitation (MAP), the WC province is one of the driest provinces in South Africa, receiving far less than the ~500 mm average for the entire country (Dennis & Dennis, 2012). The austral winter months (between May and September) receive the most annual rainfall, which is usually brought on by extratropical cyclones and cold fronts, as well as sporadic westerly disturbances, including cut-off lows (Driver & Reason, 2017). However, the distribution of rainfall is very varied, ranging from semi-arid regions to comparatively moist regions on the windward slopes of mountains (Blamey et al., 2017). The present study focuses on the six of South Africa's AEZs, which include subtropical warm/arid (STWA), subtropical cool arid (STCA), subtropical warm semi-arid (STWSA), subtropical cool semi-arid (STCSA), subtropical warm subhumid (STWSH) and subtropical cool subhumid (STCSH). The AEZs are categorised based on the duration of the cropping season (Mugido & Shackleton, 2017). Arid regions have a cropping season that lasts for two months; semi-arid regions have a length farming season ranging between two and three months; warm sub-humid regions have a cropping season of three to four months, while cool sub-humid zones have a cropping season of four to five months (Muimba-Kankolongo, 2018).

The WC Province has a network of water storage infrastructure that includes dams, weirs, pipelines and pumping stations that supply water to urban areas and irrigators in the STWSA (Piketberg), STCSH (Malmesbury) and part of the STCSH (Bredasdorp). The WC water resource system supplies water to several districts, including STCSH (Hermanus), STWSA (Piketberg) and STCSH (Ceres). According to DWS (2016), between 2015 and 2017, nearly 70% of the unrestricted water supply in the WC was allotted to urban and agricultural consumers (Archer et al., 2017). The WC province water supply system provides water to commercial farmers in the STWSH (Matroosberg) and STWSA (Swellendam) AEZs. South Africa's Department of Water and Sanitation (DWS) manages

the water storage infrastructure found in the AEZs of WC. The WC province is home to the STWSH (Cape Town) metropolitan area, South Africa's second-largest city with a population of 4.618 million (StatsSA, 2020). Farming is crucial to the Western Cape economy, particularly in the STWSH, STWSA and STCSH (Kam et al., 2021). It involves the cultivation of grapes for winemaking and winter crops such as wheat and barley, poultry, and livestock (Kruger & Sekele, 2013). Because of seasonal precipitation variation experienced, the WC requires large water storage reservoirs to store austral winter surface runoff for supply during the warm, dry summer months when demand is usually higher (du Plessis & Schloms, 2017). The province is supplied with water from 44 main dams, and these dams collectively have a maximum storage capacity of 1870.4 million cubic meters (Western Cape Govt, 2023). According to DWAF (2003), most of the significant dams store water from the basin in which they are located, except for Voëlvlei Dam, which is an off-channel storage dam. Water is transferred to Voëlvlei Dam from the Klein Berg and 24 Rivers, using abstraction points and open channels (Rawlins, 2019). The WC water resources management system is based on optimising yield and reducing water loss through spillages. The DWS's water resources planning model (WRPM) is employed in modelling the annual water availability of the WC, including assessing the possibility of instituting water restrictions (Maitre et al., 2019). The WC water resources management system operates the WRPM yearly in October/November when the water storage season is complete, and there is knowledge of water availability for the approaching hydrological year. The models provide a valuable decision support tool and utilise numerous stochastically derived rainfall and runoff sequences to simulate plausible short to medium-term storage responses (Hay et al., 2012). The DWS and stakeholders such as water-user associations (WUAs) undertake management decisions to enforce water restrictions. While water resources planning in the WCP is done collaboratively, it is the mandate of the DWS to institute water restrictions (National Water Act, 1998) officially.

The topography of the Western Cape Province is rugged with subterranean ravines, steep slopes, the geology is Cape sandstones, while the soils are shallow, sandy. The elevation extends from 1 300m above mean sea level, with most regions lying between 500 and 1000m. The primary vegetation forms comprise mesic and dry mountain fynbos scrublands (Molle, 2008). Jacobsen et al. (2007) reported that the northern and lower slopes are covered with low to mid-high ericoid scrublands of low to medium stature (0.1-1m) with patchy proteoid scrublands. Upper northern slopes carry tall (1-2 m) shrub-lands dominated by shrubs from the families Proteaceae and Bruniaceae (Sieben et al., 2004).

Tall scrublands occur on southern slopes, with retinoid herb lands on peaty soils. Many endemic plant species occur in the area, making it important for nature conservation. Forests are restricted to small patches and riverine strips. The area is managed by prescribed burning on a 12-15-year cycle. The forest areas have been largely kept free of alien plants compared with most other mountain catchment areas, but dense stands occur on adjacent lands and their seeds disperse into forest areas (McDonald et al., 2014). The most abundant aliens include *Pinus pinaster*, *Acacia cyclops*, *A. longifolia*, *A. saligna* and *Leptospermum laevigatum* (Molle, 2008).

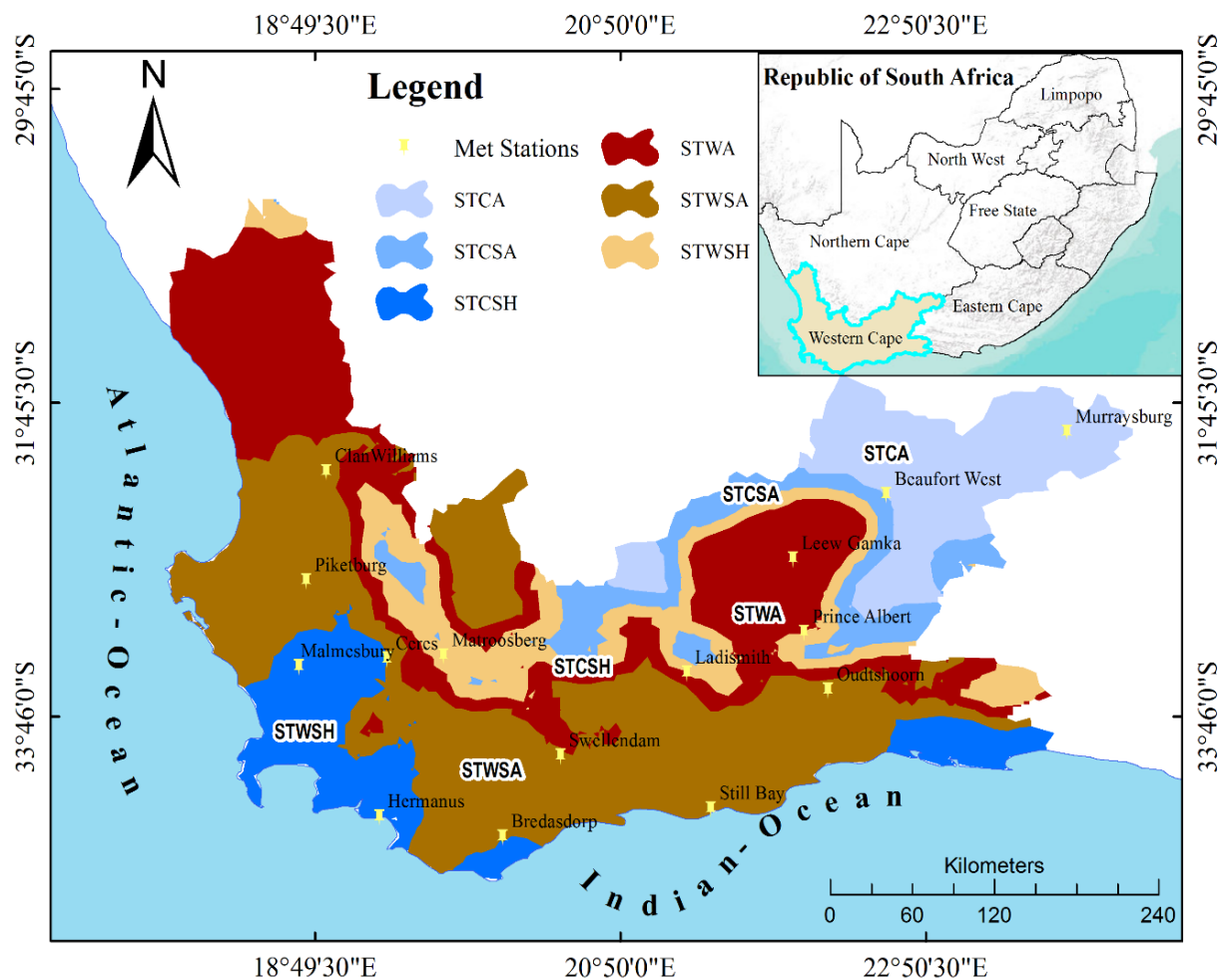


Figure 3.3 Location of the study area (Source: Ngwenya et al., 2024)

3.3.2 Data instrumentation

The present study focused on historical (1980-2020) and future (2021-2050) precipitation distribution in the agroecological zones. While the principal focus of the research was on precipitation distribution agricultural environment, historical and future precipitation records across the province were chosen and analysed, enabling the mapping of findings across the research area. The potential precipitation data sources in the study area were the South African Weather Service (SAWS), Water Resources of South Africa Study, 2012 (WR2012), and remotely sensed data from several satellites. SAWS offers weather and climate forecasting services and maintains a network of approximately 231 automatic weather stations, 1180 rainfall stations and 153 automatic rainfall stations (McDonald et al., 2014). The WR2012 was commissioned and funded by the Water Research Commission to make hydrological information across South Africa available to practitioners and researchers (Fikileni & Wolski, 2022). The chosen precipitation datasets had to satisfy the research's drought index requirements, including a minimum stretch of datasets of 30 years, continuity of data and resolution of data daily or monthly precipitation. The historical precipitation datasets had to have records from 1980 to facilitate drought characterisation. Statistical testing was done on the selected records by determining the mean, standard deviation, minimum and maximum precipitation. The difference between the past 30-year and long-term mean of each record was calculated to indicate any significant change in recent precipitation.

Some of the more frequently applied drought monitoring techniques were deliberated in section 2.9. The Standardised Precipitation Index (SPI) was applied in this study because the World Meteorological Organization (WMO) has globally recommended it as a reliable index to be used by research and meteorological institutions (WMO, 2012). The SPI was developed by McKee et al. (1993) and further advanced by Edwards (1997) as a stochastic methodology to characterise drought severity, intensity, duration, and frequency. It was developed to solve the restrictions of other indices, mainly the Palmer Drought Severity Index (PDSI), an empirically based index. McKee et al. (1993) detected that water managers found that drought characteristics are better articulated using deviation from the long-term mean of historical precipitation records. Different aggregation periods of precipitation can be evaluated; however, 1-, 3-, 6-, 12-, 18-, and 24-month time scales are usually preferred. The shorter timescales swiftly detect changes in monthly precipitation, while the longer timescales gradually detect changes to monthly precipitation. The SPI applies precipitation as the only input variable and is standardised; hence, it can be utilised to relate drought features at several

places. The SPI uses 1-, 3-, 6-, 12-, 18-, and 24-month timescales to analyse drought characteristics and does not require precipitation datasets to be calibrated to use them in a particular region. The SPI also requires appropriately lengthy records for fitting a distribution to the data. The WMO (2012) proposes that shorter timescales of 1 – 6 months are appropriate for assessing the drought impacts on soil moisture conditions, while longer timescales of 12 – 48 months are more appropriate for assessing the impacts on surface water availability. Using longer timescales is usually preferred, as the datasets and derived drought episodes are more established and less inconsistent. For this research, a 12-month timescale was chosen because the filling and drawdown cycles of dams and the operation of supply systems are usually done annually. In addition, 12-month timescales eliminate the seasonal variation in the precipitation records. The WMO (2012) recommends that precipitation datasets should have at least 30 years for SPI analysis and that there should not be any gaps in the datasets. Since this study applied the SPI values to characterise droughts, a record length of 30 years was selected for both the historical and future analysis. The requisite for continuity in the precipitation datasets necessitated that precipitation datasets had to be tested for gaps and multiple imputation techniques applied if necessary. The SPI fundamentally measures the deviation of precipitation datasets from the long-term average and then transforms the deviation into a normal cumulative distribution function (CDF) with a mean of zero and a standard deviation of one. Since precipitation datasets are generally not distributed, the datasets are fitted to a gamma distribution function and transformed into a normal probability distribution. This results in the standardised index for assessing drought characteristics at various positions. The SPI CDF indicates the likelihood that observed precipitation would be equivalent to or a lesser amount than a particular precipitation measure.

3.3.3 Data collection

Table 3.4 illustrates the selected meteorological stations used to acquire the daily observed, reanalysis and future precipitation datasets. Two forms of datasets were employed in the study: observational data and model simulations. Observed precipitation data (1980–2020), were gathered from the University of East Anglia’s Climate Research Unit gridded Time Series (CRU TS Version 4.07) <https://www.cru.uea.ac.uk/cru/data/hrq> database using Google Earth engine interface, while future precipitation datasets (2021–2050) under SSP5–8.5, SSP2–4.5 and SSP1–2.6 climate scenarios were generated by <https://esgf-node.llnl.gov/search/cmip6/> using the sixth version of Model for

Interdisciplinary Research on Climate, (MIROC6). CRU TS Version 4.07 datasets have 0.5° by 0.5° resolution and are available across all regions except Antarctica (Harris, 2020). The spatial resolution of the precipitation data generated by the MIROC6 model is 0.11° in latitude and longitude (12.5km×12.5km). Since historical data had missing values and there was large distances between gauging stations reanalysis data played a key part in solving these challenges (Gidey et al., 2018). Additional precipitation data were also obtained from the South Africa Weather Service from the period 1980–2020. These datasets were employed as a standard for forecasting the likelihood of drought occurrence in the study area.

Table 3.1 Location of stations in the Western Cape Province (Source: Based on field observation)

Station	Location		Mean Annual Precipitation (MAP)	Daily Average Temperature (°C)		Altitude (m)	AEZ
	Long. (E)	Lat. (N)		Minimum	Maximum		
MG	23.8	−32.0	310.6	2.0	29	1185	STCA
BW	22.6	−32.4	252.2	3.0	30	849	STCSA
MM	18.7	−33.5	638.1	6.0	32	203	STCSH
HM	19.3	−34.4	700.5	8.0	28	27	
CR	19.3	−33.4	716.3	6.0	31	457	
BD	20.1	−34.5	446.2	7.0	25	84	
LG	21.9	−32.8	133.1	3.0	32	555	STWA
LS	21.3	−33.5	364.7	5.0	31	544	
CW	18.9	−32.2	310.1	8.0	33	96	
PK	18.8	−32.9	388.1	6.0	32	203	
SW	20.4	−34.0	509.9	7.0	29	128	STWSA
SB	21.4	−34.4	435.1	7.0	26	36	
OD	22.2	−33.6	470.9	6.0	28	319	
MB	19.7	−33.4	311.0	4.0	29	2249	STWSH
PA	22.0	−33.2	354.3	4.0	29	633	

MG= Murraysburg, BW = Beaufort West, MM = Malmesbury, HM = Hermanus, CR = Ceres, BD = Bredasdorp, LG = Leew Gamka, LS = Ladismith, SB =Still Bay, OD = Oudtshoorn, SW = Swellendam, PK = Piketberg, MB = Matroosberg, CW = Clan William, MB= Matroosberg, PA = Prince Albert)

3.4 Data analysis

The methodology involved assessing the historical (1980-2020) and future (2021-2050) spatio-temporal characteristics of precipitation and drought trends and identifying climate anomalies. Secondly, drought vulnerability and water scarcity risk assessment (DRVA) were done using the reliance-resilience-vulnerability framework. After dataset acquisition, the historical daily precipitation datasets were transformed to monthly and mean annual precipitation resolutions. Precipitation time series datasets consist of three main components: residual noise, seasonal variations, and trend components (Das et al., 2019). To adequately analyze historical precipitation data, analysis techniques need to be applied. An overview of techniques applied in processing the historical precipitation datasets is given below.

3.4.1 Trend-free pre-whitening

The presence of residual noise components created a substantial challenge in identifying patterns of seasonality and trends in precipitation time series data, necessitating their removal through decomposition. Therefore, before evaluating the attributes of meteorological drought patterns, it was essential to evaluate the remaining interference component of precipitation data. The present study employed a pre-whitening procedure. The technique relied on the existence of both residual noise and a persistent trend in the time series data of precipitation. This allowed for the integration of a linear regression model with serially correlated residuals, as described in Eq. 3-1.

$$\delta_t = \mu + T_t + \varepsilon_t \quad 3.1;$$

Where δ_t is the precipitation at time t , T_t is the trend at time t , and ε_t is the residual noise at time t and μ is the constant term. By assuming a linear trend, Eq. 3-2 was abridged so that:

$$\delta_t = \omega_t \quad 3.2;$$

Where ω was the slope of the linear region between precipitation and time. Similarly, the noise may be represented by Eq. 3-3:

$$\varepsilon_t = \sum_{r=1}^m \sigma_r \varepsilon_{t-r} + \rho_t \quad 3.3;$$

Where σ_r represented the parameters of the auto-regressive process, m was the order of the regression, and ρ_t was the residual noise so that Eq. 3-4:

$$\delta_t = \mu + \omega_t + \sigma_r \varepsilon_{t-r} + \rho_t \quad 3.4;$$

Whereby lag-one autocorrelation, AR (1) was applied.

3.4.2 Trend analysis

The Mann– Kendall trend tests were utilized for trend analysis. A trend refers to a consistent and established pattern in climatic data that may indicate a changing trend across the duration of the study period (Ndebele et al., 2020). The Mann–Kendall test is highly recommended by the World Meteorological Organization (WMO) because climatic time series data is not necessarily required to conform to a normal distribution. The Mann–Kendall test exhibits limited sensitivity towards abrupt inconsistencies and discontinuities in the data (Alhaji et al., 2018). The Mann– Kendall trend analysis technique was used to analyze the ranked precipitation data, where the data was ranked from $i = 1, 2, \dots, n-1$ and $j = i+1, 2, \dots, n$. Each individual data point served as a reference point and was compared to all other data points using Eq. 3.3 to Eq. 3.6 so that:

$$sgn(x_j - x_i) = \begin{cases} +1, & \text{if } (x_j - x_i) > 0 \\ 0, & \text{if } (x_j - x_i) = 0 \\ -1, & \text{if } (x_j - x_i) < 0 \end{cases} \quad 3.5;$$

The M– K test parameter was calculated by:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n sgn(x_j - x_i) \quad 3.6;$$

Calculating the variation parameter involved:

$$Var(S) = \frac{1}{18} [n(n-1)(2n+5) - \sum_{i=1}^{n-1} t_i(t_i-1)(2t_i+5)] \quad 3.7;$$

Where t_i represents the measure of ties in the data series i , the test– statistic was calculated:

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0 \end{cases} \quad 3.8;$$

Where > 0 signifies a rising trend, whereas < 0 signifies a declining trend. Trend analyses are carried out at a particular significance level, α (Sonali & Nagesh Kumar, 2013). A significance level of $\alpha = 0.05$ was employed throughout the present study. At $\alpha = 0.05$, the null hypothesis of no trend is excluded if $|Z_s| > 1.96$.

3.4.3 Meteorological drought characterisation

The Palmer Drought Severity Index (Sheffield et al., 2012), Surface Water Supply Index (Shah & Mishra, 2020), Standardized Precipitation Index (McKee et al., 1993), Rainfall Anomaly Index (van Rooy, 1965), and Standardized Precipitation Evapotranspiration Index (Memon & Shah, 2019) are commonly used indices for assessing meteorological droughts. The current study utilized the Standardized Precipitation Index at 12-month timescales. The World Meteorological Organization (WMO) highly endorses the Standardized Precipitation Index (SPI) as a comprehensive global drought index, as stated by McKee et al. (1993). The system can evaluate the attributes of both arid and humid settings, and its computational requirements are solely based on past precipitation data (Morid et al., 2006). The SPI offers a comprehensive assessment of soil water surplus or deficit, depending on the time scale considered (Basak et al., 2022). Due to the non-normal distribution of long-term precipitation data, it was necessary to alter it to conform to a typical normal distribution. Therefore, the calculation of SPI values over different time periods (1, 3, 6, 12, 18, and 24 months) entailed using a gamma probability distribution function to determine the relative frequency distribution of the average rainfall recorded during the selected time frame. The Gamma Probability Distribution function was utilized to convert raw precipitation data into a standardized normal distribution function (Buttafuoco et al., 2018). The SPI index values were calculated by transforming the cumulative probability of precipitation data into the standard normal distribution using mathematical formulas 3.9 – 3.16 as shown below (AghaKouchak et al., 2015).

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \quad 3.9;$$

$$A = \ln \bar{x} - \frac{\sum \ln \bar{x}}{n} \quad 3.10;$$

where α = shape parameter, $\bar{x}$ = average monthly precipitation over assessment period, n number of precipitation values.

$$\beta = \frac{\bar{x}}{\alpha} \quad 3.11;$$

where β = scale factor,

$$\Gamma(\alpha) = \int_0^{\infty} x^{(\alpha-1)} e^{-x} dx \quad 3.12;$$

where $\Gamma(\alpha)$ = gamma function. The gamma probability density function (PDF) was then obtained using:

$$g(x) = \frac{1}{((\beta^\alpha)(\Gamma(\alpha)))} x^{(\alpha-1)} e^{-\frac{x}{\beta}} \text{ For } x > 0 \quad 3.13;$$

The gamma cumulative distribution function (CDF) was obtained by integration of the PDF using the equations below:

$$G(x) = \int_0^x g(x) dx = \frac{1}{((\beta^\alpha)(\Gamma(\alpha)))} \int_0^x x^{(\alpha-1)} e^{-\frac{x}{\beta}} dx = \frac{1}{\Gamma(\alpha)} \int_0^x y^{(\alpha-1)} e^{-y} dy \quad 3.14;$$

$$\text{where } G(x) = \text{CDF of the observed rainfall for each station and given that } y = -\left(\frac{x}{\beta}\right) \quad 3.15;$$

As the gamma function is indefinite for $x = 0$, the cumulative probability function was analyzed as follows:

$$F(x) = p + (1 - p)G(x) \quad 3.16;$$

where p = probability of zero.

However, the CDF may be obtained through statistical software and Microsoft Excel. The primary function of the SPI is to characterise the standardised nonconformity from the mean (SPI value of zero) of precipitation. SPI values greater than zero indicated wet periods, while SPI values less than zero indicated drought periods. The drought characterisation method, as determined by McKee et al. (1993), is illustrated in Table 3.2 below:

Table 3.2 Standardised Precipitation Index (SPI) classification (Source: McKee et al. 1993)

SPI Interval	Classification
$0 < \text{SPI} \leq 2$	Above Normal Condition
$-1 < \text{SPI} \leq 0$	Mild Drought
$-1.5 < \text{SPI} \leq -1$	Moderate Drought
$-2 < \text{SPI} \leq -1.5$	Severe Drought
$\text{SPI} \leq -2.0$	Extreme Drought

According to McKee et al. (1993), the drought commenced immediately after the SPI value became negative and continued until the SPI reached a positive value. The drought's length is considered the epoch between drought onsets and offset. The drought evaluation indicators (severity, intensity, and frequency) were determined using a methodology developed by McKee et al. (1993). The magnitude (M), intensity (I), and frequency (F) of the meteorological drought were evaluated using the abovementioned SPI values. The equations 3.17- 3.19 were used to calculate characteristics:

$$M = \sum_{i=1}^m |Index_j|_e \quad 3.17$$

$$I = \frac{M}{m} \quad 3.18$$

$$F = \frac{n_s}{N_s} \times 100 \quad 3.19$$

In Eq. 3.17, the subscript e corresponds to a drought event while j represents a drought year. In addition, $Index_j$ is the SPI value in year j, m is the duration of a drought event (e), while in equation 3.19, n_s is the number of drought events, N_s is the total number of years for the study period which in this research study was 41 years. This research determined the SPI values in the chosen meteorological stations in the AEZs of the WC Province and evaluated the drought evaluation indicators in both the historical and future precipitation datasets.

Although the SPI is an important instrument in characterising drought and water availability scenarios, it can be a theoretical notion for decision-makers to use, because it vaguely relates drought characteristics to water availability. This research determined the precipitation thresholds for each of the selected precipitation records. In this regard, scholars such as (Hashimoto et al., 1982; Hazbavi et

al., 2018; Van Loon et al., 2016) recommended the use of a threshold-based approach for drought analysis. In applying this approach, a drought was considered as any occurrence where the SPI value dropped lower than the predetermined threshold. In this study, drought vulnerability and risk assessment used the 70th percentile as the threshold. Each meteorological station had a different threshold value based on the 70th percentile of the values of precipitation for the study period. Previous studies by scholars such as (Laaha et al., 2017); Van Loon (2013); Van Loon et al. (2014) have applied between 70th - 90th percentile ranges, however after evaluating several percentile values (70th, 80th and 90th percentile), we chose the 70th percentile as it clearly detected both moderate and severe droughts. The other percentiles were rejected for the reason that the high coefficient of rainfall variability found in the WC Province, they either had insufficient droughts or did not detect the key drought periods. The threshold evaluations were prepared through Microsoft Excel statistical functions.

3.4.4 Downscaling and validation of GCM output

There was uncertainty in analysing simulated precipitation coarse resolution GCM outputs to catchment based finer scale resolution. As such there was a requirement to downscale GCM output for practical needs such as precipitation projection for hydrologic operations in local basins under climate change. Downscaling of MIROC6 output was conducted to provide finer resolution precipitation datasets and evaluate the output with reanalysis data. The software package Climate Change for Water Modeling (CMhyd) software obtained from <https://swat.tamu.edu/software/cmhyd> was used for bias correction and statistical downscaling. Before processing and analysis was performed on the historical, reanalysis data and downscaled climatic data, it was crucial to verify homogeneity and to perform data quality checks. To verify the homogeneity of climatic data, gross error checking, and temporal and spatial coherency tests were carried out. The accuracy of MIROC6 simulation to predict future precipitation data was evaluated using historical datasets to ensure their suitability before they were applied for calculating SPI indices. The percentage accuracy of the projected precipitation data was validated by comparing simulated reanalysis MIROC6 climate model data with historical CRU TS Version 4.07 precipitation data for the years 1980–2010. Results were evaluated in terms of mean absolute error (MAE), coefficient of determination (R^2), mean absolute percent error (MAPE) using the equations 3.20 – 3.23 shown below:

$$MAD = \frac{1}{n} \sum_1^n (A_i - F_i) \quad 3.20$$

$$MAPE = \frac{1}{n} \sum_1^n \left(\frac{A_i - F_i}{A_i} \right) * 100 \quad 3.21$$

$$R^2 = \frac{\sum_1^n (A_i - \bar{F}_i)(F_i - \bar{F}_i)}{\sum_1^n [(A_i - \bar{F}_i)^2]^{0.5} [(F_i - \bar{F}_i)^2]^{0.5}} \quad 3.22$$

$$NSE = 1 - \left(\frac{\sum_1^n (A_i - F_i)^2}{\sum_1^n ((A_i - \bar{F}_i)^2)} \right) \quad 3.23,$$

where A_i is the observed precipitation at timescale i , F_i is the projected precipitation at timescale i , $\bar{F}_i$ is the mean projected precipitation during the study period, and n is the total number of the observed data. The NSE illustrates the percentage accuracy of the modeled data. Both R^2 and MAPE are measures of best line of fit, while MAD illustrates the global climate model's ability to correctly predict the future climate with respect to recorded data. It is assumed that the GCM simulation are correct when R^2 and NSE evaluations are close to unit value, and when there is a lower MAPE value (Peng et al., 2023). A detailed explanation of techniques applied in the data analysis of the simulated precipitation data is in the sections below.

3.4.5 Drought response dynamics (Reliability, Resilience and Vulnerability)

As discussed above, it is essential for water resource managers to relate meteorological drought characteristics to potential risk to water scarcity in a region (McKee et al., 1993). The evaluation of water security risk, however, required understanding drought vulnerability and water scarcity risk assessment (DVRA). DVRA allowed for droughts occurrences to be related to water availability without having to consider various socio-economic indicators. Hazbavi et al. (2017) integrated climatic variables with reliability, resilience, and vulnerability (R_{el} R_{es} V_{ul}) indicators to assess watershed health in Foyle Watershed in Northern Ireland, the Xarrama Watershed in Portugal, and the Shazand Watershed in Iran. R_{el} R_{es} V_{ul} indicators assess different aspects of a watershed system. Reliability evaluates the frequency of the water resource system being in a satisfactory state during, resilience evaluates how quickly a water resource system recovers to a satisfactory state after reaching an unsatisfactory state and vulnerability measures how severe the unsatisfactory state is (Hazbavi et

al 2017). To this end, the methodology followed in current study to perform the joint distribution analysis is shown in Figure 3.4 below:

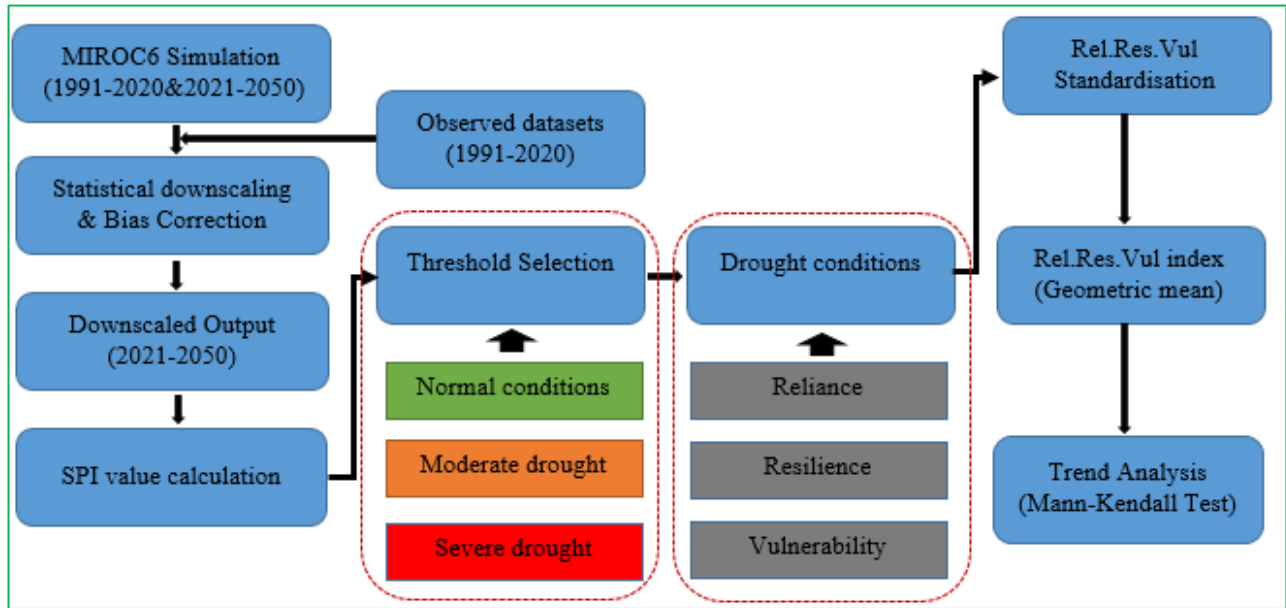


Figure 3.4 Integration of reliance, resilience, and vulnerability indicators with SPI

The risk indicators, R_{el} (frequency), R_{es} (ability to respond) and V_{ul} of each meteorological station of the WC province were computed from SPI values based on the methodologies proposed by Hashimoto et al. (1982) using equations 3.24 – 3.25 below:

$$Reliability R_{el} = 1 - \frac{\sum_{j=1}^M d_j}{T} \quad 3.24;$$

$$Resilience R_{es} = \left\{ \frac{\sum_{j=1}^M d_j}{M} \right\}^{-1} \quad 3.25;$$

$$Vulnerability V_{ul} = \frac{1}{M} \sum_{i=1}^T \{ [SPI_{obs}(i) - SPI_{std}(i)] H[SPI_{obs}(i) - SPI_{thr}(i)] \} \quad 3.26;$$

where M is the number of failure events (the number of months that SPI falls below the threshold), Δt_j is the duration of the j th failure event, T is the total number of time intervals (here 12), $SPI_{obs}(i)$ is the observed SPI at the i th time step, $SPI_{thr}(i)$ is the corresponding threshold value for the station, and H is the Heaviside Function which ensures that only failure events are involved in the

vulnerability calculation. The duration of the drought episodes was determined by the total number of consecutive months in which the variable's value was below the threshold. The Heaviside function is a mathematical and discontinuous function whose value is zero for an opposing argument and one for a positive argument. Reliability and Resilience follow a similar trend and were calculated on the probability scale, i.e., zero to one.

3.4.6 Standardisation of RRV indicators based on drought entropy.

To quantify uncertainty indicators associated with reliability, resilience, and vulnerability, we applied Equation 3.27- 3.28 proposed by Dong et al. (2010) so that we keep R_{el} , R_{es} and V_{ul} consistent,

$$Y_{ij} = \frac{(x_{ij} - \min(x_{ij}))}{\max(x_{ij}) - \min(x_{ij})} \quad 3.27;$$

while for V_{ul} we applied,

$$Y_{ij} = \frac{(\max(x_{ij}) - x_{ij})}{\max(x_{ij}) - \min(x_{ij})} \quad 3.28;$$

Where Y_{ij} is the standardized indicator and x_{ij} , $\min(x_{ij})$ and $\max(x_{ij})$ are the actual, minimum, and maximum values of each indicator before standardization, respectively.

3.4.7 Analysis of Sustainability Index (SI)

To facilitate the analysis of the results, we use the standardised reliability, resilience, and vulnerability indicators to calculate the sustainability index. Since the geometric mean is more sensitive to changes in individual variables compared to other averages (Hazbavi et al., 2018), we applied Eq. 3-29 to determine the sustainability index;

$$Sustainability\ Index = \{\prod_1^3 R_{el} \times R_{es} \times V_{ul}\}^{\frac{1}{3}} \quad 3.29$$

Based on the sustainability index we divided the results into five classes, as proposed by (Hazbavi et al., 2018) (Table 3.3). The higher the health level, the better the health condition of the AEZ under SSP2-4.5 drought conditions.

Table 3.3 Sustainability index classes (Source: Hazbavi et al., 2018)

No.	Category	Classification
1	Very high	$0.81 \leq SI < 1$
2	High	$0.61 \leq SI < 0.81$
3	Moderate	$0.41 \leq SI < 0.61$
4	Low	$0.21 \leq SI < 0.41$
5	Very low	$0 \leq SI < 0.21$

3.5 Methodological reflections

Drought characterisation is neither exact nor precise. Appropriate and reliable climate data, particularly reanalysis data as well as regular forecasts, are crucial for decision-making. If used correctly, this knowledge can help mitigate the effects of drought and other extreme weather occurrences. DEWS can provide this information to decision-makers (Chandrasekar et al. 2018). However, due to the variation of drought spatiotemporal characteristics, it was difficult to monitor and assess the potential effects of droughts. While remote sensing techniques applied in this research provided an effective method to acquire real-time water availability conditions in agricultural environments affected by drought, the methodologies applied herein were fraught with constraints in the inconsistencies of the data gathered from various sensors, pre-processing raw data, drought variables used, and bias correction of GCM simulated datasets. The inconsistency between values derived from multiple satellite resulted in uncertainty in data integration attempts and this complicated data synthesis. The inconsistency between different satellite precipitation datasets further complicated dataset selection. A series of studies have attempted to intercompare these various precipitation datasets at regional to global scales, with most finding that multi-sensor ensemble products provide the highest quality (Sun et al., 2014). Some recent studies have used intercomparisons on drought monitoring using different precipitation products (Cai et al., 2021), with the authors highlighting the benefit of integrated precipitation data. In the present study pre-whitening techniques discussed in section 3.4.1 were therefore essential as the raw data contained irregularities, atmospheric noise, sensor-earth geometry changes, and other factors that affected the data accuracy necessitating corrections on the data. Accordingly, pre-whitening techniques were a crucial pre-processing step. Another primary methodological drawback was the short record length of the many current accessible satellite datasets relative to meteorological stations. Some relevant satellite missions and sensors (e.g., GRACE) gave just a few years of data, while the research needed more

than thirty years for drought research from a climatological viewpoint. Furthermore, some satellite sensors were merely research instruments, and there was no assurance that equipment was sufficiently maintained.

Given its role as a linking mechanism between the water and energy cycles, determining evaporation dynamics presented an important metric for integration of a range of water loss processes. However, the present study noted the use of evaporation as a parameter required the use of PSDI and SPEI which required long-term ET based indices derived from coarse spatial resolution (e.g., 0.5° grid cell size for SPEI, 2.5° grid cell size for PDSI) with monthly temporal resolution and which limit their applicability for drought monitoring. A range of different statistical downscaling models was calibrated using both observed and general circulation model (GCM) generated daily precipitation time series and intercompared. The GCM used was the MIROC6. In some instances, the SD techniques performed poorly because of a failure to simulate wet-day occurrence statistics adequately. Changes in precipitation between the past and future scenarios produced by the statistical downscaling methods were generally smaller than those produced directly by the GCM and were therefore judged not to be due primarily to changes in atmospheric circulation.

CHAPTER FOUR

EVIDENCE OF INCREASING WATER SCARCITY DUE TO METEOROLOGICAL DROUGHT

4.1 Introduction

The chapter is structured and characterised around the research questions that were asked in section 1.5 of this thesis. The chapter is organised to present findings on research question (i) that sought to provide insight into the historical patterns of precipitation and drought in the Western Cape and how they impact the availability of water resources; research question (ii) that sought to offer an understanding of the future (2021-2050) precipitation and drought characteristics in the WC Province under different climate change scenarios affect future water availability; research question (iii) that explored the optimal climate change scenario that could potentially foster development pathways that could ensure sustainable water availability between 2021 and 2050 and lastly research question (iv) which sought to analyse the implications of the findings of this study in a wider context, particularly in water stressed regions of sub-Saharan Africa and provide recommendation to proactive drought management. Part of the data presented in this chapter was used to develop three research manuscripts. The first manuscript titled “Agroecological based modelling of meteorological drought at 12-month timescale in the Western Cape Province of South Africa”¹ (see appendix A) has been published in the scientific journal *Earth Science Informatics* (ESI) was devoted to an in-depth assessment and modelling of historical precipitation and drought trends in the Western Cape Province of South Africa. The second manuscript titled “Modeling future (2021–2050) meteorological droughts using CMIP6 Scenarios in Western Cape Province, South Africa”² (see appendix B) has been published in the scientific journal *Modeling Earth Systems and Environment* (MESE). Lastly, the final manuscript titled “Evidence of increasing water scarcity caused by frequent drought under SSP2-4.5 climate

¹Ngwenya, M., Gidey, E., & Simatele, M. D. (2024). Agroecological-based modeling of meteorological drought at 12-month time scale in the Western Cape Province of South Africa. *Earth Science Informatics*, 17(3), 1851-1865. <https://doi.org/10.1007/s12145-023-01193-3>.

²Ngwenya, M., & Simatele, M. D. (2024). Modeling future (2021–2050) meteorological drought characteristics using CMIP6 climate scenarios in the Western Cape Province, South Africa. *Modeling Earth Systems and Environment*, 10(2), 2957-2975. <https://doi.org/10.1007/s40808-023-01937-6>.

change scenario in the Western Cape Province, South Africa”³ (see appendix C), has been submitted to the Natural Hazards and is currently under review. The results obtained from the analysis of the datasets are presented in the following sections:

4.2 Characterising meteorological drought at 12-month time scale in the Western Cape Province of South Africa

This section presents results on the historical patterns of precipitation and drought in the Western Cape and how they impact the availability of water resources. To understand the historical impacts of drought on water availability in agricultural environments, it was crucial to analyse the historical drought characteristics as they aid in mitigating and establishment proactive water-use strategies. The study used the University of East Anglia's Climate Research Unit gridded time series (CRU TS Version 4.07) <http://www.cru.uea.ac.uk/cru/data/hrg/> database to collect historical daily precipitation data from fifteen stations located across all the AEZs of the Western Cape Province. The data spanned from January 1, 1981, to December 31, 2020. The collection process involved utilizing the Google Earth engine interface. The results of the yearly precipitation trends across the AEZs in the Western Cape are presented in Table 4.1. Between 1980 and 2020, the STCSH (Ceres) agro-ecological zone experienced the highest recorded precipitation of 1084 mm, while the STWA (Leew-Gamka) agro-ecological zone had the lowest recorded precipitation of 76 mm. The findings suggest that stations located in the STCSA and STWA agro-ecological zones had considerably greater coefficients of variability compared to stations in the STCA, STCSH, STWSA, and STWSH agro-ecological zones. The STWA (Leew-Gamka) had the highest level of rainfall variance, measuring at 27%. In comparison, the STCSH Bredasdorp zone had a rainfall variability of 18%. Based on the results collected, all agro-ecological zones show a consistent and negative decline from year to year. The stations located in STCSH, specifically the Ceres and Hermanus districts, showed the most substantial negative trends at a substantial level of 0.05, with rates of – 7.8 mm/year and – 6.5 mm/year, respectively. Following closely is Malmesbury with a rate of – 6.4 mm/year.

1. ³ **Ngwenya, M.,** Busayo, E. T., & Simatele, M. D. (2024). Evidence of increasing water scarcity due to frequent drought under SSP2-4.5 climate change scenario in the Western Cape Province, South Africa. (This paper has been submitted and is currently online as a preprint and is at the final revision stages of review in preparation for publication). <https://doi.org/10.21203/rs.3.rs-3943387/v1>

Table 4.1 Annual trends in precipitation (Source: Ngwenya et al. (2024))

Station	Min.	Mean	Max.	Std. Dev.	CV %	Annual		AEZ
						Trend (mm/year)	Sig.	
MG	176	310.6	341	61	20	– 1	– 1.2	STCA
BW	141	252.2	431	66	26	– 1	– 1.2	STCSA
MM	364	638.1	933	131	20	– 6.4	– 2.7	STCSH
HM	424	700.5	1002	130	19	– 6.4	– 2.7	
CR	407	716.3	1084	148	21	– 7.7	– 2.7	
BD	294	446.2	626	78	18	– 4.1	– 2.2	
LG	76	133.1	130	36	27	– 4.2	– 2.3	STWA
LS	205	364.7	655	90	24	– 4.2	– 2.3	
SB	173	310.1	466	63	20	– 2.4	– 2.4	STWSA
OD	223	388.1	592	80	21	– 3.6	– 2.6	
SW	315	509.9	774	103	20	– 5.2	– 2.4	
PK	246	435.1	769	98	21	– 3.9	– 1.7	
CW	516	470.9	872	113	24	– 4.4	– 1.9	STCA
MB	175	311	462	60	20	– 3.2	– 2.8	
PA	197	354.3	651	89	25	– 3.4	– 3	

The unit of magnitude are mm while the intensity is mm/year. M = Magnitude, I = Intensity, MG= Murraysburg, BW = Beaufort West, MM = Malmesbury, HM = Hermanus, CR = Ceres, BD = Bredasdorp, LG = Leew– Gamka, LS = Ladismith, SB =Still Bay, OD = Oudtshoorn, SW = Swellendam, PK = Piketberg, MB = Matroosberg, CW = Clan William, MB= Matroosberg, PA = Prince Albert.

Similarly, the changes over time illustrated in Figure 4.1 indicated that the years 2016, 2017, and 2019 experienced the least amount of rainfall during the study period, whereas 1983, 1989, and 1996 were the years with the highest precipitation levels. In general, the yearly pattern of precipitation in the studied area from 1980 to 2020 shows a continuous decrease in rainfall throughout all agro– ecological zones in the Western Cape Province.

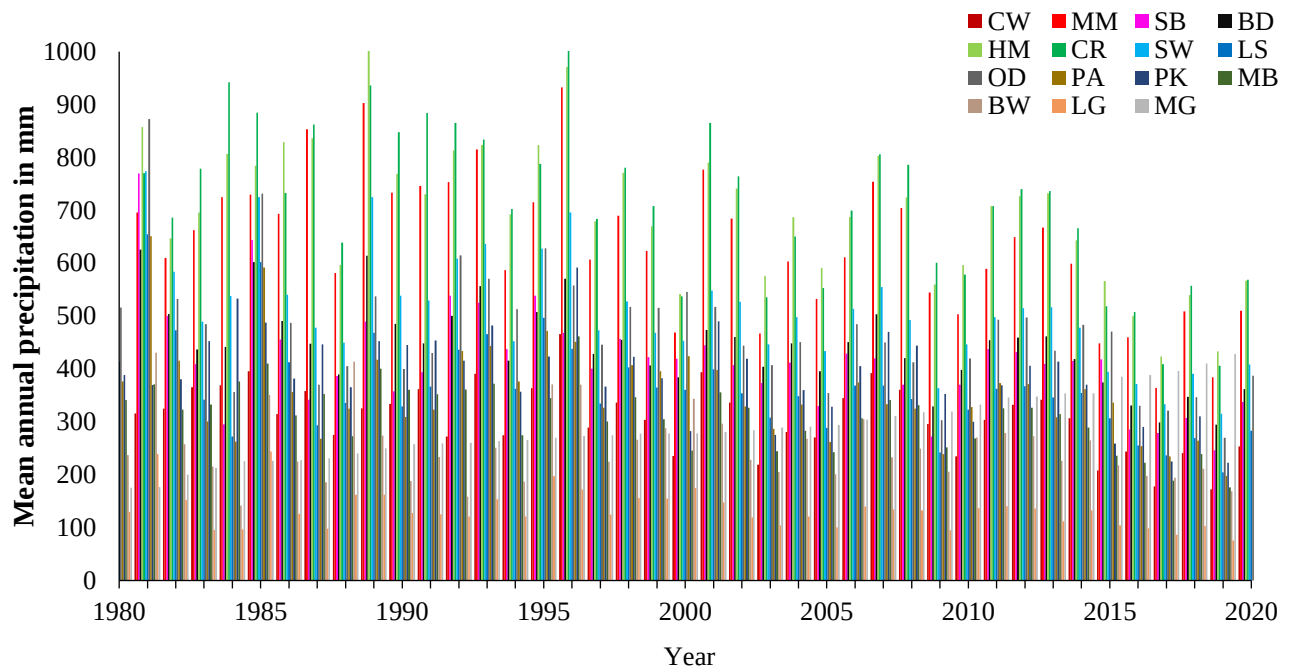


Figure 4.1 Annual precipitation distribution between 1980 and 2020 across the study area (Source: Based on field data)

4.2.1 Historical seasonal precipitation trends

Table 4.2 shows the seasonal trends in precipitation in the agro– ecological zones of the Western Cape during a span of 41 years (1980– 2020). In the summer (DJF) season, thirteen stations located in the agro– ecological zones of STCSH, STWA, STWSA, and STWSH exhibited a decline in precipitation. Only two stations, Murraysburg (STCA) and Beaufort West (STCSA), showed a positive trend in precipitation, but this trend was not statistically substantial at the $p < 0.05$ significance level. Among the thirteen stations that showed a decline in precipitation, Matroosberg in STCSH and STWSA (Piketberg and Swellendam) as well as the stations in STCSH (Malmesbury, Hermanus, Bredasdorp, and Ceres) demonstrated statistically substantial negative trends. In autumn (MAM), the agro– ecological zones of STCSA, STCSH, STWA, STWSA, and STWSH all had a decrease in precipitation, except for Murraysburg (STCA), which had a little increase in precipitation that was not statistically substantial at the 0.05 significance level. During the winter season (June, July, and August), all the different agro– ecological zones had a decrease in precipitation. However, only two stations, Malmesbury and Ceres, located in the STCSH agro– ecological zone, showed a

statistically substantial decrease in precipitation. In spring (SON), all agro– ecological zones experienced a decline in precipitation. Specifically, eleven stations (Malmesbury, Piketberg, Matroosberg, Ceres, Clan– William, Prince Albert, Ladismith, Beaufort West, Leew– Gamka, Murraysburg, and Still Bay) showed statistically substantial negative trends at the 0.05 significance level.

Table 4.2 Seasonal trends in precipitation (mm/year) (Source: Based on field data)

Station	Summer		Autumn		Winter		Spring		AEZ
	Trend	Sig.	Trend	Sig.	Trend	Sig.	Trend	Sig.	
MG	0.4	0.8	0.3	0.5	– 0.3	– 1.5	– 1.0	– 2.5	STCA
BW	0.2	0.5	– 0.0	– 0.1	– 0.2	– 1.0	– 1.0	– 2.8	STCSA
MM	– 1.0	– 2.8	– 2.6	– 3.2	– 1.9	– 2.1	– 1.2	– 2.1	STCSH
HM	– 1.4	– 3.1	– 2.6	– 3.6	– 1.4	– 1.3	– 1.0	– 1.1	
CR	– 1.2	– 2.6	– 2.9	– 3.3	– 2.2	– 2.0	– 1.6	– 2.4	
BD	– 0.9	– 3.0	– 1.8	– 3.1	– 0.6	– 1.3	– 0.6	– 1.7	
LG	– 0.1	– 0.3	– 0.5	– 2.1	– 0.1	– 1.2	– 0.5	– 2.7	STWA
LS	– 0.5	– 1.6	– 1.5	– 2.5	– 0.2	– 0.7	– 1.3	– 2.5	
SB	– 0.3	– 1.7	– 0.8	– 1.2	– 0.4	– 0.6	– 0.7	– 2.9	STWSA
OD	– 0.4	– 2.1	– 1.7	– 2.5	– 0.6	– 1.1	– 0.8	– 2.3	
SW	– 1.1	– 2.6	– 0.4	– 1.6	– 0.8	– 1.1	– 1.0	– 1.9	
PK	– 0.6	– 1.6	– 1.1	– 1.9	– 0.3	– 0.8	– 1.4	– 2.4	
CW	– 0.5	– 1.1	– 1.1	– 1.5	– 0.5	– 1.1	– 1.6	– 2.6	STWSH
MB	– 0.6	– 2.7	– 1.3	– 3.6	– 0.8	– 1.7	– 0.6	– 2.2	
PA	– 0.3	– 0.5	– 1.0	– 1.9	– 0.4	– 1.3	– 1.2	– 2.8	

4.2.2 Historical meteorological drought characteristics (SPI– 12)

Figure 4.2 illustrates the annual precipitation distribution between 1980 and 2020 across the study area. The interpolated SPI values were used as input to assess the values of SPI in each district and determine the changes in spatio– temporal distribution of historical meteorological drought across the study period. The results illustrated the interpolated annual SPI–12 patterns between the years 1980 and 2020. The results indicate that the eastern (STWA, STCA) and northern (STCSH, STCSA) parts of the Western Cape province underwent regular cycles of mild annual drought between 1980 and 2020 study period. Districts around the STWSH and STWSA agroecological zones, including Hermanus, Bredasdorp, and Malmesbury, saw average to high levels of precipitation throughout the study period, in contrast to districts located in the eastern (STWA, STCA) and northern (STCSH, STCSA) agro– ecological zones. The data shows that the years 2014, 2015, 2016, and 2017 had the

lowest Standardized Precipitation Index (SPI) values, indicating severe drought conditions. These conditions were mainly observed in regions near Leew– Gamka, Murraysburg, and Beaufort West. The findings suggest that the years 1980, 1984, and 1987 exhibited relatively milder drought conditions over the research area, as measured by the SPI 12. In general, the SPI– 12 values used in the model clearly divide the Western Cape Province into two regions: the southern half, which is wetter and includes STWSH and STCSH, and the drier northeastern zones, which include STCSA, STWA, and STCA.

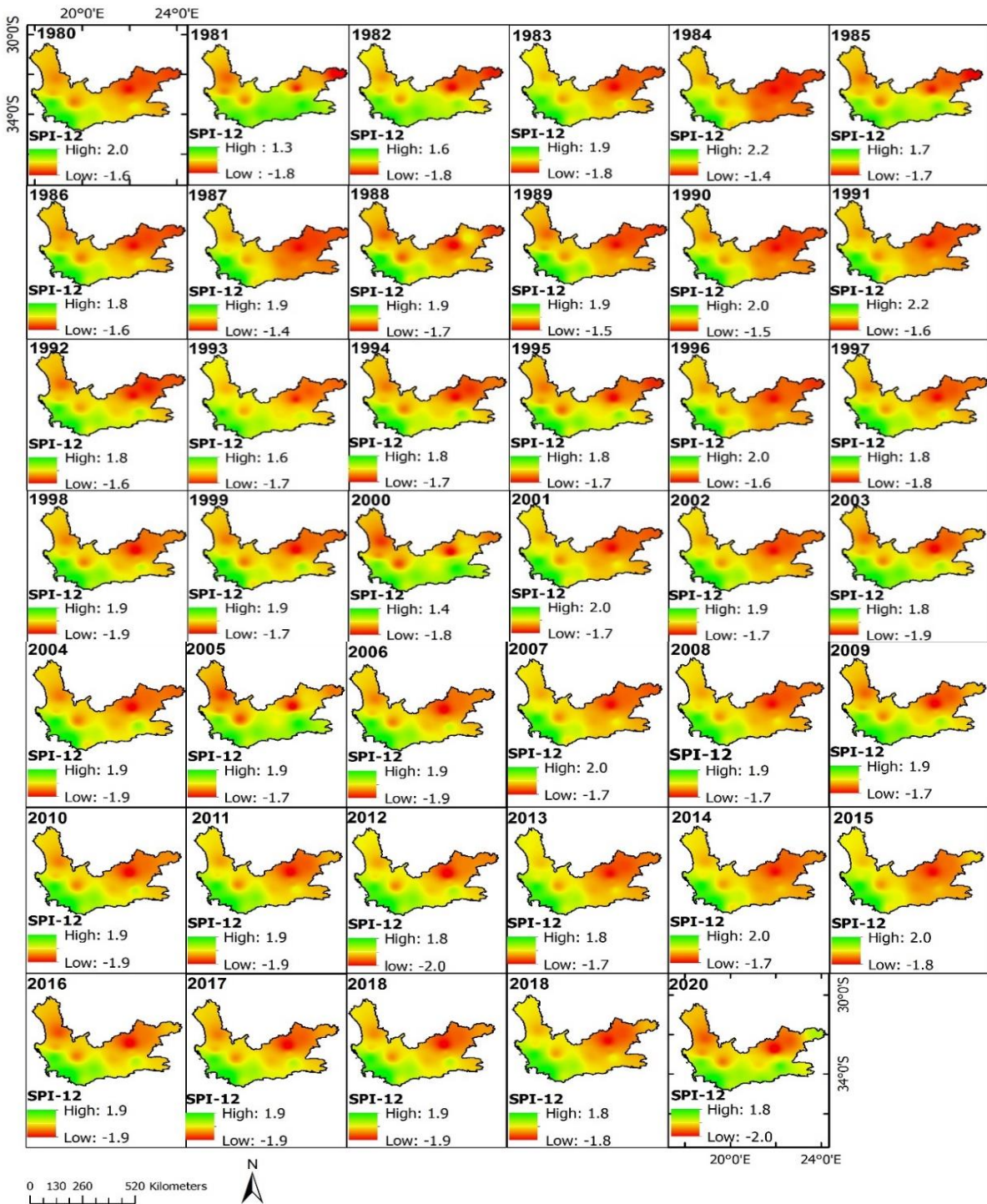


Figure 4.2 Annual precipitation distribution between 1980 and 2020 (Source: Based on field data)

4.2.3 Historical drought frequency, trends, and statistics

Table 4.3 shows the variance (var), skewness (skw), and kurtosis (Kur) values for meteorological drought, as determined by the SPI-12, across the research region from 1980 to 2020. The drought categorization findings were obtained by applying the McKee et al. (1993) method of meteorological drought classification, as described in Table 4.3. Meteorological droughts are detected using the Standardized Precipitation Index (SPI) when it falls below zero, according to the meteorological drought categorization technique. Moreover, the intensity of the drought worsens as the Standardized Precipitation Index (SPI) value falls below zero (Alam et al., 2023). The occurrence rate of mild droughts in STWSH (Matroosberg, Prince Albert), STWA (Ladismith), and STWSA (Clan William, Piketberg) exceeded 80%, while STCSH (Malmesbury, Hermanus, Ceres) did not encounter any occurrences of mild drought. The STCA, situated in Murraysburg, registered a rate of 50%, whereas the STCSA, situated in Beaufort West, reported a rate of 30%. The prevalence of moderate drought was documented at a frequency of 70% in STCSA (Beaufort West), 10% in STWA (Leew-Gamka), and 30% in STCA (Murraysburg). Conversely, the remaining agro-ecological zones (AEZs) encountered a moderate occurrence of droughts for the entire duration of the study. The area exhibiting the greatest occurrence of severe drought (SD) was observed in STWA (Leew-Gamka), with STCA (Murraysburg) following closely after at a rate of 10%. Conversely, the remaining zones did not encounter any substantial drought occurrences. STWA (Leew-Gamka) experienced an instance of severe drought just 10% of the time. To summarize, we calculated the total frequency of drought (F). STWA (Leew-Gamka) and STWSH (Matroosberg) experienced continuous drought conditions over the entire period. STCA (Murraysburg), STCSA (Beaufort West), STWA (Ladismith), and STWSH (Prince Albert) saw a drought occurrence rate exceeding 90%. The regions of Malmesbury, Hermanus, and Ceres, together known as STCSH, encountered drought conditions that ranged from normal to above-average intensity. The Murraysburg weather station (STCA) experienced a negative trend in total drought frequency of -0.5 . The Hermanus weather station (STCSH) had a trend of -0.4 , while the Matroosberg weather station (STWSH) had a trend of -0.3 . Conversely, the other AEZs exhibited favourable trends in drought frequency.

The statistical analysis of drought features showed that the least variance of 0.0 was observed in STCSH (Matroosberg), STSWA (Swellendam), STWA (Leew-Gamka), and STCSH (Hermanus),

while the largest variance of 0.6 was found in STCA (Murraysburg). The range of values for skewness is between – 0.9 and 2.5, with STCA (Murraysburg), STCSA (Beaufort West), STWA (Leew–Gamka, Ladismith), STWSH (Prince Albert, Matroosberg), and STWSA (Oudtshoorn, Still Bay, Swellendam) agro– ecological zones exhibiting positive skewness, while STCSH (Malmesbury, Hermanus, Ceres) and STWSA (Clan William and Piketberg) depicted negative skewness. According to Kurtosis results, the SPI–12 values reveal a leptokurtic distribution in STCA, STCSA, and STWSH zones and a platykurtic distribution in three districts (Clan–Williams, Leew–Gamka, and Bredasdorp) on a 12–month timescale. Analysis of the Kurtosis statistics revealed that temporal drought patterns in the Western Cape illustrate a leptokurtic pattern. Overall analysis of the results indicates that the SPI– 12 values exhibit persistent mild drought frequency across all agro– ecological zones except in Malmesbury, Hermanus, Ceres, and Swellendam, which had normal to above– very– wet conditions across the study period of 1980–2020.

Table 4.3 Drought frequency, trends, and statistics (Source: Based on field data)

Station	% Drought frequency						Trends	Var.	Skew.	Kur.	AEZ
	N	MiD	MoD	SD	ED	F					
MG	10	50	30	10	0	90	– 0.5	0.6	1.3	1.4	STCA
BW	0	30	70	0	0	100	0.8	0.1	2.5	9.2	STCSA
MM	100	0	0	0	0	0	1.4	0.1	– 0.8	0.8	STCSH
HM	100	0	0	0	0	0	– 0.4	0	– 0.9	1.1	
CR	100	0	0	0	0	0	1.1	0.1	– 0.9	1.9	
BD	70	30	0	0	0	30	1.9	0	0.3	– 0.4	
LG	0	0	10	80	10	100	0.2	0	0.4	– 0.3	STWA
LS	10	90	0	0	0	90	1.4	0.1	1.5	2.4	
SB	0	90	0	0	0	90	1.3	0.1	– 0.2	– 0.5	STWSA
OD	20	80	0	0	0	80	1.2	0.1	– 0.2	0.5	
SW	100	0	0	0	0	0	0.5	0	0.5	0.2	
PK	60	40	0	0	0	40	0.3	0.1	0.8	1.4	
CW	80	20	0	0	0	20	2.4	0.2	0.9	1.3	STWSH
MB	0	100	0	0	0	100	– 0.3	0	0.3	0.3	
PA	30	90	0	0	0	90	1.3	0.1	1.4	2.1	

4.2.4 Historical drought magnitude (M) and intensity (I)

Table 4.4 presents the measurements of the magnitude (M) and intensity (I) in millimetres per year of the meteorological drought, which were estimated during a period of five years based on the SPI– 12 readings. The assessment of the extent and severity of drought was determined every five years in

accordance with the national development plans that include five-year periods. The magnitude analysis reveals that the maximum drought magnitude in STCA (Murraysburg) was 7mm over the period from 1980 to 1985. However, from 2016 to 2020, there was no recorded drought magnitude. The agro-ecological zone known as STCSA saw the most severe drought with a magnitude of 5.9mm between 1991 and 1995. In contrast, the lowest drought magnitude of 4.2mm was recorded in 1996 and 2000, spanning the whole study period. The STCSH (Leew-Gamka) did not encounter any drought intensity throughout the study period. The STWA documented the most severe drought intensity of 9.1mm from 2001 to 2005, whereas Ladismith experienced the least severe drought magnitude of 1mm from 1991 to 1995.

During the periods of 1996 to 2005 and 2011 to 2020, STSWA (Oudtshoorn) saw no substantial drought events. Prince Albert had the lowest level of drought intensity throughout the study period, in contrast to Matroosberg, which is in the same agro-ecological Zone (AEZ). The drought intensity in Murraysburg (STCA) and in Malmesbury, Hermanus, Ceres, and Bredasdorp (STCSH) as well as in Swellendam (STSWA) showed no signs of drought between the years 2016 and 2020. Malmesbury, Hermanus, Ceres, Bredasdorp, and Swellendam saw wet conditions that were either normal or above normal. The analysis of drought intensity reveals that the highest level of drought, measuring 1.9 mm/year, was seen in the STWA (Leew-Gamka) area of the Western Cape across all six agro-ecological Zones (AEZs). Overall, the analysis of drought intensity indicates that STWA exhibited the highest level of drought intensity compared to all other districts in the research area.

Table 4.4 Temporal variability of drought magnitude (M) and intensity (I) (Source: Based on field data)

Station		1980 – 1985		1986 – 1990		1991 – 1995		1996 – 2000		2001 – 2005		2006 – 2010		2011 – 2015		2016 – 2020		AEZ
		M	I	M	I	M	I	M	I	M	I	M	I	M	I	M	I	
MG		7	1	5.1	1	5	1	5	1	3	1	3	1	2	0	0	0	STCA
BW		5.1	1	4.3	1	6	1	4	1	5	1	5	1	5	1	5	1	STCSA
MM		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	STCSH
HM		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
CR		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
BD		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
LG		8.1	2	7.7	2	8	2	9	2	9	2	9	2	10	2	10	2	STWA
LS		1.3	1	1.9	0	1	0	2	0	2	0	2	1	2	0	3	1	
SB		0.8	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	STWSA
OD		0.3	0	3.2	1	0	0	0	0	0	0	0	0	0	0	0	0	
SW		0.3	0	3.2	1	0	0	0	0	0	0	0	0	0	0	0	0	
PK		1.7	1	0.8	0	1	0	1	0	1	0	1	0	2	0	2	0	
CW		3.9	1	3.1	1	4	1	4	1	3	1	3	1	4	1	4	1	STWSH
MB		3.1	1	2.8	1	3	1	4	1	4	1	3	1	4	1	4	1	
PA		1.5	1	2.7	1	2	3	2	0	3	1	3	1	2	0	3	1	

4.3 Assessing future (2021– 2050) meteorological droughts using CMIP 6 scenarios in Western Cape Province, South Africa

This section presents the empirical evidence on the future (2021–2050) patterns of precipitation and drought in the Western Cape and how they were anticipated to impact the availability of water resources under three different projected climate scenarios. Accurate drought prediction provided an opportunity to implement efficient water management practices within the projected shared socioeconomic–representative concentration pathway (SSP–RCP). Projected meteorological drought hazards for 2021–2050 was conducted under three scenarios: SSP5– 8.5, SSP2– 4.5, and SSP1– 2.6. Two forms of datasets were employed in the study: observational data and model simulations. Observed precipitation data (1980–2020), were gathered from the University of East Anglia’s Climate Research Unit gridded Time Series (CRU TS Version 4.07) <https://www.cru.uea.ac.uk/cru/data/hrq/> database using Google Earth engine interface, while future precipitation datasets (2021–2050) under SSP5–8.5, SSP2–4.5 and SSP1–2.6 climate scenarios were generated by <https://esgf-node.llnl.gov/search/cmip6/> using the sixth version of Model for Interdisciplinary Research on Climate, (MIROC6). CRU TS Version 4.07 datasets have 0.5° by 0.5°

resolution and are available across all regions except Antarctica (Harris et al., 2020). The spatial resolution of the precipitation data generated by the MIROC6 model is 0.11° in latitude and longitude (12.5km×12.5km). Drought duration, severity, intensity, frequency, of future droughts were examined in the AEZ. MIROC6 predicted precipitation for SSP5–8.5, SSP2–4.5, and SSP1–2.6 scenarios. SPI was calculated annually. The Mann–Kendall (M– K) test was employed to assess precipitation trends and SPI values at a significance threshold of $p < 0.05$. The section validated the simulated precipitation datasets, assessed the future annual and seasonal precipitation trends under the three climate scenarios, the future drought characteristics as determined by the SPI–12, predicted the impacts of drought incidence based on the different climate scenarios and lastly ranked the projected drought incidences using the duration and intensity.

4.3.1 Validation

Table 4.5 lists the validation metrics that were used when validating the simulated precipitation datasets; the Mean Absolute Deviation (MAD), Coefficient of Determination (R^2), Mean Absolute Percent Error (MAPE) and Nash–Sutcliffe Efficiency (NSE) model. The results of validation metrics of near–term precipitation data (2021–2050) with the reanalysis precipitation data (1991–2010) in the agroecological zones of the study area gave a good insight on the accuracy of the projected precipitation data with the observed data (Table 4.5). The results indicate that the lowest MAD of 22.6mm was observed in Leew–Gamka located in the STCSA, while the highest MAD was observed in Hermanus at 134.3mm. Stations in the sub–humid zones had higher MAD values compared to stations in the arid zones. Results from Table 4.5 illustrate that MAPE values ranged from 15.75% in Beaufort West located in the STCSA to 21.50% in Prince Albert found in STWSH. The coefficient of determination results indicates a minimum value 0.83 at Beaufort West located in STCSA while 0.89 was recorded in STWSA (Still Bay) (Table 4.5). The NSE model of the projected precipitation measured in the study period (2021–2050) was illustrated to be greater than seventy percent (70%), with greatest value recorded at Beaufort West while Prince Albert recorded the lowest value at 78.5% (Table 4.5).

Table 4.5 Validation metrics of projected precipitation (Source: Based on field data)

Station	Mean Absolute Deviation (MAD) (mm)	Coefficient of Determination (R²)	Mean absolute Percent Error (MAPE)	NSE Model	AEZ
MG	59.6	0.87	19.18	80.83	STCA
BW	39.7	0.83	15.75	84.25	STCSA
MM	108.3	0.86	16.97	83.03	STCSH
HM	134.3	0.87	19.18	80.83	
CR	116.1	0.88	16.22	83.79	
BD	124.0	0.88	16.58	83.42	
LG	22.6	0.87	16.97	83.03	STWA
LS	71.1	0.86	19.49	80.51	
CW	51.4	0.88	16.56	83.44	STWSA
PK	62.9	0.86	16.22	83.79	
SW	99.4	0.87	19.50	80.50	
SB	84.8	0.89	19.49	80.51	
OD	94.1	0.87	19.99	80.01	
MB	111.8	0.87	16.66	83.34	STWSH
PA	132.1	0.86	21.50	78.50	

4.3.2 Future annual precipitation trends

Table 4.6 illustrates the calculated values of the MAP, CV, and precipitation trends between 2021 and 2050 under the SSP5–8.5, SSP2–4.5, and SSP1–2.6 climate change scenarios. The results of long-term annual precipitation variability in the agroecological zones of Western Cape Province provided a good understanding on how to cope with recurrent droughts. The results from Table 4.6 reveal that under the SSP5–8.5 climate scenario the mean annual precipitation is predicted to be between 98 mm in Leew–Gamka in STCSA and 314mm in Malmesbury found in STCSH. The results from Table 4.6 reveal that under the SSP2–4.5 climate scenario the mean annual precipitation is predicted to be between 250mm in Beaufort West in STWA and 252mm in Murraysburg found in STCA. The results from Table 4.6 also reveal that under the SSP1–2.6 climate scenario the mean annual precipitation is predicted to be between 224mm in Leew–Gamka in STWA and 311mm in Murraysburg found in STCA (Table 4.6). Overall, the results indicate that STCSA recorded the lowest mean annual precipitation under the three climate change scenarios (Table 4.6). The results from Table 4.5 reveal that under the SSP5–8.5 climate scenario the coefficient of variability is

predicted to be between 58% in Swellendam in STWSA and 32% in Hermanus found in STCSH. The results from Table 4.6 reveal that under the SSP2–4.5 climate scenario the coefficient of variability is predicted to be between 35% in Murraysburg in STCA and 48% in Bredasdorp found in STCSH. The results from Table 4.6 reveal that under the SSP1–2.6 climate scenario the coefficient of variability is predicted to be between 40% in Ceres in STCSH and 47% in Hermanus found in STCSH. Overall, the results from Table 4.6 indicate that Leew–Gamka recorded the lowest mean annual precipitation under the three climate change scenarios. The results illustrate that under the SSP5–8.5 the precipitation trends across all AEZs were predicted to be statistically significant negative trends (Table 4.6). Maximum statistically negative trends of -7.6mm/year were recorded at Ceres in STCSH while minimum values of -2.9mm/year were observed in Beaufort West in STCSA (Table 4.6). These findings from Table 4.6 indicate a steady improvement from -7.8mm/year under the observation period 1980–2020 and a worsening trend in Beaufort West in STCSA from -1.0mm/year also under the observational period (1980–2020).

The results from Table 4.6 illustrate that under the SSP2–4.5 climate change scenario the precipitation trends were predicted to be both negative and positive trends across the AEZs. Maximum statistically significant negative trends of -2.2mm/year were observed at Prince Albert in STWSH while statistically insignificant trends of 1.9mm/year were observed in Malmesbury in STCSH. These findings from Table 4.6 indicate a progressive improvement from -3.4mm/year and -6.4mm/year in the same regions respectively under the historical trends observed between 1980 and 2020 (Table 4.6). Under the SSP1–2.6 scenario the result indicates that the precipitation trends were predicted to be both negative and positive trends (Table 4.6). Maximum statistically insignificant negative trends of -1.2mm/year were recorded at Matroosberg in STWSH while maximum positive trends of 0.3mm/year were observed in Still Bay in STWSA and Malmesbury in STCSH (Table 4.6). Overall, the findings from indicate a progressive improvement across the climate change scenarios with SSP5–8.5 indicating statistically significantly negative trends while both the SSP2–4.5 and SSP1–2.6 indicated mostly positive insignificant precipitation trends in the near term (2021–2050).

Table 4.6 Changes in projected precipitation (Source: Based on field data)

Station	Mean Annual Precipitation (mm)			Coefficient of Variation (% CV)			Trends (Sig.)				AEZ
	SSP5–8.5	SSP2–4.5	SSP1–2.6	SSP5–8.5	SSP2–4.5	SSP1–2.6	Observation	SSP5–8.5	SSP2–4.5	SSP1–2.6	
MG	252	261	311	42	35	42	–1.0 (–1.2)	–3.5 (–2.1)	–1.7 (–2.0)	–0.4 (0.0)	STCA
BW	110	250	226	45	36	42	–1.0 (–1.2)	–2.9 (–2.0)	–1.2 (–1.1)	–0.1 (1.0)	STCSA
MM	98	314	254	40	37	43	–6.4 (–2.7)	–5.9 (–2.1)	1.9 (–0.7)	0.3 (1.1)	STCSH
HM	120	303	277	32	40	47	–6.5 (–2.7)	–6.6 (–2.2)	–1.5 (–2.1)	–0.1 (0.3)	
CR	111	283	234	39	48	40	–7.8 (–2.7)	–7.6 (–2.5)	–1.1 (–2.1)	–0.3 (0.1)	
BD	107	300	268	56	48	46	–4.1 (–2.3)	–5.2 (–2.1)	–0.8 (–0.4)	0.1 (0.1)	
LG	120	250	224	53	37	45	–4.2 (–2.3)	–4.8 (–2.2)	0.3 (–0.7)	–0.3 (–0.1)	STWA
LS	98	277	245	43	37	44	–4.2 (–2.3)	–4.9 (–2.1)	–1.2 (–2.1)	0.2 (0.1)	
CW	109	281	235	46	37	45	–2.4 (–2.4)	–3.8 (–2.0)	–0.2 (0.0)	0.2 (0.0)	STWSA
PK	105	291	240	56	38	45	–3.6 (–2.6)	–3.7 (–2.2)	–1.3 (–1.2)	0.1 (0.1)	
SW	110	266	227	58	39	46	–5.2 (–2.4)	–5.4 (–2.1)	–1.4 (–2.2)	–0.3 (–0.1)	
SB	104	300	268	43	37	46	–3.9 (–1.7)	–4.2 (1.9)	–0.6 (–0.1)	0.2 (–0.1)	
OD	120	276	246	41	37	45	–4.4 (–1.9)	–4.0 (–2.3)	–0.2 (0.2)	–0.1 (–0.1)	STWSH
MB	109	283	235	43	37	44	–3.2 (–2.8)	–4.6 (3.1)	–0.2 (–0.2)	–1.2 (0.1)	
PA	107	257	228	46	38	46	–3.4 (–3.0)	–4.6 (–2.7)	–2.2 (–2.1)	0.0 (0.1)	

4.3.3 Future meteorological droughts prediction based on SPI–12

The results of drought prediction were based on Figure 4.3-5 illustrate the temporal variation of future meteorological drought events derived through the SPI–12 across all the AEZs. Values of SPI < 0 across the study area indicated drought periods at various severity levels, while SPI > 0 indicated wet periods according to the McKee et al. (1993) categorization method. The results were analysed across each climate scenario for each AEZ.

4.3.4 Drought prediction based on SSP5– 8.5

In the STWSA zone under the SSP5– 8.5 climate scenario, the results suggest that throughout the study period drought episodes were predicted, in Oudtshoorn with the most severe drought occurring in 2021, 2025 – 2028 and 2041 (Figure 4.3). The results indicate that Piketberg is anticipated to observe longer duration droughts in the years 2029 to 2033; 2037, 2040, 2042 and 2047 being the only years were normal to above normal conditions were experienced (Figure 4.3). Clan William and Still Bay were predicted to experience less drought incidences compared to other stations in STWSA, with Still Bay projected to experience mild drought only four times across the study period (Figure 4.3). In the STCSH zone, the results indicate that Ceres experienced sustained drought periods

throughout the study period, with the most extreme drought incident taking place in 2022 and 2044 (Figure 4.4). Similarly, Hermanus is projected to suffer from longer drought periods, starting off as mild drought in the years 2026 to 2038, 2039 to 2040 and 2045 to 2050, while the years 2024 and 2025 are projected to be wet (Figure 4.4). Malmesbury and Bredasdorp largely experienced wet conditions during the study period with Malmesbury only experiencing mild drought conditions in 2024, 2039 and 2042, while Bredasdorp is anticipated to observe moderate drought in 2025 (Figure 4.4). In the STCSA the results indicate that Beaufort West will observe drought throughout the study period (Figure 4.4). The results indicate that in the STCA, Murraysburg experienced predominantly normal to wet conditions, while during the years 2025, 2027, 2038, 2042, 2044 there was mild drought (Figure 4.5). In STWA the results project predominantly drought conditions in Ladismith with only the years 2025– 2026, 2037, 2042 and 2042– 2045 predicted to be wet (Figure 4.5). In STWSH, sustained drought periods are expected in Murraysburg while in Prince Albert, multi– year drought periods are projected particularly between 2027 and 2037 (Figure 4.5).

4.3.5 Drought prediction based on SSP2– 4.5

In the STWSA zone under the SSP2– 4.5 climate scenario, the findings indicate that throughout the study period drought episodes were projected in Oudtshoorn with the most severe drought occurring in 2041 as well as in 2045 (Figure 4.3). The findings from Figure 4.3 indicate that the next region to be severely affected by drought is Piketberg. The results indicate that Piketberg will also undergo severe in 2043, while Clan William and Still Bay were projected to experience predominantly wet conditions (Figure 4.3). The results indicate that Still Bay will have droughts only during the years 2034, 2040– 2041 and 2046. In the STCSH, the results indicate that Ceres experienced sustained drought periods with wet conditions in 2030 – 2031, 2041, 2043 and 2050 (Figure 4.4). Hermanus is projected to experience more frequent drought conditions, however the drought episodes appear to be less compared to the ones anticipated under the SSP5– 8.5 climate scenario (Figure 4.4). Malmesbury is also expected to experience largely wet conditions like the results obtained under climate scenario SSP5– 8.5 (Figure 4.4). Bredasdorp experienced more drought events compared to the SSP5– 8.5 climate scenario. In the STCSA zone the results indicate that Beaufort West will observe drought throughout the study period (Figure 4.4). In the STCA, Murraysburg experienced predominantly normal to wet conditions, particularly between the years 2021 – 2028, 2033 – 2037

2045 to 2047 (Figure 4.5). In STWA the results project predominantly wet conditions in Ladismith with moderate drought conditions expected in 2025, 2040 and 2042 (Figure 4.5). In STWSH zone sustained drought periods are expected in Matroosberg, with only wet conditions expected in 2028, 2040– 2041 and 2046 while in Prince Albert, there is going to be more frequent drought periods with a mild drought after every two years (Figure 4.5).

4.3.6 Drought prediction based on SSP1– 2.6

In the STWSA zone under the SSP1– 2.6 climate scenario the results suggest that throughout the study period drought episodes were predicted, in Oudtshoorn with the most severe drought occurring between 2033 and 2034 (Figure 4.3). The results indicate that Piketberg is anticipated to observe longer duration of drought episodes in the years 2024 to 2032; 2037 to 2041 and between 2042 and 2049 (Figure 4.3). The years 2024, 2033– 2034, 2037 and 2050 are anticipated to be wet years in Piketberg. In Clan William it is predicted that less severe drought incidences will take place compared to climate scenarios SSP5– 8.5 and SSP2– 4.5 (Figure 4.3). Still Bay is projected to experience wet conditions across the study period (Figure 4.3). In the STCSH zone, the results indicate that Ceres experienced sustained severe drought periods throughout the study period (Figure 4.4). Similarly, Hermanus is predicted to suffer from longer drought periods starting from the year 2021 to 2033, 2036 to 2042 and 2044 to 2049 while the years 2034 to 2035, 2037 and 2050 are years that are expected to be wet (Figure 4.4). Malmesbury and Bredasdorp largely experienced wet conditions during the study period with Bredasdorp only recording mild drought conditions in 2036, 2042 and 2050 (Figure 4.4). In the STCSA the results indicate that Beaufort West will observe drought throughout the study period (Figure 4.4). The results indicate that in the STCA zone, Murraysburg experienced predominantly wet conditions, particularly between the years 2021 to 2033 and 2045–2049, while in the years 2034, 2036, 2040 and 2050 severe drought conditions were anticipated (Figure 4.5). In the STWA zone the results project predominantly wet conditions in Ladismith with 8 drought incidences throughout the 30-year study period, while Leew–Gamka is expected to undergo mild to severe drought conditions with the year 2032– 2033, 2036 and 2050 expected to be wet years (Figure 4.5). In the STWSH zone sustained drought periods are expected in Matroosberg while in Prince Albert, multi– year drought periods are projected particularly between 2025 and 2032 and 2045 to 2048 (Figure 4.5).

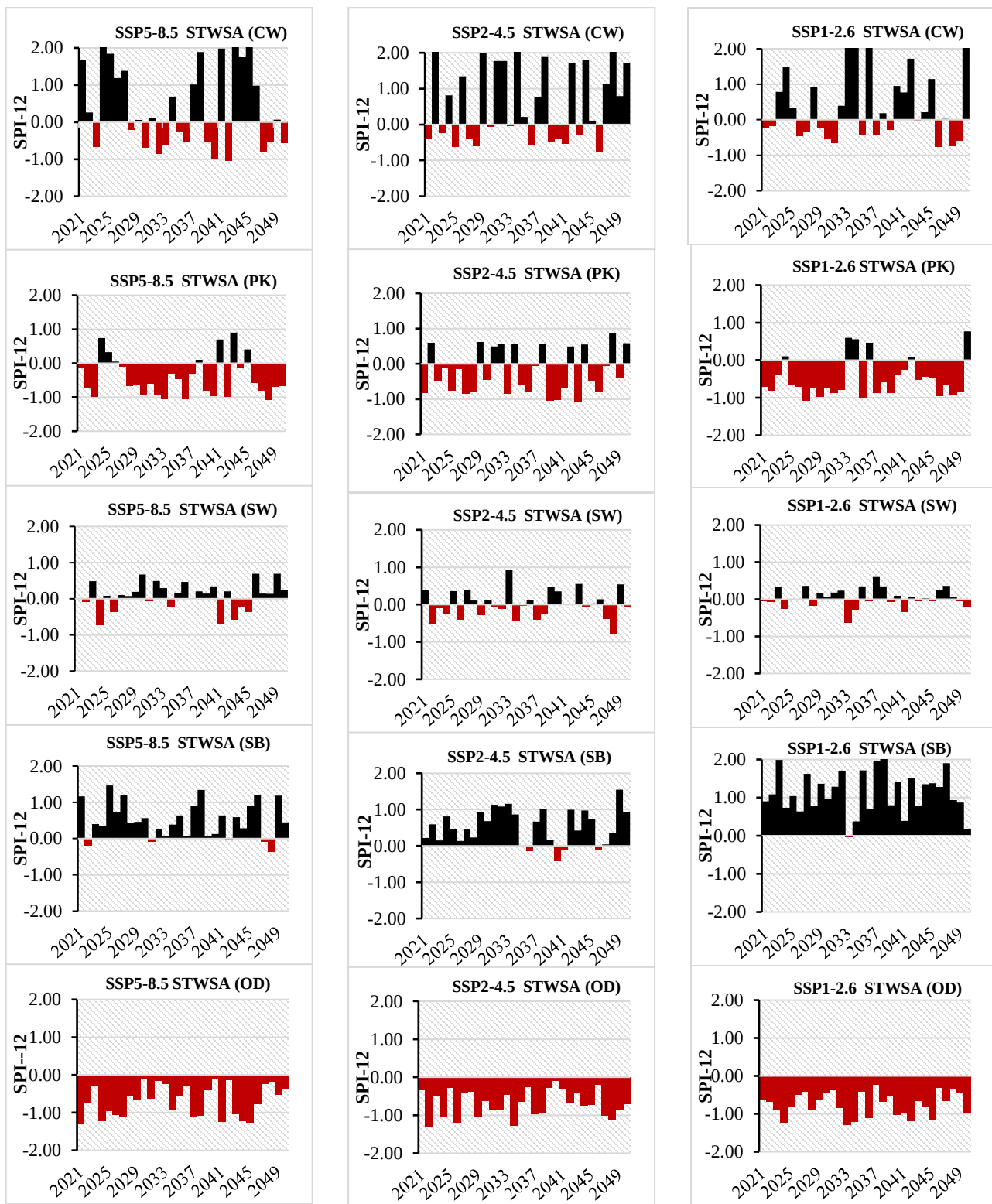


Figure 4.3 Temporal variation of future meteorological drought events (Source Based on field data)

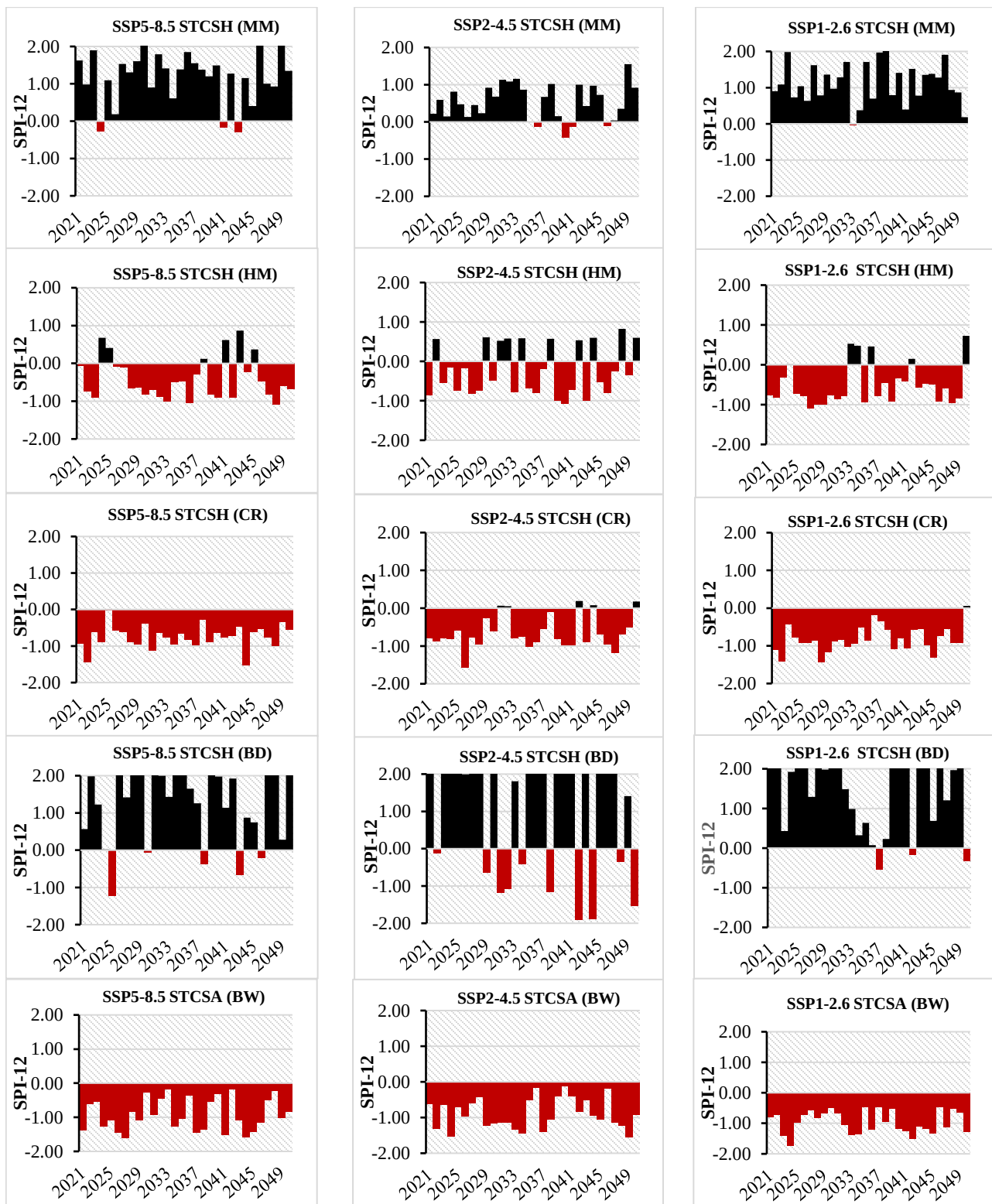


Figure 4.4 Temporal variation of future meteorological drought events (Source: Based on field data)

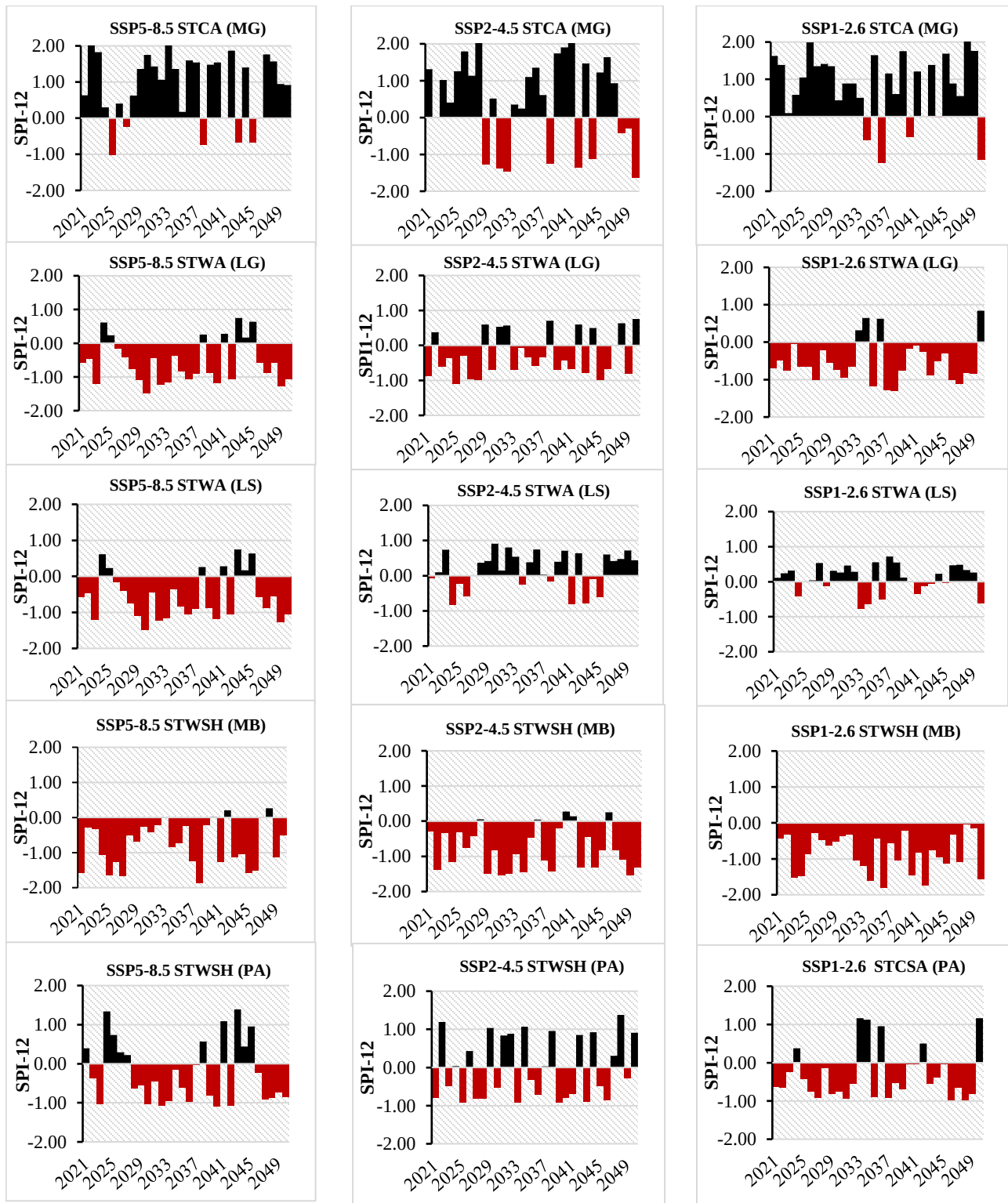


Figure 4.5 Temporal variation of future meteorological drought events (Source: Based on field data)

4.3.7 Future drought magnitude, intensity, and frequency

Table 4.7 gives the findings of the magnitude (M), intensity (I) and frequency (F) of the meteorological drought calculated over the study period (2021–2050). The magnitude, intensity and frequency of future drought calculated using the SPI–12 based on projected values of precipitation from MIROC6 was particularly crucial in the assessment of projected water availability in streams in the various AEZs. The results from Table 4.7 illustrate that in areas around STCA maximum drought magnitude and frequency of 10.1mm and 1mm/year were predicted under the SSP2–4.5 climate change scenario while the greatest drought frequency was also predicted to be 33% (Table 4.7). The results indicate that in STCSA the SSP1–2.6 was the worst with a drought magnitude of 28.5mm while the drought intensity and frequency were expected to be maximum at 1.0mm/year and 100% respectively (Table 4.6). In the STCSH regions, Ceres district was predicted to have the greatest drought magnitude and intensity of 24.6mm and 0.85mm/year under the SSP1–2.6 climate change scenario while the greatest drought frequency was expected under the SSP2–4.5 climate change scenario at 100% (Table 4.7).

The results from Table 4.7 illustrate that in the STWA regions the greatest drought magnitude was predicted to be in Leew-Gamka at 19.6mm, with a maximum intensity of 0.9mm/year under the SSP5–8.5 climate scenario while the greatest frequency was expected in under the SSP1–2.6 climate scenario. The results indicated that under STWSA regions Oudtshoorn recorded the greatest drought magnitude of 22.4mm under the SSP1–2.6 climate scenario with a frequency of 100% (Table 4.7). The drought intensity was expected to be greatest in Piketberg under the SSP5–8.5 climate scenario. Meanwhile in the STWSH regions Matroosberg had the greatest drought magnitude, intensity, and frequency at 24.9mm, 1.0mm/year and 100% respectively (Table 4.7). Overall, the results indicate that across all the AEZs of the Western Cape, the most severe drought and ultimately greatest water availability challenges were predicted in Beaufort West under the SSP1–2.6 climate scenario with a drought magnitude of 28.5mm while the drought intensity and frequency were expected to be 1.0mm/year and 100% respectively (Table 4.7).

Table 4.7 Predicted drought magnitude, intensity, and frequency (Source: Based on field data)

Station	SSP5–8.5			SSP2–4.5			SSP1–2.6			AEZ
	M (mm)	I	F (%)	M	I (mm)	F (%)	M (mm)	I	F (%)	
MG	3.33	0.7	20	10.1	1.0	33	3.6	0.7	17	STCA
BW	27.5	0.9	100	26.6	0.9	100	28.5	1.0	100	STCSA
MM	0.8	0.3	10	0.8	0.2	0.2	0.0	0.0	0	STCSH
HM	15.5	0.6	80	12.6	0.6	67	17.7	0.7	80	
CR	22.4	0.7	100	19.6	0.8	83.3	24.6	1.0	97	
BD	2.5	0.5	17	10.2	1.0	30	1.0	0.3	10	
LG	19.6	0.9	77	12.9	0.6	70	17.9	0.7	87	STWA
LS	4.4	0.4	37	6.7	0.5	46	3.7	0.3	43	
CW	8.3	0.6	46	5.3	0.4	46	5.8	0.4	47	STWSA
PK	15.6	0.8	77	12.2	0.6	0.7	17.4	0.7	80	
SW	3.3	0.3	40	4.1	0.3	50	2.9	0.2	50	
SB	0.7	0.2	16	0.8	0.2	17	0.0	0.0	0.0	
OD	20.4	0.7	100	20.4	0.1	100	22.4	0.7	100	STWSH
MB	23.2	0.9	86	24.2	0.9	83	24.9	1.0	100	
PA	14.4	0.7	70	11.2	0.7	53	14.2	0.6	80	

MG= Murraysburg, BW = Beaufort West, MM = Malmesbury, HM = Hermanus, CR = Ceres, BD = Bredasdorp, LG = Leew Gamka, LS = Ladismith, SB =Still Bay, OD = Oudtshoorn, SW = Swellendam, PK = Piketberg, MB = Matroosberg, CW = Clan William, MB= Matroosberg, PA = Prince Albert)

4.3.8 Drought ranking

Table 4.8 and Table 4.9 present the characteristics of five high-ranked droughts in the AEZs based on maximum drought magnitude ($M_{\max}$) and maximum drought intensity ($I_{\max}$) respectively across the study period (2021–2050). The results from Table 4.8 indicate that the top three greatest drought magnitudes will take place in the STCSA (BW). The results indicate that the greatest drought magnitude of 28.5mm will occur under SSP1–2.6 climate change scenario. Similarly, in the STWSH and STCSH regions the fourth (24.9mm) and fifth (24.6mm) ranked drought magnitudes in Matroosberg and Ceres are occurring under the SSP1–2.6 climate scenario (Table 4.8). For drought events classified by their magnitude, there appears to be a logical positive correlation between the magnitude and frequency of drought for all events. The greatest future drought magnitude ($M_{\max}$ =

28.6mm) is projected to elongate for as long as 620 days and the lowest magnitude future drought ($M_{\min} = 24.6\text{mm}$) in the top five ranked drought lasted only for 317 days as presented in (Table 4.8).

Table 4.8 Drought ranking by magnitude (Source: Based on field data)

Ranking	Magnitude (mm)	AEZ (Station)	Scenario	Most Extreme Drought Period Between 2021–2050		
				Start Date	End Date	Duration (days)
1	28.5	STCSA (BW)	SSP1–2.6	11 August 2023	22 March 2025	620
2	27.5	STCSA (BW)	SSP5–8.5	15 June 2044	30 August 2045	441
2	26.6	STCSA (BW)	SSP2–4.5	21 April 2026	13 May 2027	387
4	24.9	STWSH (MB)	SSP1–2.6	03 July 2036	10 April 2037	281
5	24.6	STCSH (CR)	SSP1–2.6	29 June 2028	11 May 2029	317

Meanwhile the results from Table 4.9 illustrated the characteristics of the top five drought events based on the intensity of the drought event calculated across the near 2021–2050 together with the duration of the most intense drought between 2021 and 2050. The results from Table 4.9 indicate that the top five ranked intense droughts are predicted to occur at 1.0mm/year. Results from Table 4.9 indicate that 60% of these most intense drought events are expected to occur under the SSP1–2.6 climate scenario. The most affected regions are STCSH (BD and CR), STCA (MG), STWSH (MB) and STCSA (BW). The duration of the most intense drought event is expected to be 558 days in STCSA in Beaufort West while the least intense drought will have a duration of 638 days in STWSH (MB) (Table 4.9). Importantly Table 4.9 this event far exceeds the threshold of a severe drought for which the SPI–12 value is less than –1.5.

Table 4.9 Drought ranking by intensity (Source: Based on field data)

Ranking	Intensity (mm/year)	AEZ (Station)	Scenario	Most Intense Drought Period Between 2021–2050		
				Start Date	End Date	Duration (days)
1	1.0	STCSA (BW)	SSP1–2.6	11 August 2023	22 March 2025	620
2	1.0	STCSH (BD)	SSP2–4.5	21 April 2030	13 May 2031	388
3	1.0	STCSH (CR)	SSP1–2.6	29 June 2028	11 May 2029	317
4	1.0	STWSH (MB)	SSP1–2.6	03 July 2036	10 April 2037	281
5	1.0	STCA (MG)	SSP2–4.5	17 September 2039	30 June 2040	287

4.4 Exploring optimal water management scenarios under drought conditions.

This section presented evidence of increasing water scarcity caused by frequent drought under SSP2-4.5 climate change scenario in the Western Cape Province, South Africa. A commonly used risk assessment approach based on the reliance, resilience, and vulnerability framework using future precipitation datasets (2021–2050) under the SSP5–8.5 climate scenario and sustainability index (SI) was used to assess the variability of water shortages in WC under drought conditions. Reliability indicators were defined as a region's probability of being in the range of satisfactory Standardized Precipitation Index (SPI) values. Resilience was defined as the speed of recovery from an unsatisfactory condition. Vulnerability was defined using the SPI as a function of the exposure of a region to climate change and variation. RRV assessments were done by analysing SPI threshold values, the drought entropy method and RRV indicators. The findings in this section can aid policymakers in designing a drought early warning system to reduce risk and thus develop resilience in vulnerable communities towards recurrent meteorological drought.

4.4.1 Precipitation characteristics under SSP2-4.5 climate change

Table 4.10 shows the findings of the validation metrics for the simulated precipitation, the mean annual precipitation (MAP), the coefficient of variation (CV) and the respective percentage changes between the base period and the SSP2-4.5 climate scenario. The results indicate that STWA (Leew Gamka) exhibited the lowest MAD of 22.6mm, while STCSH (Hermanus) observed the highest MAD of 134.3mm. Stations in the sub-humid zones exhibited greater MAD values against stations in the arid zones. The MAPE values ranged from 15.8% in STCSA (Beaufort West) to 21.5% in STWSH (Prince Albert). The R^2 results exhibited a minimum value 0.83 in STCSA (Beaufort West while STWSA (Still Bay) exhibited the highest R^2 of 0.89. The results from the NSE model were greater than seventy percent (70%), with the highest and lowest values of 84.25% and 78.50% recorded at STCSA (Beaufort West) and STWSH (Prince Albert respectively. Accordingly, the highest MAP of 252mm and lowest MAP of 213 under the influence of the SSP2-4.5 climate scenario was observed in STCA (Malmesbury) and STCSA (Beaufort West) respectively. The greatest change is expected in STCSH (Malmesbury) at -28.16% while in STCA (Murraysburg) minimal change of 3.57% is expected under SSP2-4.5 compared to the base period. Meanwhile, the greatest change in CV is expected STCSH (Bredasdorp) at 30% while the least change is expected at 9% in STCSA (Beaufort West). Overall, the results indicate that under the SSP2-4.5 climate scenario there will be a decrease

in expected precipitation across all districts, with the greatest decrease expected in sub-tropical cool sub humid zone (STCSH).

Table 4.10 Characteristic values of MAD, MAPE, R², NSE, MAP and CV (Source: Based on field data)

Stat ion	MAD	MAPE	R ²	NSE	MAP		%Coefficient of variation			AEZ	
					Base Period	SSP2- 4.5	% Change	Base Period	SSP2- 4.5		% Change
1	59.6	19.18	0.87	80.83	261	252	-3.57	20	35	15	STCA
2	39.7	15.75	0.83	84.25	250	218	-14.68	24	37	9	STCSA
3	108.3	16.97	0.86	83.03	314	245	-28.16	20	37	17	STCSH
4	134.3	19.18	0.87	80.83	303	264	-14.77	19	40	21	
5	116.1	16.22	0.88	83.79	283	227	-24.67	21	48	27	
6	124.0	16.58	0.88	83.42	300	243	-23.46	18	48	30	
7	22.6	16.97	0.87	83.03	252	213	-17.37	27	37	10	STWA
8	71.1	19.49	0.86	80.51	277	233	-18.88	24	37	13	
9	51.4	16.56	0.88	83.44	281	224	-25.45	20	37	17	STWSA
10	62.9	16.22	0.86	83.79	291	232	-25.43	21	38	17	
11	99.4	19.50	0.87	80.50	266	217	-22.58	20	39	19	
12	84.8	19.49	0.89	80.51	300	255	-17.65	21	37	16	
13	94.1	19.99	0.87	80.01	276	236	-16.95	24	37	13	STWSH
14	111.8	16.66	0.87	83.34	283	227	-24.67	20	37	17	
15	132.1	21.50	0.86	78.50	257	218	-17.89	25	38	13	

4.4.2 SPI characteristics under SSP2-4.5 climate change

Figure 4.6 and Figure 4.7 illustrate both the spatial and temporal variations of SPI-12 in the base period and the SSP2-4.5 climate scenario. According to Figure 4.6 the highest SPI-12 value in the base period was obtained in STCSH (Bredasdorp) at 4.3, while the lowest SPI-12 value was obtained in STCSA (Beaufort West) at -2.3. The SSP2-4.5 index variation shows that STWSA (Clan William) is expected to exhibit the highest SPI-12 value of 2.5 while the lowest SPI-12 value under the SSP2-4.5 climate scenario is expected to be in STCSA (Beaufort West). A comparison of the of the base period and SSP2-4.5 climate scenario SPI-12 values indicates that STCSA (Beaufort West) and STWSH (Matroosberg) will exhibit the lowest values of -2.37 and -2.41 respectively. Spatial changes in SPI-12 values suggest that in the SSP2-4.5 climate scenario stations such as STCSA (Beaufort West), STWA (Leew Gamka), STWSA (Oudtshoorn) and STWSH (Matroosberg) that

observed extreme drought events under the base will likely have less severe drought conditions under the SSP2-4.5 climate scenario.

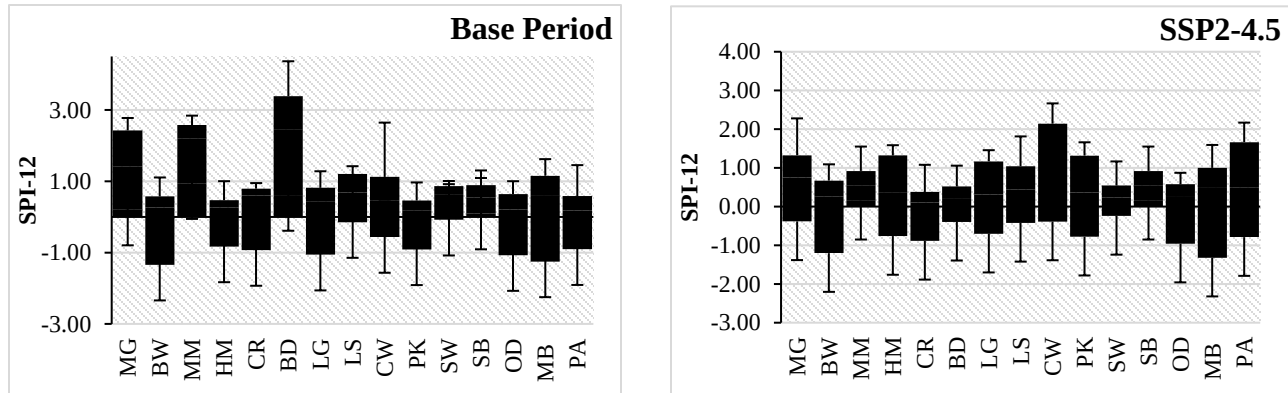


Figure 4.6 Spatial variation of SPI-12 values across the study area (Source: Based on field data)

Meanwhile, according to Figure 4.7 the highest SPI-12 value in the WCP in the base period was obtained in the years 1998 and 2001 at 3.81 and 3.80 respectively, while the lowest SPI-12 values were obtained in the years 2001 and 2008 at -2.0. On the other hand, the SSP2-4.5 index variation shows that highest SPI-12 values are expected in 2033 and 2038 at 2.41 and 2.39 respectively, while the lowest values are expected in 2031 and 2037 at -2.00. Overall, the results indicate that under the SSP2-4.5 climate scenario there will be more severe drought conditions compared to the historical observations.

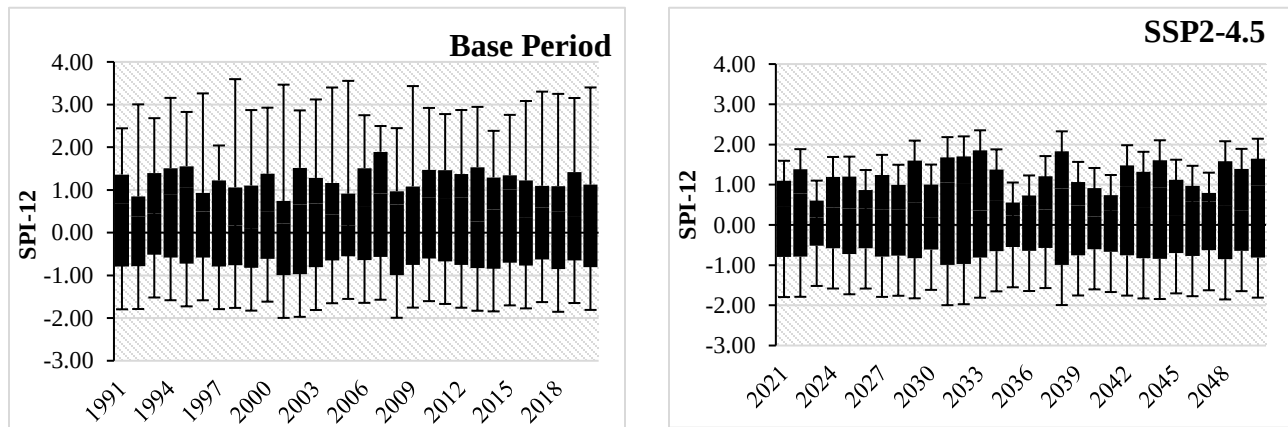


Figure 4.7 Temporal variation of SPI-12 values across the study period (Source: Based on field data)

4.4.3 Characteristics of reliance, resilience, and vulnerability indicators under SSP2-4.5 scenario

In Figure 4.8, the spatial variation of the R_{el} index across the study area and the quantitative changes between the baseline period and under the influence of SSP2–4.5 climate scenario are presented. The maximum R_{el} index in the base period is 0.83 observed in STCSA (Beaufort West), while the minimum value of 0.34 were observed in STCSH (Ceres; Bredasdorp). However, under the SSP2–4.5 climate scenario, maximum values of 0.71 were expected in STCA (Murraysburg), while the lowest values of 0.32 were expected in STCSH (Hermanus). Both positive and negative percentage changes are projected. The highest positive percentage change is expected to be observed in STCSH (Hermanus) at 42.86%, while the greatest negative percentage change is expected in STCSH (Ceres) at –35.29%. The average R_{el} index across the study area in the base period was calculated to be 0.53, which changed to 0.49 in the SSP2–4.5 scenario, a decrease of 1.43%.

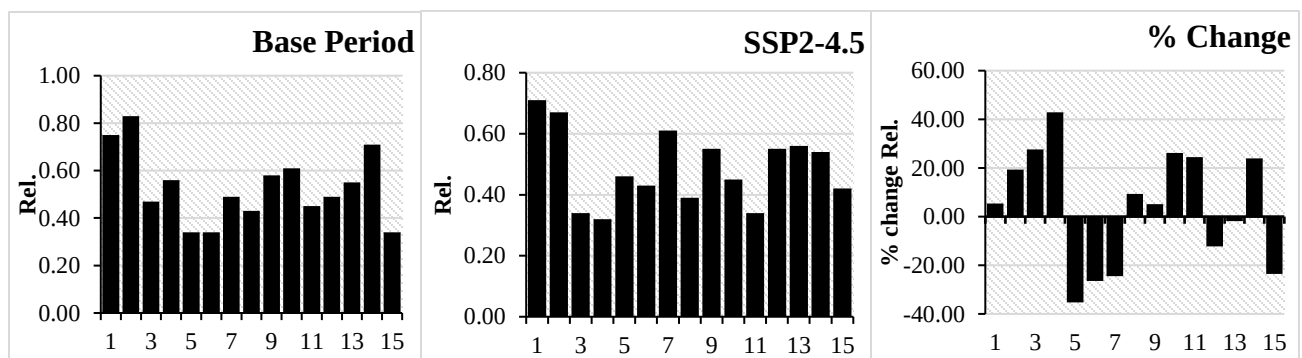


Figure 4.8 Spatial variation of reliance indicators (Source: Based on field data)

In Figure 4.8, the spatial variation of the R_{es} index across the study area and the quantitative changes between the base period and under the influence of SSP2–4.5 climate scenario are presented. The results show that the maximum R_{es} index in the base period is 0.58 were observed in STCSA (Beaufort West), while the minimum value was observed in STWA (Ladismith) at 0.27. However, under the SSP2–4.5 climate scenario, maximum R_{es} index values of 0.67 were expected in STCA (Murraysburg), while the lowest R_{es} index values of 0.36 were expected in STWSA (Clan William). The highest and lowest changes in resilience are projected at –51.11% in STWSA (Still Bay) and 50% in STWSA (Clan William) respectively. There was no change in average R_{es} index across the study area for both base period and SSP2–4.5 climate scenario, calculated to be 0.42.

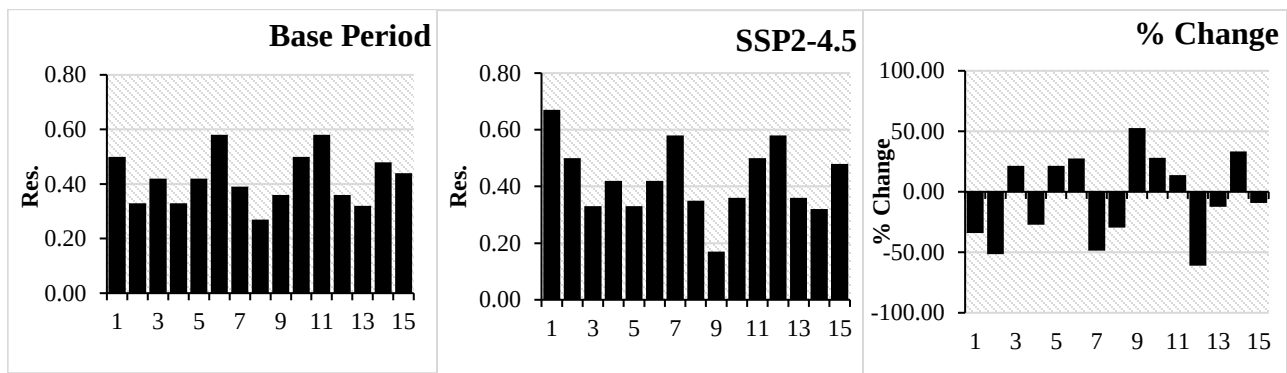


Figure 4.9 Spatial variation of resilience indicators (Source: Based on field data)

In Figure 4.9, the spatial variation of the V_{ul} index across the study area and the quantitative changes between the base period and under the influence of SSP2–4.5 climate scenario are presented. Results indicate that the maximum V_{ul} index in the base period value was 0.76 observed in STCA (Murraysburg), while the minimum value was observed in STCSH (Hermanus) at 0.33. Under the SSP2–4.5 climate scenario, the highest resilience values of 0.71 were expected in STCA (Murraysburg), while the lowest values were observed again in STCSH (Hermanus) at 0.29. The highest and lowest changes in vulnerability are projected at –32.35% in STCSH (Bredasdorp) and 28.88% in STCSH (Malmesbury) respectively. The average V_{ul} index across the study area in the base period was calculated to be 0.51, which changed to 0.47 in the SSP2–4.5 scenario, an increase of 7.08%.

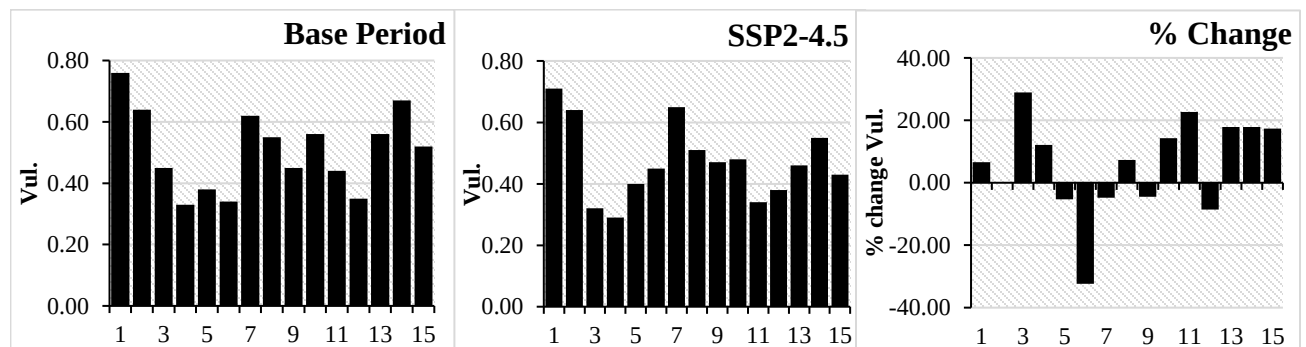


Figure 4.10 Spatial variation of vulnerability indicators across the study area (Source: Based on field data)

In Figure 4.10, the spatial variation of the sustainability index (SI) across the study area and the changes between the base period and under the SSP2–8.5 climate scenario are presented. The results

indicate that the highest sustainability index (SI) value in the base period was 0.75 observed in STWA (Ladismith), while the lowest value was recorded in STWSA (Swellendam) at 0.49. However, under the SSP2–4.5 climate scenario maximum SI values of 0.79 were expected in STCA (Murraysburg), while the lowest SI values of 0.39 were expected in STWSH (Prince Albert). The highest and lowest changes in SI values are projected at 32.76% in STWSH (Prince Albert) and –9.72% in STCA (Murraysburg), respectively. Overall, the results indicate that under the SSP2–4.5 climate scenario there will be an increase in the SI values across all districts, with all stations excluding STCA (Murraysburg) and STCSH (Malmesbury) expected to have higher SI values compared to the base period.

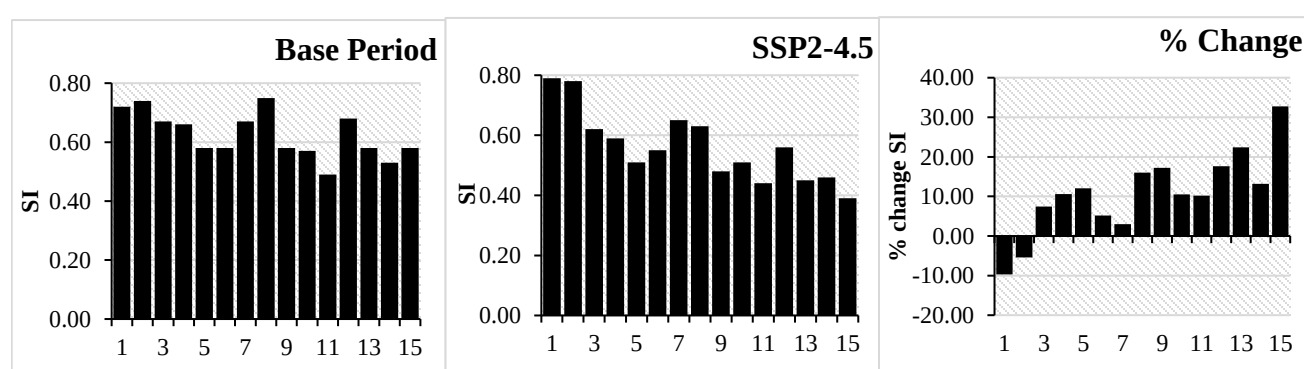


Figure 4.11 Spatial variation of sustainability index across study area (Source: Based on field data)

Figure 4.12 and 4.13 presents the mapped sustainability index across the study area between the base period and under the SSP2–8.5 climate scenario. The interpolated sustainability index values were used to evaluate the values in each district and determine the projected spatio-temporal characteristics of Rel.Res.Vul index values and consequently water resources availability across the study period. The results in the base period show that the years 1994, 2012, 2015, 2017 and 2020 had the lowest sustainability index values, of 0.17 indicating normal to above normal water shortages. The highest value of SI values of 0.98 and 0.92 were observed in the years 2007 and 2014, mainly in eastern parts of the WCP. The results also show that under the SSP2–4.5 climate scenario the lowest value of 0.24 was observed in the year 2036. Similarly, the results indicate that the highest value of 0.83 was observed in the year 2035 and 2047. These conditions were mainly observed in regions near Leew Overall, the surface maps of the Rel.Res.Vul index clearly separate the Western Cape Province

into two regions: the western half, which is projected to experience and includes STWSH and STCSH, and the drier eastern zones, which include STCSA, STWA, and STCA.

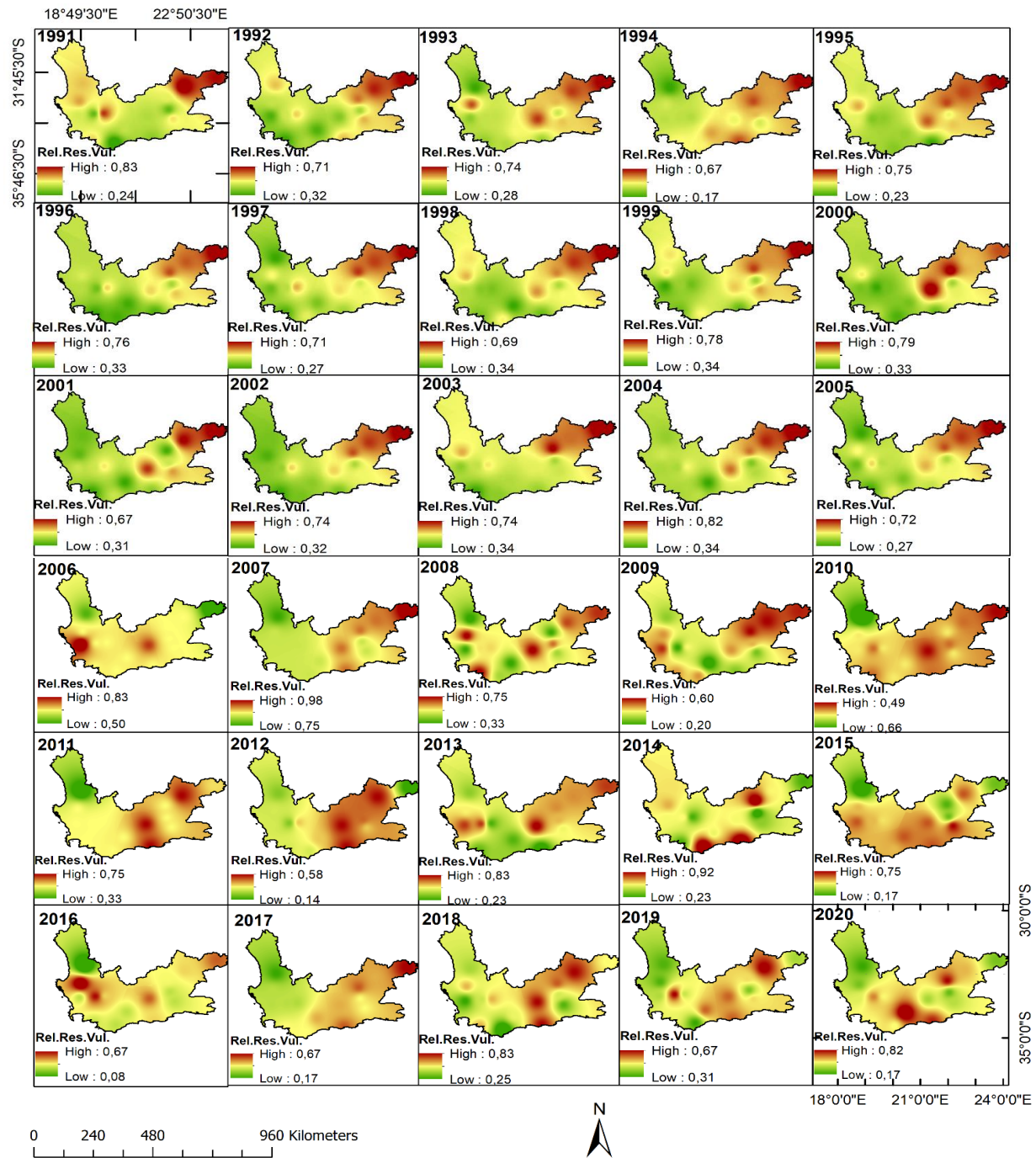


Figure 4.12 Spatial variation of SI in the base period across the study area (Source: Based on field data)

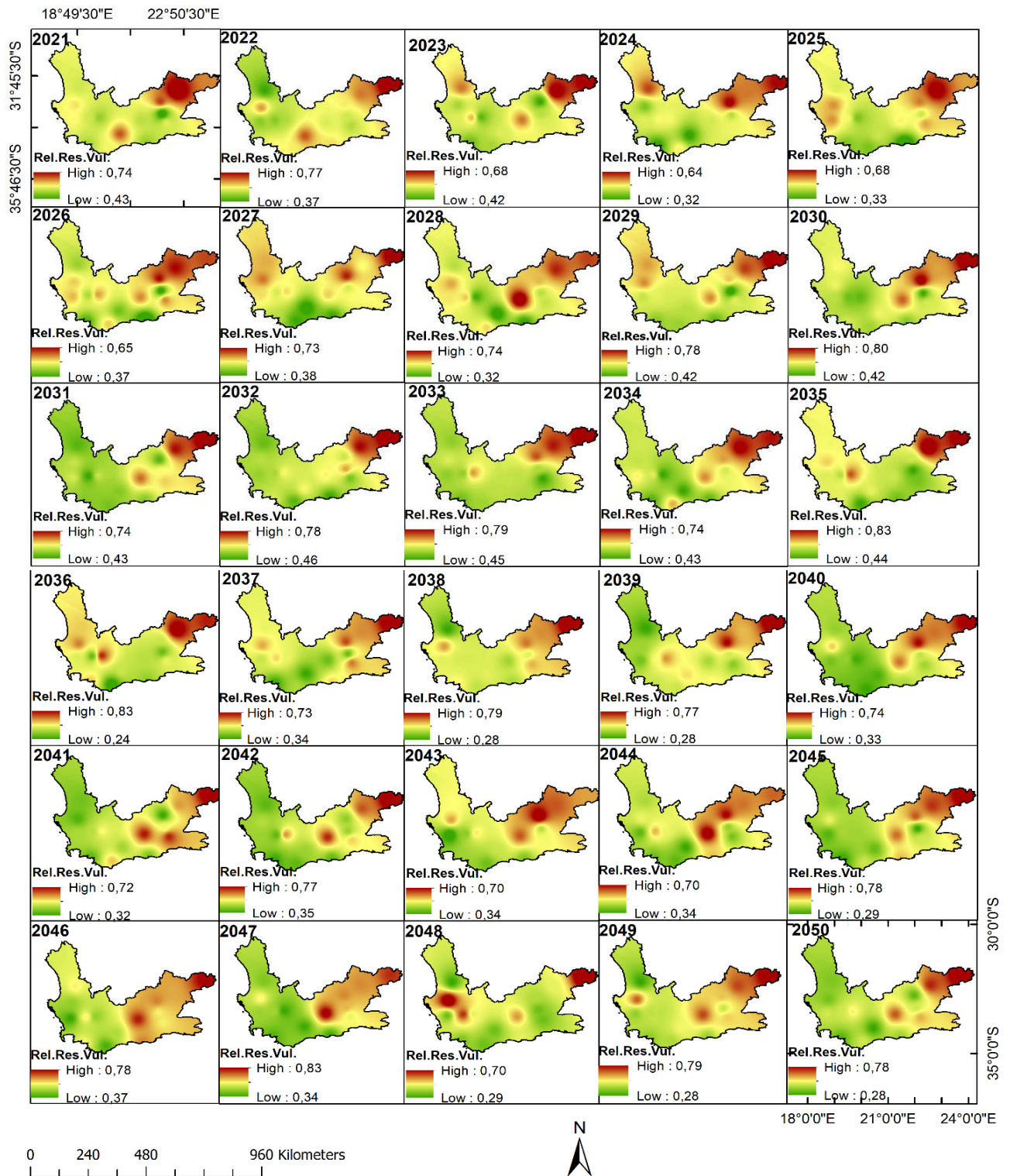


Figure 4.13 Spatial variation of SI between 2021 and 2050 across the study area (Source: Based on field data)

4.4.5 Trends

Table 4.11 shows the trends in reliance, resilience and vulnerability indicators expected in the AEZs between 2021 and 2050. The results indicate that for the reliance indicator, nine stations located in STCA (Murraysburg), STCSH, STWSA (Oudtshoorn; Piketberg), and STWSH (Matroosberg; Piketberg) are expected to experience negative trends across the study period. The remaining stations are expected to experience non-significant positive trends in reliance. Of the stations that exhibited negative trend in the reliance indicator, only three stations, Ceres (STCSH) and STWSA (Oudtshoorn; Swellendam) exhibited statistically significant trends ($z > 1.96$). The results indicate that for the resilience indicator, thirteen stations are expected to exhibit negative trends, however only four station STWSH (Prince Albert), STWSA (Piketberg; Oudtshoorn) and STCSH (Hermanus) exhibited statistically significant negative trends. In terms of vulnerability, the results indicate that twelve stations exhibited negative trends, with STCSH (Malmesbury, Ceres) expected to be significant at 5% significance level. STWSA (Oudtshoorn, Swellendam) and STWSA (Prince Albert) exhibited non-significant positive trends for the vulnerability indicators. Meanwhile, the results from Rel.Res.Vul trend analysis suggest that ten station were expected to experience negative trends, with six stations STCA (Murraysburg), STCSA (Beaufort West), STCSH (Ceres), STWA (Leew Gamka, Ladismith) and STWSA indicating significant negative trends at 5% significant testing.

Table 4.11 Trends (mm/year)

Station	Rel.		Res.		Vul.		Sustainability Index.		AEZ
	Trend	Sig.	Trend	Sig.	Trend	Sig.	Trend	Sig.	
1	-0.31	0.87	0.33	0.57	-1.33	-1.05	-1.10	-2.15	STCA
2	0.57	0.58	-0.20	-0.13	-0.25	-1.07	-1.50	-2.86	STCSA
3	-1.43	-2.48	-2.67	-1.27	-1.91	-2.14	1.23	2.21	STCSH
4	-0.48	-1.11	-2.65	-3.68	-1.42	1.37	1.60	-1.41	
5	-1.29	-2.66	-2.49	-1.73	-2.28	-2.80	-1.26	-2.44	
6	0.19	3.10	-1.18	-3.12	-0.62	1.32	0.63	-1.72	
7	1.12	0.38	-0.52	-1.18	-0.17	-1.25	-0.56	-2.17	STWA
8	0.15	-1.26	-1.56	-1.51	-0.21	0.17	1.13	-2.55	
9	0.35	-1.71	-0.85	-1.23	-0.49	-0.63	-0.17	-2.29	STWSA
10	-0.49	-2.11	-1.75	-2.50	0.56	-1.17	-0.84	-2.13	
11	1.12	-2.62	0.47	-1.63	0.87	-1.16	-1.30	-1.29	
12	-0.56	-1.35	-2.98	-1.92	-0.32	0.58	-1.43	-2.42	
13	-0.15	-1.16	-1.61	-1.58	-0.50	-1.13	-1.26	2.16	STWSH
14	-0.64	-1.47	-1.33	-1.65	-0.84	1.67	0.61	-2.23	
15	-0.34	-0.57	-1.01	-2.98	0.45	-1.33	-1.32	-2.28	

CHAPTER FIVE

ANALYSIS AND DISCUSSION

5.1 Overview

This chapter is dedicated to the analysis and discussion of the results presented in chapter four. The primary aim of this chapter is to interpret and discuss the implication of the findings in relation to drought incidence and the associated impacts on water availability and agricultural productivity, while elucidating on any new insights in research. The chapter is structured and organised into three sections that draw on the overarching aim and objectives of the study. Section 5.2 seeks to discuss and address research objective (i) which was to examine the variations in severity, intensity, and frequency of meteorological drought across different AEZs in the Western Cape Province. The section identified the intersectionality of observed (1980-2020) hydroclimatic variability trends with water scarcity the six AEZs. Section 5.3 seeks to discuss and address research objective (ii) and (iii) that aimed to downscale, and bias correct three climate change scenario (SSP5–8.5, SSP2–4.5 and SSP1–2.6) datasets projected from the sixth version of Model for Interdisciplinary Research on Climate (MIROC6) and consequently evaluate the spatiotemporal trends in projected water availability in the AEZs. Additionally, a sub-section is dedicated to discussing the most severe future drought episodes through ranking the drought events according to intensity and duration to determine the best future mitigation pathway. Finally, section 5.4 seeks to address research objective (iii) and (iv) through providing evidence of increasing water scarcity caused by frequent drought under SSP2-4.5 climate change scenario in the Western Cape Province, South Africa.

5.2 Lesson learnt from observed climate variability and water scarcity in WC Province

This section analyses findings from research objective (i) that examined the variations in severity, intensity, and frequency of meteorological drought across different AEZs in the Western Cape Province. To this end, the current investigation employed two classifications of drought indicators derived from precipitation datasets (1980–2020) obtained from 15 meteorological stations located in the Western Cape Province, South Africa. The initial classification pertained to the accumulation of the Standardized Precipitation Index (SPI) over a period of 12 months. The second category has three indicators for evaluating drought: drought magnitude, intensity, and frequency. The examination of

SPI- 12 reveals that from 1980 to 2020, the Western Cape Province consistently encountered mild meteorological drought conditions, characterized by regional and temporal fluctuations. This implies that the present drought circumstances in the Western Cape Province are an indirect result of previous drought conditions. The sole distinction between previous and current drought circumstances lies in the fact that the Western Cape Province has now seen the longest or most enduring period of drought. Moreover, examination of patterns in drought assessment measures reveals a significant spatial-temporal correlation, with the southern and western areas of the province encountering more frequent, intense, and severe droughts in comparison to the eastern portions of the Western Cape Province. In general, the persistent drought in the Western Cape Province has had a negative influence on agricultural productivity.

The findings from addressing observed drought characteristics implied that because of drought in the Western Cape Province there was a reduction in water levels in reservoirs whilst some rivers may run dry resulting in direct slowing down of agricultural production. Some impacts of drought will be visible in the short-term whilst other impacts take longer to appear. Whereas surface water levels in rivers and streams will reflect the absence of rainfall in the short-term, groundwater levels may not fall until a year later. The results from the study suggest that poor drought impacts may lead to artificial shortages and demand for water in certain regions. Overgrazing and over cultivation cause land degradation which, in the long term, may lead to desertification. Thus, impacts of drought are a function of the vulnerability of a region to precipitation deficiency (AMS, 1997) and other socio-physical variables. Precipitation is a key meteorological variable in SSA countries as it influences agricultural patterns for food security and sustainable livelihoods. In addition, the research findings suggest that water availability of a region is heavily dependent on its rainfall climatology. Thus, precipitation will be a critical factor in determining agricultural yields in SSA, particularly South Africa where there are limited irrigation technologies.

The results indicated substantial negative trends in annual precipitation across all AEZs. An examination of seasonal precipitation patterns revealed a rise in summer precipitation in subtropical cool- arid regions and subtropical warm semi- arid regions, with increases of 0.4 and 0.2 mm/year, respectively. Conversely, the overall annual precipitation trend fell by - 1.0 mm/year in both AEZs. The SPI values consistently fell within the range of - 2 to 0 in the subtropical warm- arid, subtropical

cool– arid, and subtropical cool– arid zones. Conversely, the SPI values were consistently positive in the subtropical warm– arid, subtropical cool– humid, and subtropical warm– humid zones. This finding suggests that there will be persistent drought conditions that will affect agricultural production, surface flows in rivers, and groundwater levels across the WC province. The findings provided fresh insights into the characteristics of meteorological droughts and their correlation with surface flows in rivers, and groundwater levels in the Western Cape Province. The research’s characterization of meteorological drought differed from that of other scholars who focused on drought characterisation using alternative approaches. Nevertheless, the findings of the research aligned with the outcomes of prior research conducted by researchers including Botai et al. (2017), Orimoloye et al. (2019), Otto et al. (2018), and De Kock et al. (2022). For instance, the observed – 4.2mm/year statistically substantial trends in STCA (Murraysburg) align with prior findings by Botai et al. (2017), which indicated that the same areas within the Tsitsikamma water management region might anticipate reduced precipitation. The observed decline in the SPI values across all the AEZs aligns with the findings of Botai et al. (2017), who also identified negative trends in precipitation. The current study found that there were severe and intense drought conditions from 2015 to 2017. The minimum Standardized Precipitation Index (SPI) value was – 2.0 in 2014 and 2015, which is consistent with the findings of Orimoloye et al. (2019), who used remotely sensed data from the United States Geological Survey (USGS) repository and Geographic Information Systems (GIS) from 2014 to 2018 to evaluate the severity of drought in the WC region. The study conducted by Orimoloye et al. (2019) identified substantial land– use changes, with a decrease in vegetation, water bodies, and bare surface area from 2095 km² to 141 km², 616 km² to 167 km², and 2 337 km² to 1 381 km², respectively.

Equally, the analysis of drought frequency, amplitude, and intensity revealed a consistent upward trend across the entire region. These findings are consistent with the conclusions found by Otto et al. (2018), who examined how human activities contributed to the occurrence of the 2015– 2017 WC droughts. The findings of Otto et al. (2018) also indicated that the Western Cape (WC) can anticipate the persistence of more severe, frequent, and intense drought conditions, consistent with the scientific understanding of the effects of climate change. Furthermore, the findings of this study suggest that there is a rising pattern of summer rainfall at STCA and STCSA, with an increase of 0.4 and 0.2 mm per year respectively. In contrast, the overall trend of yearly precipitation has fallen by – 1.0 mm per year. These findings can be attributed to De Kock et al. (2022), who examined the broad– scale

processes associated with unusually wet summers in the southern Cape, South Africa. According to De Kock et al. (2022), they proposed that this phenomenon may be caused by increased incidences of summer rainy days associated with abnormalities in cyclones over the STCSA and STCA, as well as enhanced moisture flow from the west across the mid– latitude South Atlantic. The findings of the current study, which showed a high coefficient of variability, align with similar observations made in other regions of Africa and with the variability in precipitation witnessed in Kenya in recent years according to a study by Raphael Muli Wambua et al. (2018). The study's findings indicate that a rise in drought occurrence could have consequences for food production in the AEZs. Additionally, there is a pressing need for more focused and comprehensive research on the future variations of drought in agricultural settings. Overall, the findings of this study indicate that extended periods of drought in the study region will substantially affect the water supply and consequently, agricultural productivity. The study findings also emphasize the need for the development of proactive strategies for managing drought and the creation of accurate tools for predicting drought.

The findings presented in this study indicate that the Western Cape Province has been undergoing a period of moderate drought conditions from 1980 to 2020. The Western Cape exhibits a distinct climatic variation from other provinces in South Africa, owing to its Mediterranean climate. The province's rainfall patterns facilitate the cultivation of diverse crops such as pome fruit (apples and pears), stone fruit (apricots, peaches, nectarines, and plums), table grapes, and viticulture. Consequently, the prolonged duration of droughts has had an impact on the cultivation of these crops. Furthermore, agriculture plays a crucial role in the economy of the Western Cape. Consequently, the continued presence of drought conditions will have an adverse impact on the region. Specifically, the agriculture sector serves as the primary source of employment in the province. This sector also ensures the sustainability of South Africa's food security status, ensuring that citizens have access to the required food for a healthy and prosperous existence. Consequently, a rise in drought conditions will significantly affect the agricultural industry, resulting in unemployment, a surge in food costs, and several socio– economic consequences. Furthermore, a reduction in precipitation combined with other severe climatic elements (such as temperature and evapotranspiration), specifically in the Leew–Gamka and Beaufort West regions, will worsen drought conditions, resulting in a significant decrease in the available water in the water reservoirs of the Western Cape Province. Overall, the study's findings on observed drought dynamics suggest the following conclusions: i) The Western

Cape Province has consistently suffered droughts of different intensities and frequencies over the past thirty years; ii) The current drought circumstances in the Western Cape Province seem to be a recurring natural phenomenon. Despite the drought circumstances in the 21st century, the province has consistently seen recurring drought patterns during the 20th century (iii) analysing historical drought characteristics using drought indicators is a crucial initial step in: (i) contextualizing the current drought conditions; (ii) facilitating action and responses for drought preparedness; and (iii) establishing the basis for drought monitoring and the creation of early warning systems.

5.3 Future climate variability and water scarcity in WC Province.

This section discusses findings that sought to address research objective (ii) and (iii) of assessing the spatio-temporal characteristics of future meteorological drought in the near term (2021–2050) on the agroecological zones of the Western Cape Province in South Africa under the SSP5–8.5, SSP2–4.5 and SSP1–2.6 climate scenarios. These findings from the analysis indicated a progressive improvement from 1980 to 2020, from a 7.8– millimeter decline to a 6.4– millimeter rise in the STCSH and STCA zones. The SSP2–4.5 scenario predicts a – 2 to – 1.5 Standardized Precipitation Index (SPI) reduction in Bredasdorp between 2042 and 2044. However, the SSP5–8.5 scenario predicts an SPI over –2 for Matroosberg in 2038. The assessment sought to augment studies carried out by other scholars such as Orimoloye et al. (2019); Otto et al. (2018); Ziervogel (2019); Ziervogel et al. (2022) by assessing the seasonality of the projected precipitation trends as well as understanding the perceptions of the communities on the future drought incidence. The drought magnitude, intensity frequency and drought ranking based on the magnitude and intensity was investigated in the near term (2021–2050) under the three climate change scenarios. The results of trend analysis of projected precipitation indicated a progressive improvement across the SSP5–8.5, SSP2–4.5 and SSP1–2.6 climate change scenarios.

The research findings implied that climate change and anthropogenic activities have considerably aggravated the prospects of sustained future drought incidence, there remains little awareness on this phenomenon from communities in countries in the global south. This research served as a prelude to possibilities of more detailed analyses to come. Although the best readily available regional projections of climate change were used here, it was admittedly an incomplete comparison. The drought prediction findings from the current study revealed that this trend will significantly affect

water availability and consequently affect agricultural production in agro-ecological regions. Trend analysis results from previous research revealed a projected decline in precipitation received across all the climate change scenarios as well as in drought incidence across all AEZs. This enthused the present study to focus on precipitation as the single most important variable from which to predict the effects of human induced climate change on water availability and agricultural production in the Western Cape. The negative trend in annual precipitation revealed by the research in the AEZs mean less available water for crops amplifying the gap between water supply and demand in crop production for farmers. The impact of drought in the agroecological zones will increase the water stress and consequently water related conflicts from farmers withdrawing water from the same reservoirs because of competition for the same resource. Conclusively, while the Western Cape Province averted 'Day Zero', at the cost of agricultural production the predicted drought incidence in the present study, the dependence on domestic and agricultural water supply from rain-fed reservoirs coupled with population growth, provides a need to review the current water governance frameworks to adapt to changing risks. Possible solutions include expanding existing domestic water sources through desalination and groundwater abstraction along with nature-based solutions that ensure natural groundwater recharge. Furthermore, this study proposes more research that seeks to gain more insight on the role of not only precipitation but also temperature on future drought prediction and the associated impacts on water availability and agricultural production.

The results obtained under the SSP5-8.5 implied statistically significantly negative trends while both the SSP2-4.5 and SSP1-2.6 indicated mostly positive insignificant precipitation trends in the near term (2021-2050). The negative trends in projected precipitation under the SSP5-8.5 indicated protracted drought across all the AEZs of the Western Cape Province. These results are in parity with those reported by Engelbrecht & Monteiro (2021), that suggested that not only will there be universal decreases in precipitation over southern Africa under the SSP5-8.5 climate change regime but recurrent droughts are also predicted to take place. Similarly, both negative and positive in SSP2-4.5 and SSP1-2.6 climate scenarios were expected to ease off the drought periods across the study period. These findings implied that in the near term, agricultural production in the agroecological zones was expected to substantially decline particularly in areas that relied mostly on rainfed agriculture. These findings were also in agreement with studies by Thomson et al. (2011) who reported on the RCP4.5 as a stabilization pathway to climate change. The study noted that the probable source of negative

trends in precipitation could be climate change and anthropogenic activities such as increased population growth and urbanisation as suggested by scholars such as Park et al. (2015) who have under taken similar studies in Korea.

Based on the SPI-12 results regions in STWSH (Matroosberg), STCSA (Beaufort West) and STWSA (Oudtshoorn) were predicted to have sustained drought period throughout the near term across the climate change scenarios. This implied that these AEZs were expected to have chronic water shortages as will be evidenced through reduced stream-flows. The greatest drought magnitude was predicted to happen in the STCSA (Beaufort West) under the SSP1-2.6 climate change scenario. This projection was almost similar with the projection suggested by Botai et al. (2017) who used historical observed station data and reported that in the near term the Western Cape was expected to experience more severe drought incidences unless strict climate change mitigation strategies were implemented. The AEZs that were found close to coastal regions of South Africa revealed mostly positive SPI values, although future drought episodes appeared to become milder, particularly in the western coast because of changes in land-use and land cover patterns. This finding was in contrast with other findings from previous studies by scholars such as Otto et al. (2018) and thus necessitates further focused investigation.

Based on analysis of the results of the SPI-12 a maximum intensity of 0.5 – 1.0mm/year was deducted for most agroecological zones. This finding concurred with the projected increase in drought intensity previously found by Orimoloye et al. (2019) using geospatial datasets. Another important outcome of this study was the numerical predictability of drought in the Western Cape using the SPI within the framework of global climate model (MIROC6) under the three climate change scenarios used in the present study. The results from this study also indicated that community members within the agroecological zones were not fully aware of when future drought episodes will occur, and this affected their adaptive capacity to the impacts of projected frequent, severe, and intense drought events. These results were in parity with studies undertaken by Baudoin et al. (2017), which suggested that early warning signals were generally not reliable. Conclusively, future drought characterisation in the WC province of South Africa provided suitable reference information for judicious monitoring and prediction of drought incidence based on a suitable index (e.g., SPI-12) and household survey. A blend of drought evaluation indicators was useful to assess the relative impacts of drought in

different AEZs of future drought incidence, support proactive agricultural planning to reduce the influences of recurrent drought on sustainable livelihoods.

5.4 Evidence of increasing water scarcity under SSP2-4.5 climate scenario

This section provides evidence that water resource management systems in the Western Cape Province are likely to become progressively vulnerable to more frequent and severe drought events under future climate change. Summarily, the findings of the present study provided new insights into the response to drought impacts in terms of reliance, resilience and vulnerability offered by water resource systems in the Western Cape Province. The present study's assessment of drought impacts on water availability differs from that of previous studies by scholars such as Bhaga et al. (2023); De Kock et al. (2022); Naik & Abiodun (2020); Pires de Souza Araujo et al. (2021); Thomson et al. (2011) who focused on drought characterisation using either SPI or SPEI values. Nevertheless, the study findings were in general agreement with the findings of these scholars, indicating that the proposed research approach is effective. For instance, in terms of reliance the current study findings suggested that because of frequent and severe droughts, the probability of drought conditions over the next three decades (2021-2050) will gradually increase, particularly from the south-western parts to the north-eastern parts of the Western Cape Province (the most water shortages are projected to occur in Leew Gamka). These findings aligned with a study conducted by Bhaga et al. (2021) who monitored surface water variability through the Normalized Difference Water Index (NDWI) in the drought prone WC and reported that the results indicated that while surface waterbodies varied spatially over time, there was declining trend in the storage levels. In terms of the resilience, the present study findings revealed that speed of recovery from an unsatisfactory condition from future water shortages in the Western Cape is projected to be impaired by increasing drought intensity, and this increase will lead to decreases in surface water availability, water reservoir levels and consequently food security.

The current study findings revealed that proactive drought management strategies are crucial in diminishing water scarcity challenges in arid and semi-arid areas, especially in the Western Cape Province. The study finding revealed that fully understanding water scarcity and water resource system reliance, resilience and vulnerability under drought conditions is crucial in alleviating the

primary impacts of drought. Furthermore, while catchment reliance, resilience and vulnerability play a vital role in shaping the drought response, it is also essential to study seasonality and autocorrelation of soil moisture and surface flow caused by infiltration and evaporation. Therefore, analysing the impacts of drought on water security through the hydrological cycle and incorporating the sub-surface water resources component would afford a complete depiction and assessment of the satisfactory and non-satisfactory state of water resources and consequently agricultural production in a region. In addition, the impact of seasonality on drought propagation should be further investigated. Seasonality is essential for the proliferation from meteorological to hydrological drought. Finally, the limited availability of hydrological records for observation-based drought studies is a limitation as we anticipate that the analysis period (2021–2050) does not capture the full range of hydrological variability. We anticipate that longer historical records could shed more light on the accumulation periods presented here, although the same regional picture and propagation characteristics would likely emerge. In addition, using simulated data has introduced some uncertainty into the analysis that does not represent transient flow processes typical in dry regions. The dataset tends to overestimate/underestimate the streamflow in arid and semi-arid areas. Therefore, a modelling Rel.Res.Vul index framework is crucial for (semi-) arid areas where hydrological processes differ from those in humid regions. This model has been used to investigate the role of gridded precipitation resolution in rainfed agroecological zones that rely on water stores from streamflow soil moisture and groundwater recharge to make water balance predictions based on seasonal climate projections in the WC. However, a more catchment-based version of this model would provide a better alternative for follow-up studies given the limitations associated with global climate model predictions.

The findings of this research study suggest that the impacts of future climate change induced drought and natural climatic variability will produce more frequent severe water scarcity for higher tier (SSP5–8.5) than is estimated for low tier future climate scenarios (SSP2– 4.5 and SSP3– 7.0) models. The findings of the research suggest an increased vulnerability to severe drought driven water shortages, with increases in both frequency and duration. This is due to a combination of increases in summer temperatures that might lead to an increase in potential evapotranspiration leading to a decline summer rainfall that will exacerbate the probability of summer water shortages. Although the DMA is the authority under which identification, monitoring and reporting on the risks and impacts of cross-scale drought characteristics are triggered, these processes establish the DMA's reactive

approach to disaster risk reduction. However, the DMA encourages provinces, researchers, and other stakeholders to assess risks and prevent the occurrence of disaster by using early warning information and implementing preventive measures such as using water-saving irrigation systems or setting up saving schemes. Additionally, the DMA stresses the need to have operational weather equipment across the country that can assist in diminishing the impacts of droughts –such as a water storage reservoirs and bulk water supply pipelines to transfer water from surplus regions to scarcity regions during droughts.

The findings aligned with findings from Naik & Abiodun (2019) who assessed the impacts of drought in the WC province using both the SPI and Standardised Evapotranspiration Index (SPEI) and identified that droughts have gradually had far-reaching consequences on water availability in the WC province and this continues to cause catastrophic consequences on the environment, society, and economy. While in terms of vulnerability the present study findings revealed a progressive weakening of water resources system between the 2021 and 2050 and this was expected to result in lower than anticipated agricultural yields as the province relied heavily on rainfed agriculture for its sustenance. The results concurred with the reported by Theron et al. (2023) who assessed agricultural resilience and adaptive capacity in the Western Cape during drought conditions and found out that there was a gradual weakening of the natural and physical capital between 2015 and 2015 and argued that this trend was projected to increase unless drought mitigation strategies were implement.

Furthermore, findings of the study indicated that the SI values calculated for the AEZs in arid climates (STWA and STCA) was in the moderate water shortage category (0.6–0.8) with values ranging between 0.62 and 0.71; in the semiarid climate (STCSA and STWSA) it was in the mild water shortage category (0.2–0.4) with values ranging between 0.52 and 0.58, while in the humid climates (STWSH & STCSH) it was in the normal to above normal water condition category with values ranging between 0.08 and 0.19. The findings agree with findings by Ngwenya et al. (2024) who investigated the impacts of meteorological drought using the SPI calculated at 12-months' timescale and reported that the WC can expect the more frequent and severe drought impacts on water availability, in line with the scientific appreciation of the consequences of climate change. These findings presented in the study suggest that the vast majority of Western Cape Province is projected to significantly ($p > 0.05$) be affected by chronic water shortage conditions (particularly in the STWA,

STCA, STCSA and STWSA). Overall, the findings suggested that higher vulnerability and lower reliability and resilience indicators are projected to lead to a higher threat of drought conditions and water resource availability in the AEZs. This implies that natural climate variability will exacerbate vulnerability to drought driven water shortages and this will have severe implications for water resource systems in the western and interior parts of South Africa.

Consequently, the findings presented in this study suggest that water resource managers should focus on strengthening the recovery from persistent drought to diminish the consequences of drought in water stressed AEZs. The study findings suggest that climate change impacts will lead to environmental, societal, and economic degradation because of a decline in agricultural yields and this could be mitigated by the cultivation of drought-resistant and cost-effective crops in these AEZs. The study findings suggest that unmitigated water shortages will result in food shortages, and in severe cases they can trigger water related conflicts. Moreover, in the past few decades the WC province has experienced massive growth in terms of urbanization and irrigated agriculture, and this has increased the water requirements and reduced the soil moisture availability and surface runoff resulting in discernible environment degradation. Therefore, failure to mitigate the negative impacts of drought will considerably affect food security resulting in widespread famine, an increase in food prices and numerous socio-economic concerns. Additionally, a decrease in projected precipitation combined with increases in temperature and evapotranspiration, specifically in the agricultural environments, will cause considerable decline in water storage reservoirs. While numerous water storage reservoirs have been built in the WC province to store water and diminish the impacts of drought, these reservoirs have reduced the downstream flow. In this regard the present study recommends that water resource managers in the WC should also consider anthropological activities such as over abstraction by water users upstream to ensure equitable, efficient, and sustainable availability of water to all users.

For instance, it is crucial for water resource managers to reflect on the effect of upstream water abstraction on downstream water users. Upstream irrigation water requirements particularly in dryland environments affect river flow yield and reliability. Similarly, fluctuations in inflow discharge patterns due to upstream irrigation demands can pointedly impact agricultural production downstream. Therefore, legislative frameworks are required to set restrictions on water use, so as to preserve healthy river systems and environmental health.

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

This chapter of the thesis concludes the research by synthesizing the key findings of the research and proposing recommendations for future research on the subject area. The first section 6.2 summarizes the key findings of the study and how they align with or diverge from the research questions that framed the project. The second section 6.3 outlines recommendations for practitioners, policy makers and academia. The third section 6.4 presents areas of possible future research informed by identified knowledge gaps and then lastly section 6.5 concludes the thesis.

6.2 Summary of Key Findings

This study was motivated by four research questions, namely (i) what are the historical patterns (1980-2020) of precipitation and drought characteristics in the WC Province and how do they impact the availability of water resources;(ii) how will the future (2021-2050) precipitation and drought characteristics in the WC Province under different climate change scenarios affect future water availability; (iii) which climate change scenario will enable sustainable water availability between 2021 and 2050, through which proactive and risk-based water resources management strategies could be pursued to deal with drought related water scarcity in agricultural environments and (iv) what will be the implications of the findings of this study in a wider context, particularly in water stressed regions of sub-Saharan Africa. Finding answers to these research questions involved exploring historical and future climate datasets from satellites and global climate models.

6.2.1 Historical precipitation and drought trends

In response to research question (i), the results of long-term historical (1980-2020) annual precipitation variability in the agroecological zones of Western Cape Province provided a good understanding on how to cope with recurrent droughts. The key findings of the study suggested that between 1980 and 2020, stations located in the STCSA and STWA agro-ecological zones had considerably greater coefficients of variability compared to stations in the STCA, STCSH, STWSA,

and STWSH agro-ecological zones. The agro-ecological zone STWA (Leew Gamka) had the highest level of rainfall variance, measuring at 27%. In comparison, the STCSH Bredasdorp zone had a rainfall variability of 18%. Based on the results collected, all agro-ecological zones show a consistent and negative decline from year to year. The stations located in STCSH, specifically the Ceres and Hermanus districts, showed the most substantial negative trends at a substantial level of 0.05, with rates of -7.8 mm/year and -6.5 mm/year, respectively. Following closely was Malmesbury with a rate of -6.4 mm/year. The findings of this study indicate that extended periods of drought in the study region will substantially affect the water supply and consequently, agricultural productivity. The study findings also emphasize the need for the development of proactive strategies for managing drought and the creation of accurate tools for predicting drought.

6.2.2 Future precipitation and drought trends

In response to research question (ii), the findings of long-term future (2020-2050) annual precipitation variability revealed that under the SSP5–8.5 climate scenario, precipitation is predicted to be between 98 mm in Leew Gamka in STCSA and 314mm in Malmesbury found in STCSH, under the SSP2–4.5 climate scenario the mean annual precipitation was found to be between 250mm in Beaufort West in STWA and 252mm in Murraysburg found in STCA, whilst under the SSP1–2.6 climate scenario the mean annual precipitation was projected to be between 224mm in Leew Gamka in STWA and 311mm in Murraysburg found in STCA. Overall, the results projected that STCSA will likely have the lowest mean annual precipitation under the three climate change scenarios. These results are in parity with those reported by Engelbrecht & Monteiro (2021), that suggested that not only will there be universal decreases in precipitation over southern Africa under the SSP5–8.5 climate change regime but recurrent droughts are also predicted to take place. Similarly, both negative and positive in SSP2–4.5 and SSP1–2.6 climate scenarios were expected to ease off the drought periods across the study period, however the key was that the under the SSP2-4.5 climate scenario less frequent and milder drought and water scarcity conditions were anticipated. These findings implied that in the near term, water availability and consequently agricultural production in the agroecological zones was expected to be substantially better under the SSP2-4.5 climate change scenario in areas that relied mostly on rainfed agriculture.

As such, based on the precipitation trend analysis under the SSP2-4.5 climate change scenario results regions in STWSH (Matroosberg), STCSA (Beaufort West) and STWSA (Oudtshoorn) were predicted to have optimal water availability throughout the near term. The greatest drought magnitude was predicted to happen in the STCSA (Beaufort West) under the SSP2–4.5 climate change scenario. This projection was almost similar with the projection suggested by Botai et al. (2017) who used historical observed station data and reported that in the near term the Western Cape was expected to experience more severe drought incidences unless strict climate change mitigation strategies were implemented. The AEZs that were found close to coastal regions of South Africa revealed mostly positive SPI values, although future drought episodes appeared to become milder, particularly in the western coast because of changes in land–use and land cover patterns.

6.2.3 Proactive and optimal water availability strategies pursued under SSP2-4.5

In response to question (iii) of the research study, both historical (1991-2020) and future (2021-2050) precipitation datasets under the SSP2-4.5 climate scenario were obtained from the sixth version of Model for Interdisciplinary Research on Climate, (MIROC6). Using the Reliability ($R_{el.}$) –Resilience ($R_{es.}$) –Vulnerability ($V_{ul.}$) framework and Standardized Precipitation Index (SPI), the sustainability index (SI) quantified water availability condition in different agroecological zones (AEZs) using the geometric mean method. The key findings from research questions (i) and (ii) suggested that between 2021 and 2050 under the SSP2-4.5 climate scenario drought conditions will aggravate water availability in AEZs compared to the historical observations better than in other climate scenarios. Spatial assessment of SPI–12 values under the SSP2–4.5 climate scenario implied that in stations such as STCSA (Beaufort West), STWA (Leew Gamka), STWSA (Oudtshoorn) and STWSH (Matroosberg) observed extreme drought events will likely have less severe drought conditions under the SSP2–4.5 climate scenario. The findings indicated that in arid climates, future SI, exhibited moderate water shortage ($0.60 < SI < 0.80$), while in semiarid climates future SI values, exhibited mild water shortages ($0.62 < SI < 0.71$); while in the humid climates future SI values projected normal to above normal water availability condition ($0.52 < SI < 0.58$). Overall, trend analysis indicated non-insignificant positive vulnerability trends and significant negative trends for both reliability and resilience indicator.

6.3 Recommendations on key findings of this study in a wider context

In view of the key findings presented above, the study recommends that:

- i. Restoring arid regions provides a huge opportunity to address climate change in this drought prone environment. It is recommended that actions such as preserving soil health can be realised by increasing vegetative plant cover. It is recommended that the crucial element to climate change adaptation in drought prone regions is understanding the importance of local authorities in building resilience. Similarly, other climate adaptation strategies could possibly include planting drought resistant crops, water use efficient cropping practice, crop diversification.
- ii. Integrated drought management strategies need to be adopted by water resource managers in South Africa in response to persistent drought challenges to build resilience to climate change and achieve food security. One of the strategies involved the implementation of a three-pillar drought management plan that involved: (i) drought monitoring and early warning systems (DEWS) This view is supported by Pulwarty and Sivakumar (2014), who added that drought monitoring must be coupled with indigenous knowledge and communication to enhance drought preparedness and early warning systems. Similarly, Glantz (2004) suggested that effective drought monitoring must answer five questions which can be used to mitigate the primary impacts: (i) what are the historical drought characteristics, (ii) which key economic sectors are expected to be affected, (iii) when is it expected to impact, (iv) where are the areas that are more vulnerable, and (v) who are the people most at risk who need to be warned. As such, the evaluation of historical drought characteristics in the present study provided the foundation of a drought plan that enhanced proactive response, and triggers mitigation efforts. The presented study provided timely data and an opportunity for information acquisition, synthesis, and analysis by water resources manager to trigger drought and water scarcity mitigation strategies within a drought management plan. The present study employed drought indicators and indices to provide drought information for water resource managers and farmers, through simplifying complex GCM outputs. The indicators and indices were appropriate for quantitative assessment of drought intensity, duration, and spatial extent. However, indigenous knowledge systems, including traditional knowledge of farmers and

pastoralists, could have been incorporated into drought information systems to enhance community-based solutions.

- iii. Drought impacts on water scarcity indicated by the research study even under the SSP2-4.5 climate scenario, heightened the requirement for more robust drought vulnerability and water scarcity risk assessments. In this regard, the current study proposed that drought vulnerability and risk assessment be viewed as emanating from climatological influences or processes that exacerbated proneness of the WC Province water resource system to the impact of drought. Drought vulnerability and water scarcity assessment in the present focused on providing insight on natural processes (system reliance, resilience, and vulnerability of the WC Province). However, the study noted from a review of literature that despite various government programs, and the development of new tools and technologies, the costs resulting from droughts around the world are still high and rising, indicating growing societal vulnerability to drought, and argued for more research studies in drought vulnerability and water scarcity assessment. The study conducted water sustainability index mapping for vulnerable agroecological zones to assess water scarcity hotspot and recommend mitigation strategies. The DVRA included assessing (i) the frequency or probability of the system being in a satisfactory state during the total assessment period (reliance) (ii) how quickly, on average, a system rebounds to a satisfactory state after reaching an unsatisfactory state; the likely damage to the system caused as a result of an unsatisfactory state (vulnerability). However, drought vulnerability studies are enhanced by identifying vulnerable population groups and communities that include gender, age, ethnicity, dependency on agriculture and livestock, poverty level, and education level). Therefore, the study further recommended the use of integrated approach to analysing water scarcity under drought conditions can provide insight into ecosystem response under changing and undesirable climatic conditions such as drought.
- iv. To promote resilience and eradicate or significantly lessen water scarcity, the research study suggests mitigation and response strategies for drought risk management. The study recommends that national drought management agencies must classify drought mitigation strategies as either structural (growing drought-resistant crops, building hydraulic

infrastructure) or non-structural (policies, laws, and operational procedures that are put in place to lessen the adverse effects of drought). To meet the immediate or short-term life preservation and basic subsistence needs of those affected, the study suggests non-structural strategies to drought management, such as offering support during or immediately after a drought disaster. One can categorize mitigation and response actions into three-time frames: medium, short, and long. Long-term mitigation and response plans need to be developed, according to recommended mitigation strategies, and these plans need to be routinely reviewed. Medium-term strategies are intended to mitigate impacts before they arise and are executed in response to triggers (e.g., preset thresholds of particular drought index values that are supplied by monitoring in early warning systems). In accordance with the long-term strategy for managing drought, immediate relief is provided through the implementation of emergency response or short-term measures in the event of a sudden occurrence of severe to extreme drought.

6.4 Areas of possible future research work

In the present study, one of the constraints was the reliance on the SPI as the sole measure for assessing drought features. The SPI exclusively considers precipitation as a climate variable and disregards other influential factors like temperature, humidity, and wind speed that impact atmospheric water availability. It is therefore recommended that comparable future research endeavors employ alternative metrics such as the Standardized Precipitation Evapotranspiration Index (SPEI), which integrates temperature as an additional factor to evaluate drought attributes. Similarly, other limitations of investigating the impacts of future drought dynamics on water resources were that projections used were not wholly consistent with historical observed data and in terms of periods and boundary forcing. A more consistent set of projections was not available, which is a common state for climate science in the developing world. The most extensive sets of consistently produced climate projections currently existing have been made for Europe. However, an initiative is underway to provide an extensive quality-controlled dataset of future regional climate projections for other regions around the globe—the Coordinated Regional Climate Downscaling Experiment organised under the World Climate Research Programme (WCRP). Africa is a priority region within CORDEX. With a more extensive and consistent set of future climate projections, more detailed

analyses can be performed for assessing impacts on hydrology and water resources, including improved methods to prioritise or weigh results within the ensemble of outcomes.

Another caveat to modelling using the reliance-resilience and vulnerability approach was the assumption that the climate process is stationary. The precipitation time series modelling approach adopts a stationary 1000-year timeline for the SSP5-8.5 climate scenario. However, climate simulations are a quasi-stationary process that change in pseudo-random manner. Despite addressing uncertainties in the quantification of the contribution of the reliability, resilience and vulnerability indicators using the drought entropy method uncertainty was present in other modelling processes. For instance, uncertainties in the climate change scenario were aggregated to by precipitation simulation as well uncertainties in the estimates of the impacts of climate change. Future modelling approach could address the quantification of uncertainty in all the projected stages. Future work should focus on investigating the sensitivity of the Rel.Res.Vul. Index framework using the SPEI thresholds to assess the effectiveness of the methodology to differentiate failure (drought) and non-failure (wet) conditions as determined by the SPI. Furthermore, it is crucial to assess the compound effects of other factors such as human activities on the AEZs.

6.5 Conclusions

To this end, the impact of drought in South Africa, particularly on water availability has prompted various short- and long-term response strategies from disaster management institutions, most of them humanitarian in nature. The South African government, the private sector, and non-profit organizations (NPOs) need to support and encourage early detection, monitoring, prediction, and warning on a variety of weather-, climate-, and water-scarcity hazards. Furthermore, capacity development initiatives on National Drought Management Policies (NDMP) as implemented by WMO, FAO, UNCCD, and the Convention on Biological Diversity (CBD) in partnership with the UN-Water Decade Programme on Capacity Development (UNW-DPC) need to be adopted. Increasing the ability of developing and transitioning nations, particularly South Africa, to create risk-based national drought management policies needs to be the primary objective of collaborative efforts. Likewise, the best data from functional and trustworthy drought monitoring instruments that offer unbiased information for almost real-time drought risk management are necessary for an efficient, proactive risk management strategy. Nevertheless, drought prone nation may have different

requirements for what constitutes a drought, how to monitor drought using climatological and environmental factors, and which kind of drought index to use. Therefore, sharing effective practices for early warning and drought monitoring in drought-affected countries can also act as a model for other nations.

REFERENCES

- Aadhar, S. and Mishra, V. (2020). On the projected decline in droughts over South Asia in CMIP6 multi-model ensemble. *Journal of Geophysical Research: Atmospheres*, 125(20), p.e2020JD033587.
- Abel, G. J., Brottrager, M., Crespo Cuaresma, J., & Muttarak, R. (2019). Climate, conflict and forced migration. *Global Environmental Change*, 54, 239–249. <https://doi.org/10.1016/j.gloenvcha.2018.12.003>
- Abiodun, B. J., Makhanya, N., Petja, B., Abatan, A. A., & Oguntunde, P. G. (2019). Future projection of droughts over major river basins in Southern Africa at specific global warming levels. *Theoretical and Applied Climatology*, 137(3), 1785–1799. <https://doi.org/10.1007/s00704-018-2693-0>
- Adaawen, S. (2021). Understanding climate change and drought perceptions, impact and responses in the rural Savannah, West Africa. *Atmosphere*, 12(5), 594.
- AghaKouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D., & Hain, C. R. (2015). Remote sensing of drought: Progress, challenges and opportunities. *Reviews of Geophysics*, 53(2), 452–480. <https://doi.org/10.1002/2014RG000456>
- Ahmadi, F., Mehdizadeh, S., & Mohammadi, B. (2021). Development of Bio-Inspired- and Wavelet-Based Hybrid Models for Reconnaissance Drought Index Modeling. *Water Resources Management*, 35(12), 4127–4147. <https://doi.org/10.1007/s11269-021-02934-z>
- Alam, J., Saha, P., Mitra, R., & Das, J. (2023). Investigation of spatio-temporal variability of meteorological drought in the Luni River Basin, Rajasthan, India. *Arabian Journal of Geosciences*, 16(3), 201. <https://doi.org/10.1007/s12517-023-11290-8>
- Alhaji, U. U., Yusuf, A. S., Edet, C. O., Oche, C. O., & Agbo, E. P. (2018). Trend Analysis of Temperature in Gombe State Using Mann Kendall Trend Test. *Journal of Scientific Research and Reports*, 1–9. <https://doi.org/10.9734/JSRR/2018/42029>
- Alizadeh, M. R., & Nikoo, M. R. (2018). A fusion-based methodology for meteorological drought estimation using remote sensing data. *Remote Sensing of Environment*, 211, 229–247. <https://doi.org/10.1016/j.rse.2018.04.001>
- Amani, M., Salehi, B., Mahdavi, S., Masjedi, A., & Dehnavi, S. (2017). Temperature-Vegetation-soil Moisture Dryness Index (TVMDI). *Remote Sensing of Environment*, 197, 1–14.

- <https://doi.org/10.1016/j.rse.2017.05.026>
- Anik, A. H., Sultan, M. B., Alam, M., Parvin, F., Ali, M. M., & Tareq, S. M. (2023). The impact of climate change on water resources and associated health risks in Bangladesh: A review. *Water Security*, 18, 100133. <https://doi.org/10.1016/j.wasec.2023.100133>
- Archer, E. R., Engelbrecht, F. A., Hänsler, A., Landman, W., Tadross, M., & Helmschrot, J. (2018). *Seasonal prediction and regional climate projections for southern Africa*. Klaus Hess Publishers. <https://doi.org/10.7809/b-e.00296>
- Archer, E. R. M., Landman, W. A., Tadross, M. A., Malherbe, J., Weepener, H., Maluleke, P., & Marumbwa, F. M. (2017). Understanding the evolution of the 2014–2016 summer rainfall seasons in southern Africa: Key lessons. *Climate Risk Management*, 16, 22–28. <https://doi.org/10.1016/j.crm.2017.03.006>
- Ardiansyah, W., & Ujihanti, M. (2017). Constructivism and Its Perspectives Related to Teaching and Learning Process in The Classroom: A Conceptual Framework. *Tarbawy: Journal Pendidikan Islam*, 4(1), 117-143.
- Arun Kumar, K. C., Reddy, G. P. O., Masilamani, P., Turkar, S. Y., & Sandeep, P. (2021). Integrated drought monitoring index: A tool to monitor agricultural drought by using time-series datasets of space-based earth observation satellites. *Advances in Space Research*, 67(1), 298–315. <https://doi.org/10.1016/j.asr.2020.10.003>
- Asaad, S., & Suleiman, A. (2023). Socio-demographic factors and treated wastewater reuse in the MENA region: insights and implications. *Desalination*, 565, 116830. <https://doi.org/10.1016/j.desal.2023.116830>
- Asefa, T., Clayton, J., Adams, A., & Anderson, D. (2014). Performance evaluation of a water resources system under varying climatic conditions: Reliability, Resilience, Vulnerability and beyond. *Journal of Hydrology*, 508, 53–65. <https://doi.org/10.1016/j.jhydrol.2013.10.043>
- Awal, M. A. (2015). Vulnerability to disaster: Pressure and release model for climate change hazards in Bangladesh. *International journal of environmental monitoring and protection*, 2(2), 15-21.
- Ayugi, B., Eresanya, E. O., Onyango, A. O., Ogou, F. K., Okoro, E. C., Okoye, C. O., Anoruo, C. M., Dike, V. N., Ashiru, O. R., Daramola, M. T., Mumo, R., & Ongoma, V. (2022). Review of Meteorological Drought in Africa: Historical Trends, Impacts, Mitigation Measures, and

- Prospects. *Pure and Applied Geophysics*, 179(4), 1365–1386. <https://doi.org/10.1007/s00024-022-02988-z>
- Aziz, T. (2018). Myth and reality of vulnerability to disaster: Pressure and release model for hazards in Bangladesh. *Journal of South Asian Studies*, 6(1), 23-31.
- Bacon, C. M., Sundstrom, W. A., Stewart, I. T., & Beezer, D. (2017). Vulnerability to Cumulative Hazards: Coping with the Coffee Leaf Rust Outbreak, Drought, and Food Insecurity in Nicaragua. *World Development*, 93, 136–152. <https://doi.org/10.1016/j.worlddev.2016.12.025>
- Baderin, A. (2014). Two forms of realism in political theory. *European Journal of Political Theory*, 13(2), 132–153. <https://doi.org/10.1177/1474885113483284>
- Basak, A., Rahman, A. T. M. S., Das, J., Hosono, T., & Kisi, O. (2022). Drought forecasting using the Prophet model in a semi-arid climate region of western India. *Hydrological Sciences Journal*, 67(9), 1397–1417. <https://doi.org/10.1080/02626667.2022.2082876>
- Baudoin, M. A., Vogel, C., Nortje, K., & 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. <https://doi.org/10.1016/j.ijdrr.2017.05.005>
- Bayissa, Y., Tadesse, T., Demisse, G., & Shiferaw, A. (2017). Evaluation of satellite-based rainfall estimates and application to monitor meteorological drought for the Upper Blue Nile Basin, Ethiopia. *Remote Sensing*, 9(7), 669. Article 7. <https://doi.org/10.3390/rs9070669>
- Bealer, G., & Strawson, P. F. (1992). The Incoherence of Empiricism. *Proceedings of the Aristotelian Society, Supplementary Volumes*, 66, 99–143.
- Beck, G., & Kropp, C. (2011). Infrastructures of risk: A mapping approach towards controversies on risks. *Journal of Risk Research*, 14(1), 1–16. <https://doi.org/10.1080/13669877.2010.505348>
- Beguería, S., Vicente-Serrano, S. M., Reig, F., & 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. <https://doi.org/10.1002/joc.3887>
- Bergaoui, K., Mitchell, D., Zaaboul, R., McDonnell, R., Otto, F., & Allen, M. (2015). 14. The Contribution of Human-Induced Climate Change to the Drought of 2014 in the Southern Levant Region. *Bulletin of the American Meteorological Society*, 96(12), S66–S70.

- Bhaga, T. D., Dube, T., Shekede, M. D., & Shoko, C. (2023). Investigating the effectiveness of Landsat-8 OLI and Sentinel-2 MSI satellite data in monitoring the effects of drought on surface water resources in the Western Cape Province, South Africa. *Remote Sensing Applications: Society and Environment*, 32, 101037. <https://doi.org/10.1016/j.rsase.2023.101037>
- Bhaskar, R. (2008). *A Realist Theory of Science* (1st ed.). Routledge. London. <https://doi.org/10.4324/9780203090732>
- Biasutti, M., Held, I. M., Sobel, A. H., & Giannini, A. (2008). SST Forcings and Sahel Rainfall Variability in Simulations of the Twentieth and Twenty-First Centuries. *Journal of Climate*, 21(14), 3471–3486. <https://doi.org/10.1175/2007JCLI1896.1>
- Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D., Zeil, P., & Welle, T. (2013). Framing vulnerability, risk and societal responses: The MOVE framework. *Natural Hazards*, 67(2), 193–211. <https://doi.org/10.1007/s11069-013-0558-5>
- Birkmann, J., Cutter, S. L., Rothman, D. S., Welle, T., Garschagen, M., van Ruijven, B., O'Neill, B., Preston, B. L., Kienberger, S., Cardona, O. D., Siagian, T., Hidayati, D., Setiadi, N., Binder, C. R., Hughes, B., & Pulwarty, R. (2015). Scenarios for vulnerability: Opportunities and constraints in the context of climate change and disaster risk. *Climatic Change*, 133(1), 53–68. <https://doi.org/10.1007/s10584-013-0913-2>
- Blamey, R. C., Middleton, C., Lennard, C., & Reason, C. J. C. (2017). A climatology of potential severe convective environments across South Africa. *Climate Dynamics*, 49(5), 2161–2178. <https://doi.org/10.1007/s00382-016-3434-7>
- Blamey, R., & Reason, C. (2007). Relationships between Antarctic sea-ice and South African winter rainfall. *Climate Research*, 33, 183–193. <https://doi.org/10.3354/cr033183>
- Bokal, S., Grobicki, A., Kindler, J., & Thalmeinerova, D. (2014). From national to regional plans – the Integrated Drought Management Programme of the Global Water Partnership for Central and Eastern Europe. *Weather and Climate Extremes*, 3, 37–46. <https://doi.org/10.1016/j.wace.2014.03.006>
- Booyesen, M. J., Visser, M., & Burger, R. (2019). Temporal case study of household behavioural response to Cape Town’s “Day Zero” using smart meter data. *Water Research*, 149, 414–420.

- <https://doi.org/10.1016/j.watres.2018.11.035>
- Botai, C. M., Botai, J. O., De Wit, J. P., Ncongwane, K. P., & Adeola, A. M. (2017). Drought characteristics over the western cape province, South Africa. *Water*, 9(11), 876. <https://doi.org/10.3390/w9110876>
- Botai, C. M., Botai, J. O., Dlamini, L. C., Zwane, N. S., & Phaduli, E. (2016). Characteristics of droughts in South Africa: A case study of free state and North West provinces. *Water*, 8(10), 439. <https://doi.org/10.3390/w8100439>
- Botterill, L. C., & Cockfield, G. (2013). *Drought, Risk Management, and Policy: Decision-Making Under Uncertainty*. CRC Press, New York.
- Boukary, A. G., Garba, I., Abdourahamane, Z. S., & Mirzabaev, A. (2023). Proactive policy options for drought resilience in the Sahel region. *Journal of Arid Environments*, 218, 105054. <https://doi.org/10.1016/j.jaridenv.2023.105054>
- Bressers, H., Bressers, N., & Larrue, C. (Eds.). (2016). *Governance for Drought Resilience: Land and Water Drought Management in Europe*. Springer International Publishing. Switzerland <https://doi.org/10.1007/978-3-319-29671-5>
- Brown, J. F., Wardlow, B. D., Tadesse, T., Hayes, M. J., & Reed, B. C. (2008). The Vegetation Drought Response Index (VegDRI): A New Integrated Approach for Monitoring Drought Stress in Vegetation. *GIScience & Remote Sensing*, 45(1), 16–46. <https://doi.org/10.2747/1548-1603.45.1.16>
- Bründl, M., Romang, H. E., Bischof, N., & Rheinberger, C. M. (2009). The risk concept and its application in natural hazard risk management in Switzerland. *Natural Hazards and Earth System Sciences*, 9(3), 801–813. <https://doi.org/10.5194/nhess-9-801-2009>
- Brunner, M. I., Björnson Gurung, A., Zappa, M., Zekollari, H., Farinotti, D., & Stähli, M. (2019). Present and future water scarcity in Switzerland: Potential for alleviation through reservoirs and lakes. *Science of The Total Environment*, 666, 1033–1047. <https://doi.org/10.1016/j.scitotenv.2019.02.169>
- Buitink, J., Swank, A. M., van der Ploeg, M., Smith, N. E., Benninga, H.-J. F., van der Bolt, F., Carranza, C. D. U., Koren, G., van der Velde, R., & Teuling, A. J. (2020). Anatomy of the 2018 agricultural drought in the Netherlands using in situ soil moisture and satellite vegetation indices. *Hydrology and Earth System Sciences*, 24(12), 6021–6031.

- <https://doi.org/10.5194/hess-24-6021-2020>
- Burke, E. J., Brown, S. J., & Christidis, N. (2006). Modeling the Recent Evolution of Global Drought and Projections for the Twenty-First Century with the Hadley Centre Climate Model. *Journal of Hydrometeorology*, 7(5), 1113–1125. <https://doi.org/10.1175/JHM544.1>
- Busby, J. W., Smith, T. G., & Krishnan, N. (2014). Climate security vulnerability in Africa mapping 3.01. *Political Geography*, 43, 51–67. <https://doi.org/10.1016/j.polgeo.2014.10.005>
- Bushra, N., Rohli, R. V., Lam, N. S. N., Zou, L., Mostafiz, R. B., & Mihunov, V. (2019). The relationship between the Normalized Difference Vegetation Index and drought indices in the South Central United States. *Natural Hazards*, 96(2), 791–808. <https://doi.org/10.1007/s11069-019-03569-5>.
- Busico, G., Ntona, M. M., Carvalho, S. C. P., Patrikaki, O., Voudouris, K., & Kazakis, N. (2021). Simulating Future Groundwater Recharge in Coastal and Inland Catchments. *Water Resources Management*, 35(11), 3617–3632. <https://doi.org/10.1007/s11269-021-02907-2>
- Buttafuoco, G., Caloiero, T., Ricca, N., & Guagliardi, I. (2018). Assessment of drought and its uncertainty in a southern Italy area (Calabria region). *Measurement*, 113, 205–210. <https://doi.org/10.1016/j.measurement.2017.08.007>.
- Cai, W., Santoso, A., Collins, M., Dewitte, B., Karamperidou, C., Kug, J.-S., Lengaigne, M., McPhaden, M. J., Stuecker, M. F., Taschetto, A. S., Timmermann, A., Wu, L., Yeh, S.-W., Wang, G., Ng, B., Jia, F., Yang, Y., Ying, J., Zheng, X.-T., ... Zhong, W. (2021). Changing El Niño–Southern Oscillation in a warming climate. *Nature Reviews Earth & Environment*, 2(9), 628–644. <https://doi.org/10.1038/s43017-021-00199-z>
- Calow, R. C., MacDonald, A. M., Nicol, A. L., & Robins, N. S. (2010). Ground Water Security and Drought in Africa: Linking Availability, Access, and Demand. *Groundwater*, 48(2), 246–256. <https://doi.org/10.1111/j.1745-6584.2009.00558.x>
- Calverley, C. M., & Walther, S. C. (2022). Drought, water management, and social equity: Analyzing Cape Town, South Africa's water crisis. *Frontiers in Water*, 4, 910149. <https://www.frontiersin.org/articles/10.3389/frwa.2022.910149>
- Caminade, C., & Terray, L. (2010). Twentieth century Sahel rainfall variability as simulated by the ARPEGE AGCM, and future changes. *Climate Dynamics*, 35(1), 75–94. <https://doi.org/10.1007/s00382-009-0545-4>

- Campbell, B. M., Hansen, J., Rioux, J., Stirling, C. M., Twomlow, S., & (Lini) Wollenberg, E. (2018). Urgent action to combat climate change and its impacts (SDG 13): Transforming agriculture and food systems. *Current Opinion in Environmental Sustainability*, 34, 13–20. <https://doi.org/10.1016/j.cosust.2018.06.005>
- Carvalho, L., Mackay, E. B., Cardoso, A. C., Baattrup-Pedersen, A., Birk, S., Blackstock, K. L., Borics, G., Borja, A., Feld, C. K., Ferreira, M. T., Globevnik, L., Grizzetti, B., Hendry, S., Hering, D., Kelly, M., Langaas, S., Meissner, K., Panagopoulos, Y., Penning, E., Solheim, A. L. (2019). Protecting and restoring Europe's waters: An analysis of the future development needs of the Water Framework Directive. *Science of The Total Environment*, 658, 1228–1238. <https://doi.org/10.1016/j.scitotenv.2018.12.255>
- Cattani, E., Ferguglia, O., Merino, A., & Levizzani, V. (2021). Precipitation products inter-comparison over East and Southern Africa 1983–2017. *Remote Sensing*, 13(21), 4419. <https://doi.org/10.3390/rs13214419>
- Chakraborty, A., Veerasha, P., Ciancio, A., Baskonus, H. M., & Alsulami, M. (2023). The effect of climate change on the dynamics of a modified surface energy balance-mass balance model of Cryosphere under the frame of a non-local operator. *Results in Physics*, 54, 107031. <https://doi.org/10.1016/j.rinp.2023.107031>
- Chamani, R., Vafakhah, M., & Sadeghi, S. H. (2023). Changes in reliability–resilience–vulnerability-based watershed health under climate change scenarios in the Efin Watershed, Iran. *Natural Hazards*, 116(2), 2457–2476. <https://doi.org/10.1007/s11069-022-05774-1>
- Chami, D. E., & Moujabber, M. E. (2016). Drought, climate change and sustainability of water in agriculture: A roadmap towards the NWRS2. *South African Journal of Science*, 112(9–10), 1–4. <https://doi.org/10.17159/sajs.2016/20150457>
- Chandrasekara, S. S., Kwon, H. H., Vithanage, M., Obeysekera, J., & Kim, T. W. (2021). Drought in South Asia: A review of drought assessment and prediction in South Asian countries. *Atmosphere*, 12(3), 369. <https://doi.org/10.3390/atmos12030369>
- Chen, T., Werf, G. R., Jeu, R. a. M., Wang, G., & Dolman, A. J. (2013). A global analysis of the impact of drought on net primary productivity. *Hydrology and Earth System Sciences*, 17(10), 3885–3894. <https://doi.org/10.5194/hess-17-3885-2013>
- Choi, M., Jacobs, J. M., Anderson, M. C., & Bosch, D. D. (2013). Evaluation of drought indices via

- remotely sensed data with hydrological variables. *Journal of Hydrology*, 476, 265–273. <https://doi.org/10.1016/j.jhydrol.2012.10.042>
- Chrisman, J. J. (2019). Stewardship Theory: Realism, Relevance, and Family Firm Governance. *Entrepreneurship Theory and Practice*, 43(6), 1051–1066. <https://doi.org/10.1177/1042258719838472>
- Christensen, J H, Hewitson, B, Busuioc, A, Chen, A, Gao, X, Held, I, Jones, R, Kolli, R K, Kwon, W T, Laprise, R, Magana Rueda, V, Mearns, L, Menendez, C G, Raisanen, J, Rinke, A, Sarr, A, & Whetton, P. *Regional Climate Projections. Chapter 11*. United Kingdom. <https://www.osti.gov/etdeweb/biblio/20962141>
- Citakoglu, H., & Coşkun, Ö. (2022). Comparison of hybrid machine learning methods for the prediction of short-term meteorological droughts of Sakarya Meteorological Station in Turkey. *Environmental Science and Pollution Research*, 29(50), 75487–75511. <https://doi.org/10.1007/s11356-022-21083-3>
- Collins, T. W. (2008). The political ecology of hazard vulnerability: marginalization, facilitation and the production of differential risk to urban wildfires in Arizona's White Mountains. *Journal of Political Ecology*, 15(1), 21-43. <https://doi.org/10.2458/v15i1.21686>
- Conrad, J., Nel, J., & Wentzel, J. (2004). The challenges and implications of assessing groundwater recharge: A case study–northern Sandveld, Western Cape, South Africa. *Water SA*, 30(5), 75–81. <https://doi.org/10.4314/wsa.v30i5.5171>
- Cook, B. I., Mankin, J. S., & Anchukaitis, K. J. (2018). Climate Change and Drought: From Past to Future. *Current Climate Change Reports*, 4(2), 164–179. <https://doi.org/10.1007/s40641-018-0093-2>
- Cooper, P. (2013). Socio-ecological accounting: DPSWR, a modified DPSIR framework, and its application to marine ecosystems. *Ecological Economics*, 94, 106–115. <https://doi.org/10.1016/j.ecolecon.2013.07.010>
- Cosgrove, W. J., & Loucks, D. P. (2015). Water management: Current and future challenges and research directions. *Water Resources Research*, 51(6), 4823–4839. <https://doi.org/10.1002/2014WR016869>
- Cremen, G., Galasso, C., & McCloskey, J. (2022). Modelling and quantifying tomorrow's risks from natural hazards. *Science of the Total Environment*, 817, 152552.

- <https://doi.org/10.1016/j.scitotenv.2021.152552>
- Croke, B. F. W., Ticehurst, J. L., Letcher, R. A., Norton, J. P., Newham, L. T. H., & Jakeman, A. J. (2007). Integrated assessment of water resources: Australian experiences. *Water Resources Management*, 21(1), 351–373. <https://doi.org/10.1007/s11269-006-9057-8>
- Cullis, J., Strzepek, K., Tadross, M., Sami, K., Havenga, B., Gildenhuis, B., & Smith, J. (2011). Incorporating climate change into water resources planning for the town of Polokwane, South Africa. *Climatic Change*, 108(3), 437–456. <https://doi.org/10.1007/s10584-010-9891-9>
- Cuthbert, M. O., Gleeson, T., Moosdorf, N., Befus, K. M., Schneider, A., Hartmann, J., & Lehner, B. (2019). Global patterns and dynamics of climate–groundwater interactions. *Nature Climate Change*, 9(2), 137–141. <https://doi.org/10.1038/s41558-018-0386-4>
- Dai, A. (2013). Increasing drought under global warming in observations and models. *Nature climate change*, 3(1), 52–58. <https://doi.org/10.1038/nclimate1633>
- Daksiya, V., Mandapaka, P. V., & Lo, E. Y. M. (2021). Effect of climate change and urbanisation on flood protection decision-making. *Journal of Flood Risk Management*, 14(1), e12681. <https://doi.org/10.1111/jfr3.12681>
- Dallas, H. F., & Rivers-Moore, N. (2014). Ecological consequences of global climate change for freshwater ecosystems in South Africa. *South African Journal of Science*, 110(5–6), 01–11.
- Das, J., Mandal, T., & Saha, P. (2019). Spatio-temporal trend and change point detection of winter temperature of North Bengal, India. *Spatial Information Research*, 27(4), 411–424. <https://doi.org/10.1007/s41324-019-00241-9>
- De Andrés, M., Barragán, J. M., & Sanabria, J. G. (2018). Ecosystem services and urban development in coastal Social-Ecological Systems: The Bay of Cádiz case study. *Ocean & Coastal Management*, 154, 155–167. <https://doi.org/10.1016/j.ocecoaman.2018.01.011>
- De Brito, M. M. (2021). Compound and cascading drought impacts do not happen by chance: A proposal to quantify their relationships. *Science of the Total Environment*, 778, 146236. <https://doi.org/10.1016/j.scitotenv.2021.146236>
- De Kock, W. M., Blamey, R. C., & Reason, C. J. C. (2022). Large-scale mechanisms linked to anomalously wet summers over the southwestern Cape, South Africa. *Climate Dynamics*, 59(11), 3503–3517. <https://doi.org/10.1007/s00382-022-06280-7>
- Dennis, I., & Dennis, R. (2012). Climate change vulnerability index for South African aquifers. *Water*

- SA, 38(3), 417–426. <https://doi.org/10.10520/EJC121554>
- Diallo, I., Bain, C. L., Gaye, A. T., Moufouma-Okia, W., Niang, C., Dieng, M. D. B., & Graham, R. (2014). Simulation of the West African monsoon onset using the HadGEM3-RA regional climate model. *Climate Dynamics*, 43(3), 575–594. <https://doi.org/10.1007/s00382-014-2219-0>
- Diawoł-Sitko, A. (2020). Scarcity of food: a factor destabilising security in the MENA Region. *Bezpieczeństwo. Teoria i Praktyka*, 38(1), 111-130.
- Dibi-Anoh, P. A., Koné, M., Gerdener, H., Kusche, J., & N'Da, C. K. (2023). Hydrometeorological Extreme Events in West Africa: Droughts. *Surveys in Geophysics*, 44(1), 173–195. <https://doi.org/10.1007/s10712-022-09748-7>
- Dieppoīs, B., Rouault, M., & New, M. (2015). The impact of ENSO on Southern African rainfall in CMIP5 ocean atmosphere coupled climate models. *Climate Dynamics*, 45(9), 2425–2442. <https://doi.org/10.1007/s00382-015-2480-x>
- Diffenbaugh, N. S., Swain, D. L., & Touma, D. (2015). Anthropogenic warming has increased drought risk in California. *Proceedings of the National Academy of Sciences*, 112(13), 3931–3936. <https://doi.org/10.1073/pnas.1422385112>
- Ding, Y., Zhang, S., Zhao, L., Li, Z., & Kang, S. (2019). Global warming weakening the inherent stability of glaciers and permafrost. *Science Bulletin*, 64(4), 245–253. <https://doi.org/10.1016/j.scib.2018.12.028>
- Dong, Q., & Liu, X. (2014). Risk assessment of water security in Haihe River Basin during drought periods based on D-S evidence theory. *Water Science and Engineering*, 7(2), 119–132. <https://doi.org/10.3882/j.issn.1674-2370.2014.02.001>
- Dosio, A., Turner, A. G., Tamoffo, A. T., Sylla, M. B., Lennard, C., Jones, R. G., Terray, L., Nikulin, G., & Hewitson, B. (2020). A tale of two futures: Contrasting scenarios of future precipitation for West Africa from an ensemble of regional climate models. *Environmental Research Letters*, 15(6), 064007. <https://doi.org/10.1088/1748-9326/ab7fde>
- Dost, R., & Kasiviswanathan, K. S. (2023). Quantification of Water Resource Sustainability in Response to Drought Risk Assessment for Afghanistan River Basins. *Natural Resources Research*, 32(1), 235–256. <https://doi.org/10.1007/s11053-022-10129-5>
- Downing, T. E., Ringius, L., Hulme, M., & Waughray, D. (1997). Adapting to Climate Change in

- Africa. *Mitigation and Adaptation Strategies for Global Change*, 2(1), 19–44. <https://doi.org/10.1023/B:MITI.00000004663.31074.64>
- Driver, P., & Reason, C. J. C. (2017). Variability in the Botswana High and its relationships with rainfall and temperature characteristics over southern Africa. *International Journal of Climatology*, 37(S1), 570–581. <https://doi.org/10.1002/joc.5022>
- Du, L., Tian, Q., Yu, T., Meng, Q., Jancso, T., Udvardy, P., & Huang, Y. (2013). A comprehensive drought monitoring method integrating MODIS and TRMM data. *International Journal of Applied Earth Observation and Geoinformation*, 23, 245–253. <https://doi.org/10.1016/j.jag.2012.09.010>
- du Plessis, J. A., & Schloms, B. (2017). An investigation into the evidence of seasonal rainfall pattern shifts in the Western Cape, South Africa. *Journal of the South African Institution of Civil Engineering*, 59(4), 47–55. <https://doi.org/10.17159/2309-8775/2017/v59n4a5>
- Ebi, K. L., & Bowen, K. (2016). Extreme events as sources of health vulnerability: Drought as an example. *Weather and Climate Extremes*, 11, 95–102. <https://doi.org/10.1016/j.wace.2015.10.001>
- Eichler, M. (1997). Feminist Methodology. *Current Sociology*, 45(2), 9–36. <https://doi.org/10.1177/001139297045002003>
- Engelbrecht, C. J., Engelbrecht, F. A., & Dyson, L. L. (2013). High-resolution model-projected changes in mid-tropospheric closed-lows and extreme rainfall events over southern Africa. *International Journal of Climatology*, 33(1), 173–187. <https://doi.org/10.1002/joc.3420>
- Engelbrecht, F. A., & Monteiro, P. M. S. (2021). The IPCC Assessment Report Six Working Group 1 report and southern Africa: Reasons to take action. *South African Journal of Science*, 117(11–12), 1–7. <https://doi.org/10.17159/sajs.2021/12679>
- Eriksen, C., Gill, N., & Bradstock, R. (2011). Trial by Fire: Natural hazards, mixed-methods and cultural research. *Australian Geographer*, 42(1), 19–40. <https://doi.org/10.1080/00049182.2011.546317>
- Estrela, T., Pérez-Martin, M. A., & Vargas, E. (2012). Impacts of climate change on water resources in Spain. *Hydrological Sciences Journal*, 57(6), 1154–1167. <https://doi.org/10.1080/02626667.2012.702213>
- Eyring, V., Cox, P. M., Flato, G. M., Gleckler, P. J., Abramowitz, G., Caldwell, P., & Williamson,

- M. S. (2019). Taking climate model evaluation to the next level. *Nature Climate Change*, 9(2), 102–110. <https://doi.org/10.1038/s41558-018-0355-y>
- Fan, F., Dong, X., Fang, X., Xue, F., Zheng, F., & Zhu, J. (2017). Revisiting the relationship between the South Asian summer monsoon drought and El Niño warming pattern. *Atmospheric Science Letters*, 18(4), 175–182. <https://doi.org/10.1002/asl.740>
- Feizizadeh, B., & Kienberger, S. (2017). Spatially explicit sensitivity and uncertainty analysis for multicriteria-based vulnerability assessment. *Journal of Environmental Planning and Management*, 60(11), 2013–2035. <https://doi.org/10.1080/09640568.2016.1269643>
- Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. *Natural Hazards and Earth System Sciences*, 9(2), 393–403. <https://doi.org/10.5194/nhess-9-393-2009>
- Ferreira, V. G., Montecino, H. D., Yakubu, C. I., & Heck, B. (2016). Uncertainties of the Gravity Recovery and Climate Experiment time-variable gravity-field solutions based on three-cornered hat method. *Journal of applied remote sensing*, 10(1), 015015–015015. <https://doi.org/10.1117/1.JRS.10.015015>
- Ficklin, D. L., Maxwell, J. T., Letsinger, S. L., & Gholizadeh, H. (2015). A climatic deconstruction of recent drought trends in the United States. *Environmental Research Letters*, 10(4), 044009. <https://doi.org/10.1088/1748-9326/10/4/044009>
- Fikileni, S., & Wolski, P. (2022). Framework for implementation of the Pitman-WR2012 model in seasonal hydrological forecasting: a case study of Kraai River, South Africa. *Water SA*, 48(1), 62–74.
- Fitchett, J. M., Grant, B., & Hoogendoorn, G. (2016). Climate change threats to two low-lying South African coastal towns: Risks and perceptions. *South African Journal of Science*, 112(5–6), 1–9. <https://doi.org/10.17159/sajs.2016/20150262>
- Fonseca, M. G., Alves, L. M., Aguiar, A. P. D., Arai, E., Anderson, L. O., Rosan, T. M., Shimabukuro, Y. E., & de Aragão, L. E. O. e C. (2019). Effects of climate and land-use change scenarios on fire probability during the 21st century in the Brazilian Amazon. *Global Change Biology*, 25(9), 2931–2946. <https://doi.org/10.1111/gcb.14709>
- Fontaine, M. M., & Steinemann, A. C. (2009). Assessing Vulnerability to Natural Hazards: Impact-Based Method and Application to Drought in Washington State. *Natural Hazards Review*,

- 10(1), 11–18. [https://doi.org/10.1061/\(ASCE\)1527-6988\(2009\)10:1\(11\)](https://doi.org/10.1061/(ASCE)1527-6988(2009)10:1(11))
- Fooladi, M., Golmohammadi, M. H., Safavi, H. R., & Singh, V. P. (2021). Application of meteorological drought for assessing watershed health using fuzzy-based reliability, resilience, and vulnerability. *International Journal of Disaster Risk Reduction*, 66, 102616. <https://doi.org/10.1016/j.ijdr.2021.102616>
- Fowler, H. J., Blenkinsop, S., & Tebaldi, C. (2007). Linking climate change modelling to impacts studies: Recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*, 27(12), 1547–1578. <https://doi.org/10.1002/joc.1556>
- Fragaszy, S. R., Jedd, T., Wall, N., Knutson, C., Fraj, M. B., Bergaoui, K., Svoboda, M., Hayes, M., & McDonnell, R. (2020). Drought Monitoring in the Middle East and North Africa (MENA) Region: Participatory Engagement to Inform Early Warning Systems. *Bulletin of the American Meteorological Society*, 101(7), E1148–E1173. <https://doi.org/10.1175/BAMS-D-18-0084.1>
- Frischen, J., Meza, I., Rupp, D., Wietler, K., & Hagenlocher, M. (2020). Drought risk to agricultural systems in Zimbabwe: A spatial analysis of hazard, exposure, and vulnerability. *Sustainability*, 12(3), 752. <https://doi.org/10.3390/su12030752>
- Funk, C., & Shukla, S. (2020). *Drought Early Warning and Forecasting: Theory and Practice*. Elsevier.
- Garrote, L., Iglesias, A., & Granados, A. (2018). Country-level assessment of future risk of water scarcity in Europe. *Proceedings of IAHS*, 379, 455–462. <https://doi.org/10.5194/piahs-379-455-2018>
- Garschagen, M., & Kraas, F. (2010). Assessing future resilience to natural hazards—the challenge of capturing dynamic changes under conditions of transformation and climate change. In *Conference proceedings international disaster and risk conference*.
- Gebrechorkos, S. H., Peng, J., Dyer, E., Miralles, D. G., Vicente-Serrano, S. M., Funk, C., Beck, H. E., Asfaw, D. T., Singer, M. B., & Dadson, S. J. (2023). Global high-resolution drought indices for 1981–2022. *Earth System Science Data*, 15(12), 5449–5466. <https://doi.org/10.5194/essd-15-5449-2023>
- Gergis, J., & Henley, B. J. (2017). Southern Hemisphere rainfall variability over the past 200 years. *Climate Dynamics*, 48(7), 2087–2105. <https://doi.org/10.1007/s00382-016-3191-7>

- Gidey, E., Dikinya, O., Sebege, R., Segosebe, E., & Zenebe, A. (2018). Predictions of future meteorological drought hazard (~2070) under the representative concentration path (RCP) 4.5 climate change scenarios in Raya, Northern Ethiopia. *Modeling Earth Systems and Environment*, 4(2), 475–488. <https://doi.org/10.1007/s40808-018-0453-x>
- Godfrey, J. M., & Chalmers, K. (2012). *Water Accounting: International Approaches to Policy and Decision-making*. Edward Elgar Publishing. London.
- González Tánago, I., Urquijo, J., Blauhut, V., Villarroya, F., & De Stefano, L. (2016). Learning from experience: A systematic review of assessments of vulnerability to drought. *Natural Hazards*, 80(2), 951–973. <https://doi.org/10.1007/s11069-015-2006-1>
- Graham, L. P., Andersson, L., Toucher, M. W., Wikner, J. J., & Wilk, J. (2022). Seasonal local rainfall and hydrological forecasting for Limpopo communities – A pragmatic approach. *Climate Services*, 27, 100308. <https://doi.org/10.1016/j.cliser.2022.100308>
- Grasham, C. F., Korzenevica, M., & Charles, K. J. (2019). On considering climate resilience in urban water security: A review of the vulnerability of the urban poor in sub-Saharan Africa. *WIREs Water*, 6(3), e1344. <https://doi.org/10.1002/wat2.1344>
- Grasso, V. F., & Singh, A. (2011). Early warning systems: State-of-art analysis and future directions. *Draft report, UNEP*, 1, 7.
- Greenberg, M., Haas, C., Cox, A., Lowrie, K., McComas, K., & North, W. (2012). Ten Most Important Accomplishments in Risk Analysis, 1980–2010. *Risk Analysis*, 32(5), 771–781. <https://doi.org/10.1111/j.1539-6924.2012.01817.x>
- Greenwood, D. J., & Levin, M. (1998). Action research, science, and the co-optation of social research. *Studies in Cultures, Organizations and Societies*, 4(2), 237–261. <https://doi.org/10.1080/10245289808523514>
- Grobicki, A., MacLeod, F., & Pischke, F. (2015). Integrated policies and practices for flood and drought risk management. *Water Policy*, 17(S1), 180–194. <https://doi.org/10.2166/wp.2015.009>
- Gupta, V., Singh, V., & Jain, M. K. (2020). Assessment of precipitation extremes in India during the 21st century under SSP1-1.9 mitigation scenarios of CMIP6 GCMs. *Journal of Hydrology*, 590, 125422. <https://doi.org/10.1016/j.jhydrol.2020.125422>
- Habiyaremye, A. (2020). Water innovation in South Africa: Mapping innovation successes and

- diffusion constraints. *Environmental Science & Policy*, 114, 217–229. <https://doi.org/10.1016/j.envsci.2020.08.011>
- Hagenlocher, M., & Castro, M. C. (2015). Mapping malaria risk and vulnerability in the United Republic of Tanzania: A spatial explicit model. *Population Health Metrics*, 13(1), 2. <https://doi.org/10.1186/s12963-015-0036-2>
- Hagenlocher, M., Meza, I., Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., Siebert, S., & Sebesvari, Z. (2019). Drought vulnerability and risk assessments: State of the art, persistent gaps, and research agenda. *Environmental Research Letters*, 14(8), 083002. <https://doi.org/10.1088/1748-9326/ab225d>
- Hagenlocher, M., Renaud, F. G., Haas, S., & Sebesvari, Z. (2018). Vulnerability and risk of deltaic social-ecological systems exposed to multiple hazards. *Science of The Total Environment*, 631–632, 71–80. <https://doi.org/10.1016/j.scitotenv.2018.03.013>
- Haile, G. G., Tang, Q., Hosseini-Moghari, S.-M., Liu, X., Gebremicael, T. G., Leng, G., Kebede, A., Xu, X., & Yun, X. (2020). Projected Impacts of Climate Change on Drought Patterns Over East Africa. *Earth's Future*, 8(7), e2020EF001502. <https://doi.org/10.1029/2020EF001502>
- Hanel, M., Rakovec, O., Markonis, Y., Máca, P., Samaniego, L., Kyselý, J., & Kumar, R. (2018). Revisiting the recent European droughts from a long-term perspective. *Scientific reports*, 8(1), 9499. <https://doi.org/10.1038/s41598-018-27464-4>
- Hannaford, J., Collins, K., Haines, S., & Barker, L. J. (2019). Enhancing Drought Monitoring and Early Warning for the United Kingdom through Stakeholder Coinquiries. *Weather, Climate, and Society*, 11(1), 49–63. <https://doi.org/10.1175/WCAS-D-18-0042.1>
- Hao, Z., AghaKouchak, A., Nakhjiri, N., & Farahmand, A. (2014). Global integrated drought monitoring and prediction system. *Scientific data*, 1(1), 1-10. <https://doi.org/10.1038/sdata.2014.1>
- Hao, Z., & Singh, V. P. (2015). Drought characterization from a multivariate perspective: A review. *Journal of Hydrology*, 527, 668–678. <https://doi.org/10.1016/j.jhydrol.2015.05.031>
- Haraguchi, M., & Lall, U. (2015). Flood risks and impacts: A case study of Thailand's floods in 2011 and research questions for supply chain decision making. *International Journal of Disaster Risk Reduction*, 14, 256–272. <https://doi.org/10.1016/j.ijdrr.2014.09.005>
- Harris, L. M. (2020). Assessing states: Water service delivery and evolving state–society relations in

- Accra, Ghana and Cape Town, South Africa. *Environment and Planning C: Politics and Space*, 38(2), 290–311. <https://doi.org/10.1177/2399654419859365>
- Hashimoto, T., Stedinger, J. R., & Loucks, D. P. (1982). Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. *Water Resources Research*, 18(1), 14–20. <https://doi.org/10.1029/WR018i001p00014>
- Hay, E. R., Riemann, K., Van Zyl, G., & Thompson, I. (2012). Ensuring water supply for all towns and villages in the Eastern Cape and Western Cape Provinces of South Africa. *Water SA*, 38(3), 437–444.
- Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (2011). The Lincoln Declaration On Drought Indices: Universal Meteorological Drought Index. *Bulletin of the American Meteorological Society*, 92(4), 485–488.
- Hazbavi, Z., Baartman, J. E. M., Nunes, J. P., Keesstra, S. D., & Sadeghi, S. H. (2018). Changeability of reliability, resilience and vulnerability indicators with respect to drought patterns. *Ecological Indicators*, 87, 196–208. <https://doi.org/10.1016/j.ecolind.2017.12.054>
- Hejazi, M., Santos Da Silva, S. R., Miralles-Wilhelm, F., Kim, S., Kyle, P., Liu, Y., & Clarke, L. (2023). Impacts of water scarcity on agricultural production and electricity generation in the Middle East and North Africa. *Frontiers in Environmental Science*, 11, 1082930. <https://www.frontiersin.org/articles/10.3389/fenvs.2023.1082930>
- Hervás-Gámez, C., & Delgado-Ramos, F. (2019). Drought management planning policy: from Europe to Spain. *Sustainability*, 11(7), 1862. <https://doi.org/10.3390/su11071862>
- Heumann, B. W. (2011). Satellite remote sensing of mangrove forests: Recent advances and future opportunities. *Progress in Physical Geography: Earth and Environment*, 35(1), 87–108. <https://doi.org/10.1177/0309133310385371>
- Hina, S., Saleem, F., Arshad, A., Hina, A., & Ullah, I. (2021). Droughts over Pakistan: Possible cycles, precursors and associated mechanisms. *Geomatics, Natural Hazards and Risk*, 12(1), 1638–1668. <https://doi.org/10.1080/19475705.2021.1938703>
- Hoerling, M., Hurrell, J., Eischeid, J., & Phillips, A. (2006). Detection and Attribution of Twentieth-Century Northern and Southern African Rainfall Change. *Journal of Climate*, 19(16), 3989–4008. <https://doi.org/10.1175/JCLI3842.1>
- Hoque, M. A.-A., Pradhan, B., & Ahmed, N. (2020). Assessing drought vulnerability using geospatial

- techniques in northwestern part of Bangladesh. *Science of The Total Environment*, 705, 135957. <https://doi.org/10.1016/j.scitotenv.2019.135957>
- Hou, W., Feng, G., Yan, P., & Li, S. (2018). Multifractal analysis of the drought area in seven large regions of China from 1961 to 2012. *Meteorology and Atmospheric Physics*, 130(4), 459–471. <https://doi.org/10.1007/s00703-017-0530-0>
- Hsiang, S. M., & Burke, M. (2014). Climate, conflict, and social stability: What does the evidence say? *Climatic Change*, 123(1), 39–55. <https://doi.org/10.1007/s10584-013-0868-3>
- Huo-Po, C., Jian-Qi, S., & Xiao-Li, C. (2013). Future Changes of Drought and Flood Events in China under a Global Warming Scenario. *Atmospheric and Oceanic Science Letters*, 6(1), 8–13. <https://doi.org/10.1080/16742834.2013.11447051>
- Hurtado, S. I., Calianno, M., Adduca, S., & Easdale, M. H. (2023). Drylands becoming drier: Evidence from North Patagonia, Argentina. *Regional Environmental Change*, 23(4), 165. <https://doi.org/10.1007/s10113-023-02160-w>
- Iglesias, A., Quiroga, S., & Diz, A. (2011). Looking into the future of agriculture in a changing climate. *European Review of Agricultural Economics*, 38(3), 427–447. <https://doi.org/10.1093/erae/jbr037>
- Igri, P. M., Tanessong, R. S., Vondou, D. A., Mba, W. P., Jores, T. K., Kaïssassou, S., ... & Yepdo-Djomou, Z. (2022). Evaluation of the Tropical Rainfall Measuring Mission (TRMM) 3B42 and 3B43 products relative to synoptic weather station observations over Cameroon. *Congo basin hydrology, climate, and biogeochemistry: a foundation for the future*, 97-119. <https://doi.org/10.1002/9781119657002.ch7>
- Iizumi, T., Nishimori, M., Dairaku, K., Adachi, S. A., & Yokozawa, M. (2011). Evaluation and intercomparison of downscaled daily precipitation indices over Japan in present-day climate: Strengths and weaknesses of dynamical and bias correction-type statistical downscaling methods. *Journal of Geophysical Research: Atmospheres*, 116(D1). <https://doi.org/10.1029/2010JD014513>
- Ilori, O. W., & Ajayi, V. O. (2020). Change Detection and Trend Analysis of Future Temperature and Rainfall over West Africa. *Earth Systems and Environment*, 4(3), 493–512. <https://doi.org/10.1007/s41748-020-00174-6>
- İrfan, K., & Hatice, Ö. Ç. (2023). Water stress and potential water wars in the MENA

- region. *Scientific Collection «InterConf»*, (157), 32-41.
- Isaak, D. J., Wollrab, S., Horan, D., & Chandler, G. (2012). Climate change effects on stream and river temperatures across the northwest U.S. from 1980–2009 and implications for salmonid fishes. *Climatic Change*, 113(2), 499–524. <https://doi.org/10.1007/s10584-011-0326-z>
- Jacobsen, A.L., Agenbag, L., Esler, K.J., Pratt, R.B., Ewers, F.W. and Davis, S.D., 2007. Xylem density, biomechanics and anatomical traits correlate with water stress in 17 evergreen shrub species of the Mediterranean-type climate region of South Africa. *Journal of Ecology*, 95(1), 171-183.
- Jiao, W., Tian, C., Chang, Q., Novick, K. A., & Wang, L. (2019). A new multi-sensor integrated index for drought monitoring. *Agricultural and Forest Meteorology*, 268, 74–85. <https://doi.org/10.1016/j.agrformet.2019.01.008>
- Johnston, P. (2018). How Western Cape farmers are being hit by the drought. *SABI Magazine - Tydskrif*, 10(4), 40–41. <https://doi.org/10.10520/EJC-e3589c1f1>
- Jurgilevich, A., Räsänen, A., Groundstroem, F., & Juhola, S. (2017). A systematic review of dynamics in climate risk and vulnerability assessments. *Environmental Research Letters*, 12(1), 013002. <https://doi.org/10.1088/1748-9326/aa5508>
- Kam, J., Min, S.-K., Wolski, P., & Kug, J.-S. (2021a). CMIP6 Model-Based Assessment of Anthropogenic Influence on the Long Sustained Western Cape Drought over 2015–19. *Bulletin of the American Meteorological Society*, 102(1), S45–S50.
- Kam, J., Min, S.-K., Wolski, P., & Kug, J.-S. (2021b). CMIP6 Model-Based Assessment of Anthropogenic Influence on the Long Sustained Western Cape Drought over 2015–19. *Bulletin of the American Meteorological Society*, 102(1), S45–S50. <https://doi.org/10.1175/BAMS-D-20-0159.1>
- Kanyoka, P., Farolfi, S., & Morardet, S. (2008). Households' preferences and willingness to pay for multiple use water services in rural areas of South Africa: An analysis based on choice modelling. *Water Sa*, 34(6), 715-723. <https://doi.org/10.4314/wsa.v34i6>
- Kao, S.-C., & Govindaraju, R. S. (2010). A copula-based joint deficit index for droughts. *Journal of Hydrology*, 380(1), 121–134. <https://doi.org/10.1016/j.jhydrol.2009.10.029>
- Kapangaziwiri, E., Hughes, D. A., & Wagener, T. (2012). Incorporating uncertainty in hydrological predictions for gauged and ungauged basins in southern Africa. *Hydrological Sciences*

- Journal*, 57(5), 1000–1019. <https://doi.org/10.1080/02626667.2012.690881>
- Kasei, R., Diekkrüger, B., & Leemhuis, C. (2010). Drought frequency in the Volta Basin of West Africa. *Sustainability Science*, 5(1), 89–97. <https://doi.org/10.1007/s11625-009-0101-5>
- Kchouk, S., Melsen, L. A., Walker, D. W., & van Oel, P. R. (2022). A geography of drought indices: Mismatch between indicators of drought and its impacts on water and food securities. *Natural Hazards and Earth System Sciences*, 22(2), 323–344. <https://doi.org/10.5194/nhess-22-323-2022>
- Kelley, C. P., Mohtadi, S., Cane, M. A., Seager, R., & Kushnir, Y. (2015). Climate change in the Fertile Crescent and implications of the recent Syrian drought. *Proceedings of the National Academy of Sciences*, 112(11), 3241–3246. <https://doi.org/10.1073/pnas.1421533112>
- Kharraz, J. E., El-Sadek, A., Ghaffour, N., & Mino, E. (2012). Water scarcity and drought in WANA countries. *Procedia Engineering*, 33, 14–29. <https://doi.org/10.1016/j.proeng.2012.01.1172>
- Klutse, N. A. B., Ajayi, V. O., Gbobaniyi, E. O., Egbebiyi, T. S., Kouadio, K., Nkrumah, F., Quagraine, K. A., Olusegun, C., Diasso, U., Abiodun, B. J., Lawal, K., Nikulin, G., Lennard, C., & Dosio, A. (2018). Potential impact of 1.5 °C and 2 °C global warming on consecutive dry and wet days over West Africa. *Environmental Research Letters*, 13(5), 055013. <https://doi.org/10.1088/1748-9326/aab37b>
- Kogan, F. N. (1997). Global Drought Watch from Space. *Bulletin of the American Meteorological Society*, 78(4), 621–636. [https://doi.org/10.1175/1520-0477\(1997\)078<0621:GDWFS>2.0.CO;2](https://doi.org/10.1175/1520-0477(1997)078<0621:GDWFS>2.0.CO;2)
- Kornfeld, R. P., Arnold, B. W., Gross, M. A., Dahya, N. T., Klipstein, W. M., Gath, P. F., & Bettadpur, S. (2019). GRACE-FO: The Gravity Recovery and Climate Experiment Follow-On Mission. *Journal of Spacecraft and Rockets*, 56(3), 931–951. <https://doi.org/10.2514/1.A34326>
- Kristensen, P., Whalley, C., Zal, F. N. N., & Christiansen, T. (2018). European waters assessment of status and pressures 2018. *EEA Report*, No.7/2018. <https://www.cabdirect.org/cabdirect/abstract/20193272133>
- Kron, W., Löw, P., & Kundzewicz, Z. W. (2019). Changes in risk of extreme weather events in Europe. *Environmental Science & Policy*, 100, 74–83. <https://doi.org/10.1016/j.envsci.2019.06.007>

- Kruger, A. C., & Sekele, S. S. (2013). Trends in extreme temperature indices in South Africa: 1962–2009. *International Journal of Climatology*, 33(3), 661–676. <https://doi.org/10.1002/joc.3455>
- Kundzewicz, Z. W., Szwed, M., & Pińskwar, I. (2019). Climate variability and floods—A global review. *Water*, 11(7), 1399. <https://doi.org/10.3390/w11071399>
- Kusangaya, S., Warburton, M. L., Archer van Garderen, E., & Jewitt, G. P. W. (2014). Impacts of climate change on water resources in southern Africa: A review. *Physics and Chemistry of the Earth, Parts A/B/C*, 67–69, 47–54. <https://doi.org/10.1016/j.pce.2013.09.014>
- Laaha, G., Gauster, T., Tallaksen, L. M., Vidal, J.-P., Stahl, K., Prudhomme, C., Heudorfer, B., Vlnas, R., Ionita, M., Van Lanen, H. A. J., Adler, M.-J., Caillouet, L., Delus, C., Fendekova, M., Gailliez, S., Hannaford, J., Kingston, D., Van Loon, A. F., Mediero, L., Wong, W. K. (2017). The European 2015 drought from a hydrological perspective. *Hydrology and Earth System Sciences*, 21(6), 3001–3024. <https://doi.org/10.5194/hess-21-3001-2017>
- Laher, H. (2007). Research in practice, Martin Terre Blanche, Kevin Durrheim and Desmond Painter (Eds.): Book review. *African Safety Promotion*, 5(1), 120–122. <https://doi.org/10.10520/EJC93052>
- Lange, S., Volkholz, J., Geiger, T., Zhao, F., Vega, I., Veldkamp, T., Reyser, C. P. O., Warszawski, L., Huber, V., Jägermeyr, J., Schewe, J., Bresch, D. N., Büchner, M., Chang, J., Ciais, P., Dury, M., Emanuel, K., Folberth, C., Gerten, D., Frieler, K. (2020). Projecting Exposure to Extreme Climate Impact Events Across Six Event Categories and Three Spatial Scales. *Earth's Future*, 8(12), e2020EF001616. <https://doi.org/10.1029/2020EF001616>
- Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, 529(7584), 84–87. <https://doi.org/10.1038/nature16467>
- Li, H., Li, Z., Chen, Y., Liu, Y., Hu, Y., Sun, F., & Kayumba, P. M. (2021). Projected meteorological drought over Asian drylands under different CMIP6 scenarios. *Remote Sensing*, 13(21), 4409. <https://doi.org/10.3390/rs13214409>
- Liu, Z., Risi, C., Codron, F., Jian, Z., Wei, Z., He, X., Poulsen, C. J., Wang, Y., Chen, D., Ma, W., Cheng, Y., & Bowen, G. J. (2022). Atmospheric forcing dominates winter Barents-Kara sea ice variability on interannual to decadal time scales. *Proceedings of the National Academy of Sciences*, 119(36), e2120770119. <https://doi.org/10.1073/pnas.2120770119>
- Liverman, D. (2008). Assessing impacts, adaptation and vulnerability: Reflections on the Working

- Group II Report of the Intergovernmental Panel on Climate Change. *Global Environmental Change*, 18(1), 4–7. <https://doi.org/10.1016/j.gloenvcha.2007.09.003>
- Lottering, S., Mafongoya, P., & Lottering, R. (2021). Drought and its impacts on small-scale farmers in sub-Saharan Africa: A review. *South African Geographical Journal*, 103(3), 319–341. <https://doi.org/10.1080/03736245.2020.1795914>
- Loudyi, D., & Kantoush, S. A. (2020). Flood risk management in the Middle East and North Africa (MENA) region. *Urban Water Journal*, 17(5), 379–380. <https://doi.org/10.1080/1573062X.2020.1777754>
- Luo, L., Apps, D., Arcand, S., Xu, H., Pan, M., & Hoerling, M. (2017). Contribution of temperature and precipitation anomalies to the California drought during 2012–2015. *Geophysical Research Letters*, 44(7), 3184–3192. <https://doi.org/10.1002/2016GL072027>
- Lyon, B. (2014). Seasonal Drought in the Greater Horn of Africa and Its Recent Increase during the March–May Long Rains. *Journal of Climate*, 27(21), 7953–7975. <https://doi.org/10.1175/JCLI-D-13-00459.1>
- Ma, L., Li, M., Ma, X., Cheng, L., Du, P., & Liu, Y. (2017). A review of supervised object-based land-cover image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 130, 277–293. <https://doi.org/10.1016/j.isprsjprs.2017.06.001>
- Le Maitre, D., Görgens, A., Howard, G., & Walker, N. (2019). Impacts of alien plant invasions on water resources and yields from the Western Cape Water Supply System (WCWSS). *Water SA*, 45(4), 568–579. <https://doi.org/10.17159/wsa/2019.v45.i4.7538>
- Makaya, E., Rohse, M., Day, R., Vogel, C., Mehta, L., McEwen, L., Rangelcroft, S., & Van Loon, A. F. (2020). Water governance challenges in rural South Africa: Exploring institutional coordination in drought management. *Water Policy*, 22(4), 519–540. <https://doi.org/10.2166/wp.2020.234>
- Manatsa, D., Mushore, T., & Lenouo, A. (2017). Improved predictability of droughts over southern Africa using the standardized precipitation evapotranspiration index and ENSO. *Theoretical and Applied Climatology*, 127(1), 259–274. <https://doi.org/10.1007/s00704-015-1632-6>
- Maponya, P., & Mpandeli, S. (2012). Climate change and agricultural production in South Africa: Impacts and adaptation options. *Journal of Agricultural science*, 4(10), 48. <https://doi.org/10.5539/jas.v4n10p48>

- Martens, B., Schumacher, D. L., Wouters, H., Muñoz-Sabater, J., Verhoest, N. E. C., & Miralles, D. G. (2020). Evaluating the land-surface energy partitioning in ERA5. *Geoscientific Model Development*, 13(9), 4159–4181. <https://doi.org/10.5194/gmd-13-4159-2020>
- Martínez-Fernández, J., Neto, S., Hernández-Mora, N., Moral Ituarte, L. D., & La Roca, F. (2020). The role of the Water Framework Directive in the controversial transition of water policy paradigms in Spain and Portugal. *Water Alternatives*, 13 (3), 1-26.
- Marzi, S., Mysiak, J., Essenfelder, A. H., Pal, J. S., Vernaccini, L., Mistry, M. N., Alfieri, L., Poljansek, K., Marin-Ferrer, M., & Vousdoukas, M. (2021). Assessing future vulnerability and risk of humanitarian crises using climate change and population projections within the INFORM framework. *Global Environmental Change*, 71, 102393. <https://doi.org/10.1016/j.gloenvcha.2021.102393>
- Masih, I., Maskey, S., Mussá, F. E. F., & Trambauer, P. (2014). A review of droughts on the African continent: A geospatial and long-term perspective. *Hydrology and Earth System Sciences*, 18(9), 3635–3649. <https://doi.org/10.5194/hess-18-3635-2014>
- Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, Ö., Yu, R., & Zhou, B. (Eds.). (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. <https://doi.org/10.1017/9781009157896>
- Matchaya, G. C. (2020). Public spending on agriculture in Southern Africa: Sectoral and intra-sectoral impact and policy implications. *Journal of Policy Modeling*, 42(6), 1228–1247. <https://doi.org/10.1016/j.jpolmod.2020.05.002>
- McCuen, R. H., Knight, Z., & Cutter, A. G. (2006). Evaluation of the Nash–Sutcliffe Efficiency Index. *Journal of Hydrologic Engineering*, 11(6), 597–602. [https://doi.org/10.1061/\(ASCE\)1084-0699\(2006\)11:6\(597\)](https://doi.org/10.1061/(ASCE)1084-0699(2006)11:6(597))
- McDonald, R. I., Weber, K., Padowski, J., Flörke, M., Schneider, C., Green, P. A., Gleeson, T., Eckman, S., Lehner, B., Balk, D., Boucher, T., Grill, G., & Montgomery, M. (2014). Water on an urban planet: Urbanization and the reach of urban water infrastructure. *Global Environmental Change*, 27, 96–105. <https://doi.org/10.1016/j.gloenvcha.2014.04.022>

- McKee, T. B., Doesken, N. J., & Kleist, J. (1993, January). The relationship of drought frequency and duration to time scales. In *Proceedings of the 8th Conference on Applied Climatology* 17(22), pp. 179-183).
- Meehl, G. A., Boer, G. J., Covey, C., Latif, M., & Stouffer, R. J. (2000). The Coupled Model Intercomparison Project (CMIP). *Bulletin of the American Meteorological Society*, 81(2), 313–318.
- Meehl, G. A., Washington, W. M., Arblaster, J. M., Hu, A., Teng, H., Tebaldi, C., Sanderson, B. N., Lamarque, J.-F., Conley, A., Strand, W. G., & White, J. B. (2012). Climate System Response to External Forcings and Climate Change Projections in CCSM4. *Journal of Climate*, 25(11), 3661–3683. <https://doi.org/10.1175/JCLI-D-11-00240.1>
- Mehran, A., Mazdiyasni, O., & AghaKouchak, A. (2015). A hybrid framework for assessing socioeconomic drought: Linking climate variability, local resilience, and demand. *Journal of Geophysical Research: Atmospheres*, 120(15), 7520–7533. <https://doi.org/10.1002/2015JD023147>
- Meissner, H. H., Scholtz, M. M., & Engelbrecht, F. A. (2013). Sustainability of the South African Livestock Sector towards 2050 Part 2: Challenges, changes and required implementations. *South African Journal of Animal Science*, 43(3), 289-319. <https://doi.org/10.4314/sajas.v43i3.6>
- Memon, A., & Shah, N. (2019). Assessment and Comparison of SPI and RDI Meteorological Drought Indices in Panchmahals District of Gujarat, India. *International Journal of Current Microbiology and Applied Sciences*, 8, 1995–2004. <https://doi.org/10.20546/ijcmas.2019.808.233>
- Mirgol, B., Nazari, M., Etedali, H. R., & Zamanian, K. (2021). Past and future drought trends, duration, and frequency in the semi-arid Urmia Lake Basin under a changing climate. *Meteorological Applications*, 28(4), e2009. <https://doi.org/10.1002/met.2009>
- Mirza, M. M. Q. (2003). Climate change and extreme weather events: Can developing countries adapt? *Climate Policy*, 3(3), 233–248. <https://doi.org/10.3763/cpol.2003.0330>
- Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, 391(1), 202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>
- Mishra, A. K., & Singh, V. P. (2011). Drought modeling – A review. *Journal of Hydrology*, 403(1),

- 157–175. <https://doi.org/10.1016/j.jhydrol.2011.03.049>
- Mishra, S. S., & Nagarajan, R. (2011). Spatio-temporal drought assessment in Tel river basin using Standardized Precipitation Index (SPI) and GIS. *Geomatics, Natural Hazards and Risk*, 2(1), 79–93. <https://doi.org/10.1080/19475705.2010.533703>
- Miyan, M. A. (2015). Droughts in Asian Least Developed Countries: Vulnerability and sustainability. *Weather and Climate Extremes*, 7, 8–23. <https://doi.org/10.1016/j.wace.2014.06.003>
- Mizutori, M. (2020). Reflections on the Sendai Framework for Disaster Risk Reduction: Five Years Since Its Adoption. *International Journal of Disaster Risk Science*, 11(2), 147–151. <https://doi.org/10.1007/s13753-020-00261-2>
- Mohleji, S., & Pielke, R. (2014). Reconciliation of Trends in Global and Regional Economic Losses from Weather Events: 1980–2008. *Natural Hazards Review*, 15(4), 04014009. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000141](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000141)
- Mohammed, A., Zhang, K., Kabenge, M., Keesstra, S., Cerdà, A., Reuben, M., Elbashier, M. M. A., Dalson, T., & Ali, A. A. S. (2018). Analysis of drought and vulnerability in the North Darfur region of Sudan. *Land Degradation & Development*, 29(12), 4424–4438. <https://doi.org/10.1002/ldr.3180>
- Meissner, H. H., Scholtz, M. M., & Engelbrecht, F. A. (2013). Sustainability of the South African Livestock Sector towards 2050 Part 2: Challenges, changes and required implementations. *South African Journal of Animal Science*, 43(3), 289–319.
- Mortoja, Md. G., & Yigitcanlar, T. (2022). Are climate change, urbanisation and political views correlated? Empirical evidence from South East Queensland. *Urban Climate*, 41, 101061. <https://doi.org/10.1016/j.uclim.2021.101061>
- Mostafazadeh, R., & Zabihi, M. (2016). Comparison of SPI and SPEI indices to meteorological drought assessment using R programming (Case study: Kurdistan Province). *Journal of the Earth and Space Physics*, 42, 633–643.
- Mugido, W., & Shackleton, C. M. (2017). The safety net function of NTFPs in different agro-ecological zones of South Africa. *Population and Environment*, 39(1), 107–125. <https://doi.org/10.1007/s11111-017-0285-z>
- Mugiyo, H., Magadzire, T., Choruma, D. J., Chimonyo, V. G. P., Manzou, R., Jiri, O., & Mabhaudhi, T. (2023). El Niño's effects on Southern African agriculture in 2023/24 and anticipatory

- action strategies to reduce the impacts in Zimbabwe. *Atmosphere*, 14(11), 1692. <https://doi.org/10.3390/atmos14111692>
- Muimba-Kankolongu, A. (2018). *Food Crop Production by Smallholder Farmers in Southern Africa: Challenges and Opportunities for Improvement*. Academic Press.
- Murphy, C., & Gardoni, P. (2006). The Role of Society in Engineering Risk Analysis: A Capabilities-Based Approach. *Risk Analysis*, 26(4), 1073–1083. <https://doi.org/10.1111/j.1539-6924.2006.00801.x>
- Musyimi, P. K., Nduru, G. M., Huho, J. M., & Opiyo, F. E. (2018). Households' perceptions on impact of drought on water resources in Makindu sub-county, Kenya. *African Research Review*, 12(3), 64-73. <https://doi.org/10.4314/afrrrev.v12i3.7>
- Mwangi, E., Wetterhall, F., Dutra, E., Di Giuseppe, F., & Pappenberger, F. (2014). Forecasting droughts in East Africa. *Hydrology and Earth System Sciences*, 18(2), 611–620. <https://doi.org/10.5194/hess-18-611-2014>
- Naik, M., & Abiodun, B. J. (2020). Projected changes in drought characteristics over the Western Cape, South Africa. *Meteorological Applications*, 27(1), e1802. <https://doi.org/10.1002/met.1802>
- Nam, W.-H., Hayes, M. J., Svoboda, M. D., Tadesse, T., & Wilhite, D. A. (2015). Drought hazard assessment in the context of climate change for South Korea. *Agricultural Water Management*, 160, 106–117. <https://doi.org/10.1016/j.agwat.2015.06.029>
- Namdar, R., Karami, E., & Keshavarz, M. (2021). Climate change and vulnerability: the case of MENA countries. *ISPRS International Journal of Geo-Information*, 10(11), 794. <https://doi.org/10.3390/ijgi10110794>
- Nasrollahi, M., Khosravi, H., Moghaddamnia, A., Malekian, A., & Shahid, S. (2018). Assessment of drought risk index using drought hazard and vulnerability indices. *Arabian Journal of Geosciences*, 11(20), 606. <https://doi.org/10.1007/s12517-018-3971-y>
- Nazari, S., Rad, G. P., Sedighi, H., & Azadi, H. (2015). Vulnerability of wheat farmers: Toward a conceptual framework. *Ecological Indicators*, 52, 517–532. <https://doi.org/10.1016/j.ecolind.2015.01.006>
- Ndebele, N. E., Grab, S., & Turasie, A. (2020). Characterizing rainfall in the south-western Cape, South Africa: 1841–2016. *International Journal of Climatology*, 40(4), 1992–2014.

<https://doi.org/10.1002/joc.6314>

- Ngaka, M. J. (2012). Drought preparedness, impact and response: A case of the Eastern Cape and Free State provinces of South Africa : original research. *Jamba : Journal of Disaster Risk Studies*, 4(1), 1–10. <https://doi.org/10.4102/jamba.v4i1.47>
- Ngcamu, B. S., & Chari, F. (2020). Drought influences on food insecurity in Africa: a systematic literature review. *International Journal of Environmental Research and Public Health*, 17(16), 5897. <https://doi.org/10.3390/ijerph17165897>
- Nhamo, L., Mabhaudhi, T., & Modi, A. T. (2019). Preparedness or repeated short-term relief aid? Building drought resilience through early warning in southern Africa. *Water SA*, 45(1), 75–85. <https://doi.org/10.4314/wsa.v45i1.09>
- Nhemachena, C., Nhamo, L., Matchaya, G., Nhemachena, C. R., Muchara, B., Karuaihe, S. T., & Mpandeli, S. (2020). Climate change impacts on water and agriculture sectors in Southern Africa: Threats and opportunities for sustainable development. *Water*, 12(10), 2673. <https://doi.org/10.3390/w12102673>
- Niang, A., Scheren, P., Diop, S., Kane, C., & Koulibaly, C. T. (2019). Chapter 18 - The Senegal and Pangani Rivers: Examples of Over-Used River Systems Within Water-Stressed Environments in Africa. In E. Wolanski, J. W. Day, M. Elliott, & R. Ramachandran (Eds.), *Coasts and Estuaries* (pp. 311–320). Elsevier. <https://doi.org/10.1016/B978-0-12-814003-1.00018-6>
- Nicholson, S. E. (2018). The ITCZ and the Seasonal Cycle over Equatorial Africa. *Bulletin of the American Meteorological Society*, 99(2), 337–348. <https://doi.org/10.1175/BAMS-D-16-0287.1>
- Nkhonjera, G. K. (2017). Understanding the impact of climate change on the dwindling water resources of South Africa, focusing mainly on Olifants River basin: A review. *Environmental Science & Policy*, 71, 19–29. <https://doi.org/10.1016/j.envsci.2017.02.004>
- Núñez, J., Rivera, D., Oyarzún, R., & Arumí, J. L. (2014). On the use of Standardized Drought Indices under decadal climate variability: Critical assessment and drought policy implications. *Journal of Hydrology*, 517, 458–470. <https://doi.org/10.1016/j.jhydrol.2014.05.038>
- Nurbekov, A., & Mirzabaev, A. (2017). Strengthening Agricultural Resilience against Droughts in Uzbekistan: *From Crisis Management to Drought Risk Mitigation*.
- Nyam, Y. S., Kotir, J. H., Jordaan, A. J., Ogundeji, A. A., & Turton, A. R. (2020). Drivers of change

- in sustainable water management and agricultural development in South Africa: A participatory approach. *Sustainable Water Resources Management*, 6(4), 62. <https://doi.org/10.1007/s40899-020-00420-9>
- Odongo, R. A., De Moel, H., & Van Loon, A. F. (2023). Propagation from meteorological to hydrological drought in the Horn of Africa using both standardized and threshold-based indices. *Natural Hazards and Earth System Sciences*, 23(6), 2365–2386. <https://doi.org/10.5194/nhess-23-2365-2023>
- OGO, F. K., YANG, Q., DUAN, Y., & MA, Z. (2019). Comparative analysis of interdecadal precipitation variability over central North China and sub Saharan Africa. *Atmospheric and Oceanic Science Letters*, 12(3), 201–207. <https://doi.org/10.1080/16742834.2019.1593040>
- Ojara, M. A., Yunsheng, L., Babaousmail, H., Sempa, A. K., Ayugi, B., & Ogwang, B. A. (2022). Evaluation of Drought, Wet Events, and Climate Variability Impacts on Maize Crop Yields in East Africa During 1981–2017. *International Journal of Plant Production*, 16(1), 41–62. <https://doi.org/10.1007/s42106-021-00178-w>
- Okal, H. A., Ngetich, F. K., & Okeyo, J. M. (2020). Spatio-temporal characterisation of droughts using selected indices in Upper Tana River watershed, Kenya. *Scientific African*, 7, e00275. <https://doi.org/10.1016/j.sciaf.2020.e00275>
- Oki, T., & Kanae, S. (2006). Global Hydrological Cycles and World Water Resources. *Science*, 313(5790), 1068–1072. <https://doi.org/10.1126/science.1128845>
- Omodan, B. I. (2022). The potency of social constructivism on classroom productivity in universities. *Studies in Learning and Teaching*, 3(1), 36-45. <https://doi.org/10.46627/silet.v3i1.97>
- O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., van Ruijven, B. J., van Vuuren, D. P., Birkmann, J., Kok, K., Levy, M., & Solecki, W. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global Environmental Change*, 42, 169–180. <https://doi.org/10.1016/j.gloenvcha.2015.01.004>
- Ongoma, V., Chen, H., Gao, C., Nyongesa, A. M., & Polong, F. (2018). Future changes in climate extremes over Equatorial East Africa based on CMIP5 multimodel ensemble. *Natural Hazards*, 90(2), 901–920. <https://doi.org/10.1007/s11069-017-3079-9>
- Orimoloye, I. R., Ololade, O. O., Mazinyo, S. P., Kalumba, A. M., Ekundayo, O. Y., Busayo, E. T.,

- Akinsanola, A. A., & Nel, W. (2019). Spatial assessment of drought severity in Cape Town area, South Africa. *Heliyon*, 5(7), e02148. <https://doi.org/10.1016/j.heliyon.2019.e02148>
- Oroud, I. M., & Balling, R. C. (2021). The utility of combining optical and thermal images in monitoring agricultural drought in semiarid mediterranean environments. *Journal of Arid Environments*, 189, 104499. <https://doi.org/10.1016/j.jaridenv.2021.104499>
- Ortega-Gaucin, D., Ceballos-Tavares, J. A., Ordoñez Sánchez, A., & Castellano-Bahena, H. V. (2021). Agricultural drought risk assessment: A spatial analysis of hazard, exposure, and vulnerability in Zacatecas, Mexico. *Water*, 13(10), 1431. <https://doi.org/10.3390/w13101431>
- Orth, R., & Destouni, G. (2018). Drought reduces blue-water fluxes more strongly than green-water fluxes in Europe. *Nature communications*, 9(1), 3602. <https://doi.org/10.1038/s41467-018-06013-7>
- Otieno, F. A., & Ochieng, G. M. (2004). Water management tools as a means of averting a possible water scarcity in South Africa by the year 2025. *Water Sa*, 30(5), 120-124.
- Otto, F. E. L., Wolski, P., Lehner, F., Tebaldi, C., Oldenborgh, G. J. van, Hogesteeger, S., Singh, R., Holden, P., Fučkar, N. S., Odoulami, R. C., & New, M. (2018). Anthropogenic influence on the drivers of the Western Cape drought 2015–2017. *Environmental Research Letters*, 13(12), 124010. <https://doi.org/10.1088/1748-9326/aae9f9>
- Paavola, J. (2008). Livelihoods, vulnerability and adaptation to climate change in Morogoro, Tanzania. *Environmental Science & Policy*, 11(7), 642–654. <https://doi.org/10.1016/j.envsci.2008.06.002>
- Palanisamy, B., Narasimhan, B., Paul, S., Srinivasan, R., Wangpimool, W., Sith, R., & Sayasane, R. (2023). Development and propagation of hydrologic drought from meteorological and agricultural drought in the Mekong River Basin. *Hydrological Processes*, 37(7), e14935. <https://doi.org/10.1002/hyp.14935>
- Palmer, W. C., & Drought, M. (1965). US Department of Commerce. *Weather Bureau, Washington, DC, USA*.
- Pamla, A., Thondhlana, G., & Ruwanza, S. (2021). Persistent droughts and water scarcity: households' perceptions and practices in Makhanda, South Africa. *Land*, 10(6), 593. <https://doi.org/10.3390/land10060593>
- Park, C.-K., Byun, H.-R., Deo, R., & Lee, B.-R. (2015). Drought prediction till 2100 under RCP 8.5

- climate change scenarios for Korea. *Journal of Hydrology*, 526, 221–230. <https://doi.org/10.1016/j.jhydrol.2014.10.043>
- Patton, M. Q. (2002). Two Decades of Developments in Qualitative Inquiry: A Personal, Experiential Perspective. *Qualitative Social Work*, 1(3), 261–283. <https://doi.org/10.1177/1473325002001003636>
- Pamla, A., Thondhlana, G., & Ruwanza, S. (2021). Persistent droughts and water scarcity: households' perceptions and practices in Makhanda, South Africa. *Land*, 10(6), 593. <https://doi.org/10.3390/w12041135>
- Pedro-Monzonís, M., Solera, A., Ferrer, J., Estrela, T., & Paredes-Arquiola, J. (2015). A review of water scarcity and drought indexes in water resources planning and management. *Journal of Hydrology*, 527, 482–493. <https://doi.org/10.1016/j.jhydrol.2015.05.003>
- Peng, S., Wang, C., Li, Z., Mihara, K., Kuramochi, K., Toma, Y., & Hatano, R. (2023). Climate change multi-model projections in CMIP6 scenarios in Central Hokkaido, Japan. *Scientific Reports*, 13(1), 230. <https://doi.org/10.1038/s41598-022-27357-7>
- Pereira, L. (2017). Climate Change Impacts on Agriculture across Africa. In L. Pereira, *Oxford Research Encyclopedia of Environmental Science*. Oxford University Press. <https://doi.org/10.1093/acrefore/9780199389414.013.292>
- Perkins, D. M., Reiss, J., Yvon-Durocher, G., & Woodward, G. (2010). Global change and food webs in running waters. *Hydrobiologia*, 657(1), 181–198. <https://doi.org/10.1007/s10750-009-0080-7>
- Phelps, D., & Kelly, D. (2019). Overcoming drought vulnerability in rangeland communities: Lessons from central-western Queensland. *The Rangeland Journal*, 41(3), 251–270. <https://doi.org/10.1071/RJ18052>
- Piao, J., Chen, W., Wang, L., & Chen, S. (2022). Future projections of precipitation, surface temperatures and drought events over the monsoon transitional zone in China from bias-corrected CMIP6 models. *International Journal of Climatology*, 42(2), 1203–1219. <https://doi.org/10.1002/joc.7297>
- Piao, S., & Wang, X. (2023). Biological systems under climate change: What do we learn from the IPCC AR6. *Global Change Biology*, 29(18), 5120–5121. <https://doi.org/10.1111/gcb.16857>
- Pires de Souza Araujo, A. C., Souza dos Santos, D., Lins-de-Barros, F., & de Souza Hacon, S. (2021).

- Linking ecosystem services and human health in coastal urban planning by DPSIWR framework. *Ocean & Coastal Management*, 210, 105728. <https://doi.org/10.1016/j.ocecoaman.2021.105728>
- Pittman, J., Wittrock, V., Kulshreshtha, S., & Wheaton, E. (2011). Vulnerability to climate change in rural Saskatchewan: Case study of the Rural Municipality of Rudy No. 284. *Journal of Rural Studies*, 27(1), 83–94. <https://doi.org/10.1016/j.jrurstud.2010.07.004>
- Poornima, S., & Pushpalatha, M. (2019). Drought prediction based on SPI and SPEI with varying timescales using LSTM recurrent neural network. *Soft Computing*, 23(18), 8399–8412. <https://doi.org/10.1007/s00500-019-04120-1>
- Qin, J., Su, B., Tao, H., Wang, Y., Huang, J., & Jiang, T. (2021). Projection of temperature and precipitation under SSPs-RCPs Scenarios over northwest China. *Frontiers of Earth Science*, 15(1), 23–37. <https://doi.org/10.1007/s11707-020-0847-8>
- Quenum, G. M. L. D., Klutse, N. A. B., Dieng, D., Laux, P., Arnault, J., Kodja, Japhet. D., & Oguntunde, P. G. (2019). Identification of Potential Drought Areas in West Africa Under Climate Change and Variability. *Earth Systems and Environment*, 3(3), 429–444. <https://doi.org/10.1007/s41748-019-00133-w>
- Quiring, S. M. (2009). Developing Objective Operational Definitions for Monitoring Drought. *Journal of Applied Meteorology and Climatology*, 48(6), 1217–1229. <https://doi.org/10.1175/2009JAMC2088.1>
- Rahman, A. T. M. S., Jahan, C. S., Mazumder, Q. H., Kamruzzaman, Md., & Hosono, T. (2017). Drought analysis and its implication in sustainable water resource management in Barind area, Bangladesh. *Journal of the Geological Society of India*, 89(1), 47–56. <https://doi.org/10.1007/s12594-017-0557-3>
- Rajasekar, D. D., & Verma, D. R. (2020). *Research Methodology*. Archers & Elevators Publishing House.
- Rajeev, M. M. (2022). The Impact of Climate Change on Water Resources: Lessons from Villages of Tonk District of Rajasthan, India. *Journal of Climate Change*, 8(4), 35–42. <https://doi.org/10.3233/JCC220028>
- Raji, S. A., Odunuga, S., & Fasona, M. (2021). Quantifying ecosystem service interactions to support environmental restoration in a tropical semi-arid basin. *Acta Geophysica*, 69(5), 1813–1841.

- <https://doi.org/10.1007/s11600-021-00644-z>
- Rajsekhar, D., & Gorelick, S. M. (2017). Increasing drought in Jordan: Climate change and cascading Syrian land-use impacts on reducing transboundary flow. *Science Advances*, 3(8), e1700581. <https://doi.org/10.1126/sciadv.1700581>
- Ramonet, M., Ciais, P., Apadula, F., Bartyzel, J., Bastos, A., Bergamaschi, P., Blanc, P. E., Brunner, D., Caracciolo di Torchiariolo, L., Calzolari, F., Chen, H., Chmura, L., Colomb, A., Conil, S., Cristofanelli, P., Cuevas, E., Curcoll, R., Delmotte, M., di Sarra, A., ... Yver Kwok, C. (2020). The fingerprint of the summer 2018 drought in Europe on ground-based atmospheric CO₂ measurements. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 375(1810), 20190513. <https://doi.org/10.1098/rstb.2019.0513>
- Ramos, E. P., Howells, M., Sridharan, V., Engström, R. E., Taliotis, C., Mentis, D., Gardumi, F., de Strasser, L., Pappis, I., & Balderrama, G. P. (2021). The climate, land, energy, and water systems (CLEWs) framework: A retrospective of activities and advances to 2019. *Environmental Research Letters*, 16(3), 033003.
- Raphael Muli Wambua, R. M., Mutua, B. M., & Raude, J. M. (2018). Analysis of drought and wet-events using SWSI-based severity-duration-frequency (SDF) curves for the upper Tana river basin, Kenya. <https://doi.org/10.11648/j.hyd.20180602.11>
- Rashid, Md. M., Beecham, S., & Chowdhury, R. K. (2017). Simulation of extreme rainfall and projection of future changes using the GLIMCLIM model. *Theoretical and Applied Climatology*, 130(1), 453–466. <https://doi.org/10.1007/s00704-016-1892-9>
- Wambua, R. M., Mutua, B. M., & Raude, J. M. (2018). Detection of spatial, temporal and trend of meteorological drought using standardized precipitation index (SPI) and effective drought index (EDI) in the Upper Tana River Basin, Kenya. *Open Journal of Modern Hydrology*, 8(3), 83-100. <https://doi.org/10.4236/ojmh.2018.83007>
- Rawlins, J. (2019). Political economy of water reallocation in South Africa: Insights from the Western Cape water crisis. *Water Security*, 6, 100029. <https://doi.org/10.1016/j.wasec.2019.100029>
- Raziei, T. (2021). Revisiting the rainfall anomaly index to serve as a simplified standardized precipitation index. *Journal of Hydrology*, 602, 126761. <https://doi.org/10.1016/j.jhydrol.2021.126761>
- Reason, C. J. C., & Rouault, M. (2005). Links between the Antarctic Oscillation and winter rainfall

- over western South Africa. *Geophysical Research Letters*, 32(7).
<https://doi.org/10.1029/2005GL022419>
- Reyjol, Y., Argillier, C., Bonne, W., Borja, A., Buijse, A. D., Cardoso, A. C., Daufresne, M., Kernan, M., Ferreira, M. T., Poikane, S., Prat, N., Solheim, A.-L., Stroffek, S., Usseglio-Polatera, P., Villeneuve, B., & van de Bund, W. (2014). Assessing the ecological status in the context of the European Water Framework Directive: Where do we go now? *Science of The Total Environment*, 497–498, 332–344. <https://doi.org/10.1016/j.scitotenv.2014.07.119>
- Rhee, J., Park, K., Lee, S., Jang, S., & Yoon, S. (2020). Detecting hydrological droughts in ungauged areas from remotely sensed hydro-meteorological variables using rule-based models. *Natural Hazards*, 103(3), 2961–2988. <https://doi.org/10.1007/s11069-020-04114-5>
- Richardson, C. W. (1981). Stochastic simulation of daily precipitation, temperature, and solar radiation. *Water Resources Research*, 17(1), 182–190.
<https://doi.org/10.1029/WR017i001p00182>
- Rodrigues, D. T., Gonçalves, W. A., Spyrides, M. H. C., & Santos e Silva, C. M. (2020). Spatial and temporal assessment of the extreme and daily precipitation of the Tropical Rainfall Measuring Mission satellite in Northeast Brazil. *International Journal of Remote Sensing*, 41(2), 549–572. <https://doi.org/10.1080/01431161.2019.1643940>
- Rogelj, J., Meinshausen, M., & Knutti, R. (2012). Global warming under old and new scenarios using IPCC climate sensitivity range estimates. *Nature climate change*, 2(4), 248–253.
<https://doi.org/10.1038/nclimate1385>
- Rossi, E., & Sleat, M. (2014). Realism in Normative Political Theory. *Philosophy Compass*, 9(10), 689–701. <https://doi.org/10.1111/phc3.12148>
- Rossi, G., & Cancelliere, A. (2013). Managing drought risk in water supply systems in Europe: A review. *International Journal of Water Resources Development*, 29(2), 272–289.
<https://doi.org/10.1080/07900627.2012.713848>
- Prinz, J., & Rossi, E. (2018).: Political realism as ideology critique. In *Realism in Political Theory* (pp. 80-97). Routledge.
- Rowell, D. P. (2001). Teleconnections between the tropical Pacific and the Sahel. *Quarterly Journal of the Royal Meteorological Society*, 127(575), 1683–1706.
<https://doi.org/10.1002/qj.49712757512>

- Rusk, J., Maharjan, A., Tiwari, P., Chen, T.-H. K., Shneiderman, S., Turin, M., & Seto, K. C. (2022). Multi-hazard susceptibility and exposure assessment of the Hindu Kush Himalaya. *Science of The Total Environment*, 804, 150039. <https://doi.org/10.1016/j.scitotenv.2021.150039>
- S. Pulwarty, R., & Sivakumar, M. V. K. (2014). Information systems in a changing climate: Early warnings and drought risk management. *Weather and Climate Extremes*, 3, 14–21. <https://doi.org/10.1016/j.wace.2014.03.005>
- Sabater, S., Bregoli, F., Acuña, V., Barceló, D., Elozegi, A., Ginebreda, A., & Ferreira, V. (2018). Effects of human-driven water stress on river ecosystems: a meta-analysis. *Scientific reports*, 8(1), 11462. <https://doi.org/10.1038/s41598-018-29807-7>
- Sachindra, D. A., Huang, F., Barton, A., & Perera, B. J. C. (2014). Statistical downscaling of general circulation model outputs to precipitation—part 2: Bias-correction and future projections. *International Journal of Climatology*, 34(11), 3282–3303. <https://doi.org/10.1002/joc.3915>
- Sadeghi, M., Ebtehaj, A., Crow, W. T., Gao, L., Purdy, A. J., Fisher, J. B., Jones, S. B., Babaeian, E., & Tuller, M. (2020). Global Estimates of Land Surface Water Fluxes from SMOS and SMAP Satellite Soil Moisture Data. *Journal of Hydrometeorology*, 21(2), 241–253. <https://doi.org/10.1175/JHM-D-19-0150.1>
- Safari, E., Moradi, H., Seim, A., Yousefpour, R., Mirzakhani, M., Tegel, W., ... & Kahle, H. P. (2022). Regional drought conditions control *Quercus Brantii* Lindl. growth within contrasting forest stands in the central Zagros mountains, Iran. *Forests*, 13(4), 495. <https://doi.org/10.3390/f13040495>
- Saha, T. R., Shrestha, P. K., Rakovec, O., Thober, S., & Samaniego, L. (2021). A drought monitoring tool for South Asia. *Environmental Research Letters*, 16(5), 054014. <https://doi.org/10.1088/1748-9326/abf525>
- Salvi, K., Kannan, S., & Ghosh, S. (2011, September). Statistical downscaling and bias-correction for projections of Indian rainfall and temperature in climate change studies. In *4th International Conference on Environmental and Computer Science* (Vol. 19, pp. 16-18).
- Santos, M. J., Smith, A. B., Dekker, S. C., Eppinga, M. B., Leitão, P. J., Moreno-Mateos, D., Morueta-Holme, N., & Ruggeri, M. (2021). The role of land use and land cover change in climate change vulnerability assessments of biodiversity: A systematic review. *Landscape Ecology*, 36(12), 3367–3382. <https://doi.org/10.1007/s10980-021-01276-w>

- Savari, M., Eskandari Damaneh, H., & Eskandari Damaneh, H. (2022). Drought vulnerability assessment: Solution for risk alleviation and drought management among Iranian farmers. *International Journal of Disaster Risk Reduction*, 67, 102654. <https://doi.org/10.1016/j.ijdrr.2021.102654>
- Savenije, H. H., & Van der Zaag, P. (2000). Conceptual framework for the management of shared river basins; with special reference to the SADC and EU. *Water policy*, 2(1), 9-45.
- Schewe, J., Heinke, J., Gerten, D., Haddeland, I., Arnell, N. W., Clark, D. B., Dankers, R., Eisner, S., Fekete, B. M., Colón-González, F. J., Gosling, S. N., Kim, H., Liu, X., Masaki, Y., Portmann, F. T., Satoh, Y., Stacke, T., Tang, Q., Wada, Y., ... Kabat, P. (2014). Multimodel assessment of water scarcity under climate change. *Proceedings of the National Academy of Sciences*, 111(9), 3245–3250. <https://doi.org/10.1073/pnas.1222460110>
- Schmidtlein, M. C., Deutsch, R. C., Piegorsch, W. W., & Cutter, S. L. (2008). A Sensitivity Analysis of the Social Vulnerability Index. *Risk Analysis*, 28(4), 1099–1114. <https://doi.org/10.1111/j.1539-6924.2008.01072.x>
- Schneiderbauer, S., Calliari, E., Eidsvig, U., & Hagenlocher, M. (2017). The most recent view of vulnerability. Joint Research Centre (European Commission).
- Sebastian, K. (2015). *Agro-ecological Zones of Africa* (Version 2). Harvard Dataverse. <https://doi.org/10.7910/DVN/HJYYTI>
- Seibert, J., Jenicek, M., Huss, M., Ewen, T., & Viviroli, D. (2021). Chapter 4—Snow and ice in the hydrosphere. In W. Haeberli & C. Whiteman (Eds.), *Snow and Ice-Related Hazards, Risks, and Disasters (Second Edition)* (pp. 93–135). Elsevier. <https://doi.org/10.1016/B978-0-12-817129-5.00010-X>
- Senay, G. B., Velpuri, N. M., Bohms, S., Budde, M., Young, C., Rowland, J., & Verdin, J. P. (2015). Chapter 9 - Drought Monitoring and Assessment: Remote Sensing and Modeling Approaches for the Famine Early Warning Systems Network. In J. F. Shroder, P. Paron, & G. D. Baldassarre (Eds.), *Hydro-Meteorological Hazards, Risks and Disasters* (pp. 233–262). Elsevier. <https://doi.org/10.1016/B978-0-12-394846-5.00009-6>
- Shah, D., & Mishra, V. (2020). Integrated Drought Index (IDI) for drought monitoring and assessment in India. *Water Resources Research*, 56(2), e2019WR026284.
- Shahid, S., & Behrawan, H. (2008). Drought risk assessment in the western part of Bangladesh.

- Natural Hazards*, 46(3), 391–413. <https://doi.org/10.1007/s11069-007-9191-5>
- Sharafi, L., Zarafshani, K., Keshavarz, M., Azadi, H., & Van Passel, S. (2020). Drought risk assessment: Towards drought early warning system and sustainable environment in western Iran. *Ecological Indicators*, 114, 106276. <https://doi.org/10.1016/j.ecolind.2020.106276>
- Sharma, J., & Ravindranath, N. H. (2019). Applying IPCC 2014 framework for hazard-specific vulnerability assessment under climate change. *Environmental Research Communications*, 1(5), 051004. <https://doi.org/10.1088/2515-7620/ab24ed>
- Sheffield, J., Wood, E. F., Chaney, N., Guan, K., Sadri, S., Yuan, X., Olang, L., Amani, A., Ali, A., Demuth, S., & Ogallo, L. (2014). A Drought Monitoring and Forecasting System for Sub-Saharan African Water Resources and Food Security. *Bulletin of the American Meteorological Society*, 95(6), 861–882. <https://doi.org/10.1175/BAMS-D-12-00124.1>
- Sheffield, J., Wood, E. F., & Roderick, M. L. (2012). Little change in global drought over the past 60 years. *Nature*, 491(7424), 435–438. <https://doi.org/10.1038/nature11575>
- Shen, G., & Hwang, S. N. (2019). Spatial–Temporal snapshots of global natural disaster impacts Revealed from EM-DAT for 1900–2015. *Geomatics, Natural Hazards and Risk*, 10(1), 912–934. <https://doi.org/10.1080/19475705.2018.1552630>
- Shepherd, E., Milner-Gulland, E. j., Knight, A. T., Ling, M. A., Darrah, S., van Soesbergen, A., & Burgess, N. D. (2016). Status and Trends in Global Ecosystem Services and Natural Capital: Assessing Progress Toward Aichi Biodiversity Target 14. *Conservation Letters*, 9(6), 429–437. <https://doi.org/10.1111/conl.12320>
- Shilenje, Z. W., Ongoma, V., & Njagi, M. (2019). Applicability of Combined Drought Index in drought analysis over North Eastern Kenya. *Natural Hazards*, 99(1), 379–389. <https://doi.org/10.1007/s11069-019-03745-7>
- Sieben, E. J. J., Boucher, C., & Mucina, L. (2004). Vegetation of high-altitude fens and restio marshlands of the Hottentots Holland Mountains, Western Cape, South Africa. *Bothalia*, 34(2), 141–153. <https://doi.org/10.4102/abc.v34i2.428>
- Simatele, M. D., Tantoh, H. B., & Donkor, F. K. (2023). Editorial: Climate change, land, energy and food security: perspectives from Sub-Saharan Africa. *Frontiers in Sustainable Food Systems*, 7. <https://www.frontiersin.org/articles/10.3389/fsufs.2023.1164917>
- Singh, N. P., Bantilan, C., & Byjesh, K. (2014). Vulnerability and policy relevance to drought in the

- semi-arid tropics of Asia – A retrospective analysis. *Weather and Climate Extremes*, 3, 54–61. <https://doi.org/10.1016/j.wace.2014.02.002>
- Singh, V., & Xiaosheng, Q. (2019). Data assimilation for constructing long-term gridded daily rainfall time series over Southeast Asia. *Climate Dynamics*, 53(5), 3289–3313. <https://doi.org/10.1007/s00382-019-04703-6>
- Skondras, N. A., Tsesmelis, D. E., Vasilakou, C. G., & Karavitis, C. A. (2020). Resilience–Vulnerability Analysis: A Decision-Making Framework for Systems Assessment. *Sustainability*, 12(22), Article 22. <https://doi.org/10.3390/su12229306>
- Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, 16(3), 282–292. <https://doi.org/10.1016/j.gloenvcha.2006.03.008>
- Solomon, M. (2007). *Social Empiricism*. MIT Press.
- Sonali, P., & Nagesh Kumar, D. (2013). Review of trend detection methods and their application to detect temperature changes in India. *Journal of Hydrology*, 476, 212–227. <https://doi.org/10.1016/j.jhydrol.2012.10.034>
- SÖNMEZ, F. KEMAL., KÖMÜSCÜ, A. Ü., ERKAN, A., & TURGU, E. (2005). An Analysis of Spatial and Temporal Dimension of Drought Vulnerability in Turkey Using the Standardized Precipitation Index. *Natural Hazards*, 35(2), 243–264. <https://doi.org/10.1007/s11069-004-5704-7>
- Spinoni, J., Barbosa, P., De Jager, A., McCormick, N., Naumann, G., Vogt, J. V., Magni, D., Masante, D., & Mazzeschi, M. (2019). A new global database of meteorological drought events from 1951 to 2016. *Journal of Hydrology: Regional Studies*, 22, 100593. <https://doi.org/10.1016/j.ejrh.2019.100593>
- Stanke, C., Kerac, M., Prudhomme, C., Medlock, J., & Murray, V. (2013). Health effects of drought: a systematic review of the evidence. *PLoS currents*, 5. <https://doi.org/10.1371/currents.dis.7a2cee9e980f91ad7697b570bcc4b004>
- Stefanidis, S., Dafis, S., & Stathis, D. (2020). Evaluation of regional climate models (RCMs) performance in simulating seasonal precipitation over Mountainous Central Pindus (Greece). *Water*, 12(10), 2750. <https://doi.org/10.3390/w12102750>
- Su, Z., He, Y., Dong, X., & Wang, L. (2017). Drought Monitoring and Assessment Using Remote Sensing. In V. Lakshmi (Ed.), *Remote Sensing of Hydrological Extremes* (pp. 151–172).

- Springer International Publishing. https://doi.org/10.1007/978-3-319-43744-6_8
- Sun, X., Ren, G., Xu, W., Li, Q., & 任玉玉 Y. (2017). Global land-surface air temperature change based on the new CMA GLSAT data set. *Science Bulletin*, 62. <https://doi.org/10.1016/j.scib.2017.01.017>
- Sur, C., Park, S.-Y., Kim, J.-S., & Lee, J.-H. (2020). Prognostic and diagnostic assessment of hydrological drought using water and energy budget-based indices. *Journal of Hydrology*, 591, 125549. <https://doi.org/10.1016/j.jhydrol.2020.125549>
- Svoboda, M., Hayes, M., & Wood, D. (2012). Standardized Precipitation Index: User Guide. *Drought Mitigation Center Faculty Publications*. <https://digitalcommons.unl.edu/droughtfacpub/209>
- Svoboda, M., Smith, K., Bathke, D., Fuchs, B., Knutson, C. L., & Tadesse, T. (2017). *NDMC Annual Report 2017*.
- Tadesse, T. (2016, August). Strategic framework for drought risk management and enhancing resilience in Africa. In *African drought conference* (pp. 15-19).
- Tadesse, T., Haile, M., Senay, G., Wardlow, B. D., & Knutson, C. L. (2008). The need for integration of drought monitoring tools for proactive food security management in sub-Saharan Africa. *Natural Resources Forum*, 32(4), 265–279. <https://doi.org/10.1111/j.1477-8947.2008.00211.x>
- Tamarin-Brodsky, T., Hodges, K., Hoskins, B. J., & Shepherd, T. G. (2020). Changes in Northern Hemisphere temperature variability shaped by regional warming patterns. *Nature Geoscience*, 13(6), 414-421. <https://doi.org/10.1038/s41561-020-0576-3>
- Tan, M. L., & Duan, Z. (2017). Assessment of GPM and TRMM precipitation products over Singapore. *Remote Sensing*, 9(7), 720. <https://doi.org/10.3390/rs9070720>
- Tapiador, F. J., Navarro, A., Moreno, R., Sánchez, J. L., & García-Ortega, E. (2020). Regional climate models: 30 years of dynamical downscaling. *Atmospheric Research*, 235, 104785. <https://doi.org/10.1016/j.atmosres.2019.104785>
- Tapley, B. D., Bettadpur, S., Ries, J. C., Thompson, P. F., & Watkins, M. M. (2004). GRACE Measurements of Mass Variability in the Earth System. *Science*, 305(5683), 503–505. <https://doi.org/10.1126/science.1099192>
- Taylor, R. G., Favreau, G., Scanlon, B. R., & Villholth, K. G. (2019). Topical Collection: Determining groundwater sustainability from long-term piezometry in Sub-Saharan Africa.

- Hydrogeology Journal*. <https://doi.org/10.1007/s10040-019-01946-9>
- Tebaldi, C., Debeire, K., Eyring, V., Fischer, E., Fyfe, J., Friedlingstein, P., Knutti, R., Lowe, J., O'Neill, B., Sanderson, B., van Vuuren, D., Riahi, K., Meinshausen, M., Nicholls, Z., Tokarska, K. B., Hurtt, G., Kriegler, E., Lamarque, J.-F., Meehl, G., Ziehn, T. (2021). Climate model projections from the Scenario Model Intercomparison Project (ScenarioMIP) of CMIP6. *Earth System Dynamics*, 12(1), 253–293. <https://doi.org/10.5194/esd-12-253-2021>
- Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of Hydrology*, 456–457, 12–29. <https://doi.org/10.1016/j.jhydrol.2012.05.052>
- Thomas, E., Jordan, E., Linden, K., Mogesse, B., Hailu, T., Jirma, H., Thomson, P., Koehler, J., & Collins, G. (2020). Reducing drought emergencies in the Horn of Africa. *Science of The Total Environment*, 727, 138772. <https://doi.org/10.1016/j.scitotenv.2020.138772>
- Thomson, A. M., Calvin, K. V., Smith, S. J., Kyle, G. P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M. A., Clarke, L. E., & Edmonds, J. A. (2011). RCP4.5: A pathway for stabilization of radiative forcing by 2100. *Climatic Change*, 109(1), 77. <https://doi.org/10.1007/s10584-011-0151-4>
- Tigkas, D., Vangelis, H., & Tsakiris, G. (2019). Drought characterisation based on an agriculture-oriented standardised precipitation index. *Theoretical and Applied Climatology*, 135(3), 1435–1447. <https://doi.org/10.1007/s00704-018-2451-3>
- Tofa, A. I., Kamara, A. Y., Babaji, B. A., Akinseye, F. M., & Bebeley, J. F. (2021). Assessing the use of a drought-tolerant variety as adaptation strategy for maize production under climate change in the savannas of Nigeria. *Scientific Reports*, 11(1), 8983. <https://doi.org/10.1038/s41598-021-88277-6>
- Tomaszkiewicz, M. A. (2021). Future seasonal drought conditions over the CORDEX-MENA/Arab Domain. *Atmosphere*, 12(7), 856. <https://doi.org/10.3390/atmos12070856>
- Tortini, R., Noujdina, N., Yeo, S., Ricko, M., Birkett, C. M., Khandelwal, A., Kumar, V., Marlier, M. E., & Lettenmaier, D. P. (2020). Satellite-based remote sensing data set of global surface water storage change from 1992 to 2018. *Earth System Science Data*, 12(2), 1141–1151. <https://doi.org/10.5194/essd-12-1141-2020>
- Touchan, R., Anchukaitis, K. J., Meko, D. M., Sabir, M., Attalah, S., & Aloui, A. (2011).

- Spatiotemporal drought variability in northwestern Africa over the last nine centuries. *Climate Dynamics*, 37(1), 237–252. <https://doi.org/10.1007/s00382-010-0804-4>
- Tozier de la Poterie, A. S., Jjemba, W. E., Singh, R., Coughlan de Perez, E., Costella, C. V., & Arrighi, J. (2018). Understanding the use of 2015–2016 El Niño forecasts in shaping early humanitarian action in Eastern and Southern Africa. *International Journal of Disaster Risk Reduction*, 30, 81–94. <https://doi.org/10.1016/j.ijdrr.2018.02.025>
- Trenberth, K. E. (2020). Understanding climate change through Earth’s energy flows. *Journal of the Royal Society of New Zealand*, 50(2), 331–347. <https://doi.org/10.1080/03036758.2020.1741404>
- Tsakiris, G., Nalbantis, I., Vangelis, H., Verbeiren, B., Huysmans, M., Tychon, B., Jacquemin, I., Canters, F., Vanderhaegen, S., Engelen, G., Poelmans, L., De Becker, P., & Batelaan, O. (2013). A System-based Paradigm of Drought Analysis for Operational Management. *Water Resources Management*, 27(15), 5281–5297. <https://doi.org/10.1007/s11269-013-0471-4>
- Tsakiris, G., & Vangelis, H. (2004). Towards a Drought Watch System based on Spatial SPI. *Water Resources Management*, 18(1), 1–12. <https://doi.org/10.1023/B:WARM.0000015410.47014.a4>
- Turyasingura, B., Hannington, N., Kinyi, H. W., Mohammed, F. S., Ayiga, N., Bojago, E., ... & Singh, S. K. (2023). A review of the effects of climate change on water resources in Sub-Saharan Africa. *African Journal of Climate Change and Resource Sustainability*, 2(1), 84-101. <https://doi.org/10.37284/ajccrs.2.1.1264>
- Tyler, J. (2016). Sustainable Hazard Mitigation: Exploring the Importance of Green Infrastructure in Building Disaster Resilient Communities. *Consilience*, 15, 134–145.
- Ujeneza, E. L., & Abiodun, B. J. (2015). Drought regimes in Southern Africa and how well GCMs simulate them. *Climate Dynamics*, 44(5), 1595–1609. <https://doi.org/10.1007/s00382-014-2325-z>
- Ullah, I., Ma, X., Ren, G., Yin, J., Iyakaremye, V., Syed, S., ... & Singh, V. P. (2022). Recent changes in drought events over South Asia and their possible linkages with climatic and dynamic factors. *Remote Sensing*, 14(13), 3219. <https://doi.org/10.3390/rs14133219>
- Um, M.-J., Kim, Y., Jung, K., Lee, M., An, H., Min, I., Kwak, J., & Park, D. (2022). Evaluation of drought propagations with multiple indices in the Yangtze River basin. *Journal of*

- Environmental Management*, 317, 115494. <https://doi.org/10.1016/j.jenvman.2022.115494>
- Ungureanu, N., Vlăduț, V., & Voicu, G. (2020). Water scarcity and wastewater reuse in crop irrigation. *Sustainability*, 12(21), 9055. <https://doi.org/10.3390/agronomy12040970>
- Van der Schrier, G., Jones, P. D., & Briffa, K. R. (2011). The sensitivity of the PDSI to the Thornthwaite and Penman-Monteith parameterizations for potential evapotranspiration. *Journal of Geophysical Research: Atmospheres*, 116(D3). <https://doi.org/10.1029/2010JD015001>
- Van Dijk, A. I., Schellekens, J., Yebra, M., Beck, H. E., Renzullo, L. J., Weerts, A., & Donchyts, G. (2018). Global 5 km resolution estimates of secondary evaporation including irrigation through satellite data assimilation. *Hydrology and Earth System Sciences*, 22(9), 4959-4980. <https://doi.org/10.5194/hess-22-4959-2018>
- Van Loon, A. F., Stahl, K., Di Baldassarre, G., Clark, J., Rangelcroft, S., Wanders, N., Gleeson, T., Van Dijk, A. I. J. M., Tallaksen, L. M., Hannaford, J., Uijlenhoet, R., Teuling, A. J., Hannah, D. M., Sheffield, J., Svoboda, M., Verbeiren, B., Wagener, T., & Van Lanen, H. A. J. (2016). Drought in a human-modified world: Reframing drought definitions, understanding, and analysis approaches. *Hydrology and Earth System Sciences*, 20(9), 3631–3650. <https://doi.org/10.5194/hess-20-3631-2016>
- Van Niekerk, D., Coetzee, C., & Nemaconde, L. (2020). Implementing the Sendai Framework in Africa: Progress against the targets (2015–2018). *International Journal of Disaster Risk Science*, 11, 179-189.
- Van Ruijven, B. J., Levy, M. A., Agrawal, A., Biermann, F., Birkmann, J., Carter, T. R., ... & Schweizer, V. J. (2014). Enhancing the relevance of Shared Socioeconomic Pathways for climate change impacts, adaptation and vulnerability research. *Climatic Change*, 122, 481-494. <https://doi.org/10.1007/s10584-013-0931-0>
- Verner, D., Treguer, D., Redwood, J., Christensen, J., McDonnell, R., Elbert, C., ... & Belghazi, S. (2018). *Climate variability, drought, and drought management in Morocco's agricultural sector*. World Bank. <https://doi.org/10.1596/30603>
- Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 23(7), 1696–1718. <https://doi.org/10.1175/2009JCLI2909.1>

- Vicente-Serrano, S. M., & López-Moreno, J. I. (2005). Hydrological response to different time scales of climatological drought: An evaluation of the Standardized Precipitation Index in a mountainous Mediterranean basin. *Hydrology and Earth System Sciences*, 9(5), 523–533. <https://doi.org/10.5194/hess-9-523-2005>
- Vicente-Serrano, S. M., Peña-Angulo, D., Beguería, S., Domínguez-Castro, F., Tomás-Burguera, M., Noguera, I., Gimeno-Sotelo, L., & El Kenawy, A. (2022). Global drought trends and future projections. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 380(2238), 20210285. <https://doi.org/10.1098/rsta.2021.0285>
- Vicente-Serrano, S. M., Quiring, S. M., Peña-Gallardo, M., Yuan, S., & Domínguez-Castro, F. (2020). A review of environmental droughts: Increased risk under global warming? *Earth-Science Reviews*, 201, 102953. <https://doi.org/10.1016/j.earscirev.2019.102953>
- Vigaud, N., Richard, Y., Rouault, M., & Fauchereau, N. (2009). Moisture transport between the South Atlantic Ocean and southern Africa: Relationships with summer rainfall and associated dynamics. *Climate Dynamics*, 32(1), 113–123. <https://doi.org/10.1007/s00382-008-0377-7>
- Vogel, C., & van Zyl, K. (2016). Drought: In Search of Sustainable Solutions to a Persistent, ‘Wicked’ Problem in South Africa. In N. Salzmann, C. Huggel, S. U. Nussbaumer, & G. Ziervogel (Eds.), *Climate Change Adaptation Strategies – An Upstream-downstream Perspective* (pp. 195–211). Springer International Publishing. https://doi.org/10.1007/978-3-319-40773-9_11
- Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., Meinshausen, N., & Frieler, K. (2019). The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, 14(5), 054010. <https://doi.org/10.1088/1748-9326/ab154b>
- Vogt, J. V., Naumann, G., Masante, D., Spinoni, J., Cammalleri, C., Erian, W., Pischke, F., Pulwarty, R., & Barbosa, P. (2018). Drought risk assessment and management. *A Conceptual Framework*.
- Voulvoulis, N., Arpon, K. D., & Giakoumis, T. (2017). The EU Water Framework Directive: From great expectations to problems with implementation. *Science of The Total Environment*, 575, 358–366. <https://doi.org/10.1016/j.scitotenv.2016.09.228>
- Waha, K., Krummenauer, L., Adams, S., Aich, V., Baarsch, F., Coumou, D., Fader, M., Hoff, H., Jobbins, G., Marcus, R., Mengel, M., Otto, I. M., Perrette, M., Rocha, M., Robinson, A., &

- Schleussner, C.-F. (2017). Climate change impacts in the Middle East and Northern Africa (MENA) region and their implications for vulnerable population groups. *Regional Environmental Change*, 17(6), 1623–1638. <https://doi.org/10.1007/s10113-017-1144-2>
- Wambua, R. (2018). Analysis of Drought and Wet-Events Using SWSI-Based Severity-Duration-Frequency (SDF) Curves for the Upper Tana River Basin, Kenya. *Hydrology*, 6, 43. <https://doi.org/10.11648/j.hyd.20180602.11>
- Wang, Y., Leung, L. R., McGREGOR, J. L., Lee, D.-K., Wang, W.-C., Ding, Y., & Kimura, F. (2004). Regional Climate Modeling: Progress, Challenges, and Prospects. *气象集誌*. 第2輯, 82(6), 1599–1628. <https://doi.org/10.2151/jmsj.82.1599>
- Wardlow, B., Anderson, T., Tadesse, C., Hain, W., Rodell, M., & Thenkabail, P. S. (2016). Remote sensing of drought: Emergence of a satellite-based monitoring toolkit for the United States. *Remote Sensing of Water Resources, Disasters, and Urban Studies*, 367-398.
- Watson, A., Midgley, G., Künne, A., Kralisch, S., & Helmschrot, J. (2021). Determining hydrological variability using a multi-catchment model approach for the Western Cape, South Africa. *Sustainability*, 13(24), 14058. <https://doi.org/10.3390/su132414058>
- Weaver, M. J. T., Hamer, N., O, 'Keeffe J., & Palmer, C. G. (2017). Water service delivery challenges in a small South African municipality: Identifying and exploring key elements and relationships in a complex social-ecological system. *Water SA*, 43(3), 398–408. <https://doi.org/10.4314/wsa.v43i3.04>
- Weng, B. S., Yan, D. H., Wang, H., Liu, J. H., Yang, Z. Y., Qin, T. L., & Yin, J. (2015). Drought assessment in the Dongliao River basin: Traditional approaches vs. generalized drought assessment index based on water resources systems. *Natural Hazards and Earth System Sciences*, 15(8), 1889–1906. <https://doi.org/10.5194/nhess-15-1889-2015>
- West, H., Quinn, N., & Horswell, M. (2019). Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. *Remote Sensing of Environment*, 232, 111291. <https://doi.org/10.1016/j.rse.2019.111291>
- Wetherald, R. T., & Manabe, S. (2002). Simulation of hydrologic changes associated with global warming. *Journal of Geophysical Research: Atmospheres*, 107(D19), ACL 7-1-ACL 7-15. <https://doi.org/10.1029/2001JD001195>
- Wilhelmi, O. V., & Wilhite, D. A. (2002). Assessing Vulnerability to Agricultural Drought: A

- Nebraska Case Study. *Natural Hazards*, 25(1), 37–58.
<https://doi.org/10.1023/A:1013388814894>
- Wilhite, D. A. (2017). Drought management and policy: Changing the paradigm from crisis to risk management. *European Water*, 60, 181-187.
- Wilhite, D. A. (2019). Integrated drought management: Moving from managing disasters to managing risk in the Mediterranean region. *Euro-Mediterranean Journal for Environmental Integration*, 4(1), 42. <https://doi.org/10.1007/s41207-019-0131-z>
- Wilhite, D., & Pulwarty, R. S. (2017). *Drought and Water Crises: Integrating Science, Management, and Policy, Second Edition*. CRC Press.
- Williams, L., Rycroft-Malone, J., & Burton, C. R. (2017). Bringing critical realism to nursing practice: Roy Bhaskar's contribution. *Nursing Philosophy*, 18(2), e12130.
<https://doi.org/10.1111/nup.12130>
- Williams, P. A., Crespo, O., Abu, M., & Simpson, N. P. (2018). A systematic review of how vulnerability of smallholder agricultural systems to changing climate is assessed in Africa. *Environmental Research Letters*, 13(10), 103004. <https://doi.org/10.1088/1748-9326/aae026>
- Winkler, K., Gessner, U., & Hochschild, V. (2017). Identifying droughts affecting agriculture in Africa based on remote sensing time series between 2000–2016: rainfall anomalies and vegetation condition in the context of ENSO. *Remote Sensing*, 9(8), 831.
<https://doi.org/10.3390/rs9080831>
- World Food Programme Overview | World Food Programme. (2020, December 4).
<https://www.wfp.org/publications/2020-world-food-programme-overview>
- Wood, E. F., Schubert, S. D., Wood, A. W., Peters-Lidard, C. D., Mo, K. C., Mariotti, A., & Pulwarty, R. S. (2015). Prospects for Advancing Drought Understanding, Monitoring, and Prediction. *Journal of Hydrometeorology*, 16(4), 1636–1657. <https://doi.org/10.1175/JHM-D-14-0164.1>
- Woodhouse, P., & Muller, M. (2017). Water Governance—An Historical Perspective on Current Debates. *World Development*, 92, 225–241. <https://doi.org/10.1016/j.worlddev.2016.11.014>
- Wu, Z., Xu, H., Li, Y., Wen, L., Li, J., Lu, G., & Li, X. (2018). Climate and drought risk regionalisation in China based on probabilistic aridity and drought index. *Science of The Total Environment*, 612, 513–521. <https://doi.org/10.1016/j.scitotenv.2017.08.078>
- Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E., Allen,

- R. G., Anderson, M. C., Belward, A. S., Cohen, W. B., Dwyer, J., Erb, A., Gao, F., Griffiths, P., Helder, D., Hermosilla, T., Hipple, J. D., Hostert, P., Hughes, M. J., ... Zhu, Z. (2019). Current status of Landsat program, science, and applications. *Remote Sensing of Environment*, 225, 127–147. <https://doi.org/10.1016/j.rse.2019.02.015>
- Xu, F., Qu, Y., Bento, V. A., Song, H., Qiu, J., Qi, J., ... & Wang, Q. (2024). Understanding climate change impacts on drought in China over the 21st century: A multi-model assessment from CMIP6. *npj Climate and Atmospheric Science*, 7(1), 32. <https://doi.org/10.1038/s41612-024-00578-5>
- Yan, X., Zhang, B., Yao, Y., Yang, Y., Li, J., & Ran, Q. (2021). GRACE and land surface models reveal severe drought in eastern China in 2019. *Journal of Hydrology*, 601, 126640. <https://doi.org/10.1016/j.jhydrol.2021.126640>
- Zarafshani, K., Sharafi, L., Azadi, H., & Van Passel, S. (2016). Vulnerability assessment models to drought: Toward a conceptual framework. *Sustainability*, 8(6), 588. <https://doi.org/10.3390/su8060588>
- Zekri, S., & Al-Maamari, A. (2020). An Overview of the Water Sector in MENA Region. In S. Zekri (Ed.), *Water Policies in MENA Countries* (pp. 1–17). Springer International Publishing. https://doi.org/10.1007/978-3-030-29274-4_1
- Zelinka, M. D., Myers, T. A., McCoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., Klein, S. A., & Taylor, K. E. (2020). Causes of Higher Climate Sensitivity in CMIP6 Models. *Geophysical Research Letters*, 47(1), e2019GL085782. <https://doi.org/10.1029/2019GL085782>
- Zeybekoğlu, U., & Aktürk, G. (2021). A comparison of the China-Z Index (CZI) and the Standardized Precipitation Index (SPI) for drought assessment in the Hirfanli Dam basin in central Turkey. *Arabian Journal of Geosciences*, 14(24), 2731. <https://doi.org/10.1007/s12517-021-09095-8>
- Zhang, D., & Guo, P. (2016). Integrated agriculture water management optimization model for water saving potential analysis. *Agricultural Water Management*, 170, 5–19. <https://doi.org/10.1016/j.agwat.2015.11.004>
- Zhang, G., Su, X., Ayantobo, O. O., & Feng, K. (2021). Drought monitoring and evaluation using ESA CCI and GLDAS-Noah soil moisture datasets across China. *Theoretical and Applied Climatology*, 144(3), 1407–1418. <https://doi.org/10.1007/s00704-021-03609-w>

- Zhang, Y., & Li, Z. (2020). Uncertainty Analysis of Standardized Precipitation Index Due to the Effects of Probability Distributions and Parameter Errors. *Frontiers in Earth Science*, 8. <https://www.frontiersin.org/articles/10.3389/feart.2020.00076>
- Zhao, M., Liu, Y., & Konings, A. G. (2022). Evapotranspiration frequently increases during droughts. *Nature Climate Change*, 12(11), 1024-1030. <https://doi.org/10.1038/s41558-022-01505-3>
- Zhao, X., Xia, H., Liu, B., & Jiao, W. (2022). Spatiotemporal comparison of drought in Shaanxi–Gansu–Ningxia from 2003 to 2020 using various drought indices in google earth engine. *Remote sensing*, 14(7), 1570. <https://doi.org/10.3390/rs14071570>
- Ziervogel, G. (2019). Unpacking the Cape Town drought: lessons learned. *Cities support programme| Climate resilience paper. African Centre for Cities, February*.
- Ziervogel, G., Lennard, C., Midgley, G., New, M., Simpson, N. P., Trisos, C. H., & Zvobgo, L. (2022). Climate change in South Africa: Risks and opportunities for climate-resilient development in the IPCC Sixth Assessment WGII Report. *South African Journal of Science*, 118(9–10), 1–5. <https://doi.org/10.17159/sajs.2022/14492>
- Ziervogel, G., New, M., Archer van Garderen, E., Midgley, G., Taylor, A., Hamann, R., Stuart-Hill, S., Myers, J., & Warburton, M. (2014). Climate change impacts and adaptation in South Africa. *WIREs Climate Change*, 5(5), 605–620. <https://doi.org/10.1002/wcc.295>

APPENDICES

Appendix A Research Article 1

Earth Science Informatics
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RESEARCH



Agroecological-based modeling of meteorological drought at 12-month time scale in the Western Cape Province of South Africa

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Abstract

To mitigate the effects of drought in water-stressed agro-ecological zones (AEZs), it is crucial to implement efficient monitoring of drought characteristics and establish proactive water-use strategies. The Western Cape (WC) province is being confronted with an escalating threat of diminished water availability due to unsustainable human activities. The objective of this study was to assess the spatio-temporal characteristics of meteorological drought within a 12-month timescale in the WC province of South Africa spanning from 1980 to 2020. The University of East Anglia's Climate Research Unit provided precipitation datasets from fifteen stations across the six AEZs of the WC province. These datasets were processed using the Standardized Precipitation Index (SPI). The Mann–Kendall (M–K) test was used to analyze the precipitation trend and SPI values at a significance level of $p < 0.05$. The results indicated substantial negative trends in annual precipitation across all AEZs. An examination of seasonal precipitation patterns revealed a rise in summer precipitation in subtropical cool-arid regions and subtropical warm semi-arid regions, with increases of 0.4 and 0.2 mm/year, respectively. Conversely, the overall annual precipitation trend fell by -1.0 mm/year in both AEZs. The SPI values consistently fell within the range of -2 to 0 in the subtropical warm-arid, subtropical cool-arid, and subtropical cool-arid zones. Conversely, the SPI values were consistently positive in the subtropical warm-arid, subtropical cool-humid, and subtropical warm-humid zones. This finding suggests that there will be persistent drought conditions that will affect agricultural production, surface flows in rivers, and groundwater levels across the WC province.

Keywords Meteorological Drought · SPI-12 months' time scale · Trend Analysis · AEZs · Western Cape Province · South Africa

Introduction

Human practices that are not sustainable and the detrimental impacts of climate change are believed to be contributing to increasing frequency of droughts and substantial alterations in natural water flow mechanisms (Bayissa et al. 2017). According to Okal et al. (2020), recurrent

droughts have a greater impact on the global community compared to other natural hazards. As a result, they are considered the most expensive and complex challenge of the twenty-first century. Additionally, it is hypothesized that increased occurrences of droughts may lead to several issues, such as a disruption in the water budget model (Chen et al. 2013), alterations in evapotranspiration processes (Buttafuoco et al. 2018), and reduced water availability in the soil (Zhang & Li 2020). These issues will result in a scarcity of water and food. Chandrasekara et al. (2021) contended that an increase in the incidence of meteorological droughts will result in substantial difficulties in food production, especially in rainfed agro-ecological zones. This poses a substantial risk to the global community's endeavours to eradicate poverty and address climate change by 2030 (Masih et al. 2014). While scholars like Kam et al. (2021) have confirmed that more frequent droughts will greatly change the availability of

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Modeling future (2021–2050) meteorological drought characteristics using CMIP6 climate scenarios in the Western Cape Province, South Africa

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Abstract

Consistent drought modelling under plausible shared socioeconomic–representative concentration pathways (SSP–RCPs) are crucial for effectively managing future drought risk in agricultural environments. The Western Cape (WC) is one of South Africa's main agro-based provinces and faces a mounting threat of water insecurity due to recurrent drought. The objective of this study was to predict meteorological drought hazard for 2021–2050 based on three CMIP6 scenarios: SSP5–8.5, SSP2–4.5 and SSP1–2.6. Precipitation simulations generated by the sixth version of Model for Interdisciplinary Research on Climate (MIROC6) under the SSP5–8.5, SSP2–4.5 and SSP1–2.6 scenarios were used from fifteen stations across the six AEZs of the WC province. The Standardised Precipitation Index (SPI) was computed at 12-month timescales. Trend analysis of precipitation datasets and the SPI-values were done at $p < 0.05$ using the Mann–Kendall (M–K) test. The findings revealed negative precipitation trends of -7.6 mm/year in Ceres, while positive trends of 0.3 mm/year were observed in Malmesbury. These findings indicate an improvement from -7.8 and -6.4 mm/year in the same regions, respectively, compared to historical trends observed between 1980 and 2020. The results suggest that in 2042 and 2044, Bredasdorp will experience $-2 < \text{SPI} < -1.5$ under the SSP2–4.5 scenarios, while Matroosberg in 2038 under the SSP5–8.5 will experience $\text{SPI} > -2$. The findings of this study will assist in the development of proactive planning and implementation of drought mitigation strategies and policies aimed at reducing water insecurity in AEZs.

Keywords Drought prediction · Statistical downscaling · SPI · CMIP6 · Western Cape, South Africa

Introduction

Drought is one of the deadliest natural hazards that fundamentally occurs in all regions of the world (Hao et al. 2018). Drought occurs when the amount of water in soils, streams, reservoirs, and aquifers is inadequate to meet society's and the environment's needs (Vicente-Serrano et al. 2022). Geris and Henley (2017) argued that drought is characterised by periods of deficient precipitation and, if it continues over extended periods, leads to severe social, environmental and economic impacts in affected regions. Gidey et al. (2018) argued that the impacts of drought are evident through

chronic water shortages and ultimately slowing down agricultural production. Vicente-Serrano et al. (2022) noted that the global economic losses from drought incidence between 2000 and 2015 were reported to be over \$600 billion United States dollars (USD). This global trend towards more severe drought conditions has mainly been more severe in developing countries in sub-Saharan Africa that rely heavily on rainfed agriculture due to their low adaptive capacities (Okunola et al. 2023). For instance, Engelbrecht and Monteiro (2021) argued that the greatest threat to sustainable development in South Africa in the near term (2021–2040) is one or more extreme droughts occurring. Recurrent droughts are particularly concerning, considering that most of South Africa's agricultural production regions rely on rainfed agriculture to meet the rising global demand for food (Mugejo et al. 2022). One region that has been tremendously affected by the impacts of drought in South Africa is the Western Cape Province (Calverley and Walther 2022). The Western Cape Province was hardest hit by the worst inter-annual drought

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Evidence of increasing water scarcity due to frequent drought under SSP2-4.5 climate change scenario in the Western Cape Province, South Africa

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Research Article

Keywords: Drought, Reliability, Resilience, Vulnerability, Water Scarcity, Western Cape Province

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Evidence of increasing water scarcity due to frequent drought under SSP2-4.5 climate change scenario in the Western Cape Province, South Africa

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Abstract: Prolonged droughts can create severe water scarcity that can negatively affect sustainable human-environment interactions. In the Western Cape Province (WCP), South Africa, prolonged drought episodes are aggravating water scarcity and adversely affecting agricultural production. This study aimed to explore water resources sustainability in agroecological zones (AEZs) of the WC province. To this end, historical (1991-2020) and future (2021-2050) precipitation datasets under the SSP2-4.5 climate scenario were obtained from the sixth version of Model for Interdisciplinary Research on Climate, (MIROC6). Using the Reliability (Rel.) –Resilience (Res.) –Vulnerability (Vul.) framework and Standardized Precipitation Index (SPI), the sustainability index (SI) was used to quantify water availability conditions in different AEZs using the geometric mean method. The Mann-Kendall (M-K) test was applied to investigate the trends at a significance level of $p < 0.05$. The findings show that between 2021 and 2050 under the SSP2-4.5 climate scenario drought conditions will exacerbate water scarcity in AEZs compared to the historical observations. The results indicate that in arid climates, future SI, exhibited moderate water shortage ($0.60 < SI < 0.80$), while in semiarid climates future SI values, exhibited mild water shortages ($0.62 < SI < 0.71$); while in the humid climates, future SI values projected normal to above normal water availability condition ($0.52 < SI < 0.58$). Overall, trend analysis indicated non-insignificant positive vulnerability trends and significant negative trends for both reliability and resilience indicator. This study provides policy interventions and can foster development pathways to attaining the Sustainable Development Goals from a water and climate action perspective.

Keywords: Drought; Reliability, Resilience, Vulnerability; Water Scarcity; Western Cape Province

1. Introduction

In recent years, climate change impacts such as drought, coupled with unsustainable anthropological activities such as intensified agriculture and deforestation have been reported to be negatively affecting proper functioning of ecosystems (Boukary et al., 2023). Various scholars such as Fontaine & Steinemann (2009); Nurbekov & Mirzabaev (2017); Tsakiris et al. (2013) have argued that climate change has significantly altered hydro-meteorological processes such as precipitation incidence and this has exacerbated natural disasters such as drought. Drought have devastating consequences on both human-environmental couplings, particularly water resource management, agricultural production and biodiversity (Estrela et al., 2012). Due to climate change, global precipitation patterns are projected to change and consequently the frequency and severity of disasters such as drought is expected to increase (Fragaszy et al., 2020). Drought incidence will affect soil erosion, sediment control, biodiversity and protection of various species, human well-being and in some cases will lead to famine and catastrophic conflicts (Wilhite, 2019). Ndlovu et al. (2021) argued that in South Africa,