Characterization of drought over Botswana using multivariate statistics

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Declaration and copyright

I, Onneile Nomsa Keitumetse, declare that this thesis is my own original work and that it has not been presented and will not be presented to any other university for a similar or any other degree award.

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Certification

I, the undersigned certify that I have read and hereby recommend for acceptance by the Faculty of Science a thesis titled: *"Characterization of drought over Botswana using multivariate statistics"* in fulfilment of the requirements for the degree of Master of Science in Environmental Science in BIUST.

____________________________ Date 10/02/2021

Professor. Dr. Gizaw Mengistu Tsidu (Supervisor)

Dedication

I dedicate this thesis to my loving mother, Mpho D. Keitumetse for her words of encouragement, care and belief in me which really inspired me in working hard to achieve my goal.

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Abstract

Droughts pose a significant challenge to water resources, causing several socio-economic consequences. The growing economy requires improved assessments of drought-related impacts in the water sector, particularly under semi-arid environments where its climate is getting drier and warmer. This study proposes a probabilistic model (copula approach) that is intended to contribute to the drought risk assessment by providing an essential information in drought prediction, decision making and management of the limited water resources available during drought events. The three key pillars (i. Drought monitoring and early warning systems, ii.vulnerability, and impact assessments, and iii. mitigation and response measures) are recommended as the basis of national drought policy and management plans, providing a practical way to organize multiple actions and activities that the country need to implement to better prepare and respond to drought. In the study, drought events are characterized by duration, severity and intensity, and the Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) were used to analyse hydrological drought based on gridded rain gauge and potential evapotranspiration data referred to as Climatic Research Unit (CRU) covering a period of 1901-2018 at a time scale of 12 months. Both SPI and SPEI were able to detect the spatial and temporal variation of drought. But SPEI was able to identify more droughts in the severe to moderate categories over wider areas in the country than SPI did. A set of seven homogeneous drought regimes based on spatial characteristics of SPEI were obtained. Region 1 and 7 are relatively wet regions, followed by region 2 and 6, while region 2 and 4 are relatively dry regions which borders the Kgalagadi Basin. The optimal marginal distribution for drought duration, severity and intensity were identified by employing the Akaike Information Criterion (AIC). The drought duration was best described by the Generalized Extreme Value distribution while the drought severity and intensity were both found to optimally fit with Weibull distribution. Nine copula distributions, namely-Normal, Student's t, Gumbel-Hougaard, Rotated Gumbel, Clayton, Rotated Clayton, Joe Clayton, Frank, and Plackett copula distributions were applied to construct the bivariate and trivariate distributions. The most appropriate copula functions were determined also based on AIC. The joint distribution of the best marginal cumulative density functions of duration and severity is found to optimally fit Normal copula while Clayton copula distribution is the best copula function that describes joint distribution of duration and intensity as well as the joint distribution of severity and intensity over most grids in Botswana. The trivariate distribution of the univariate marginals of duration, severity and intensity is best fitted by Normal copula. The conditional return period of drought of different categories was also determined in a multivariate context by coupling duration, severity, intensity of drought based on copula distribution and cumulative density functions. Most of the historical drought events over homogenous drought regimes in Botswana have short duration, low severity, low intensity and short return period, with drought regimes 1, 3, 4 and 7 having longer drought return periods than the other three zones (2, 5 and 6). The risk of having long and severe droughts within the 10-year design lifetime of any hydrological system was low in drought events with longer duration and high severity across all the regions in Botswana. Improved information on drought characterization can be useful in evaluating the water-supply capability and the needed supplementary water resources during severe drought conditions for a specific water-supply system.

Keywords: Botswana, Copula, Drought, Drought risk assessment, SPI, SPEI

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Chapter 1. Introduction

1.1. Background of the study

A concern has arisen worldwide that droughts are and will continue to increase in duration, frequency, and severity given changing climatic conditions. Drought is considered the most complex and damaging natural hazard (Wilhite and Glantz (1985). According to Kogan, (1997), drought can recur frequently and cause substantial harm to agriculture, water resources, economy, nature, and property, potentially affecting the lives of a large number of people. For this, it is considered the costliest natural hazard in the world and the least understood weather phenomena which can cause most destruction in a short period (Wilhite, 2000). With the current rise in global temperature and a decrease in precipitation, impacts from droughts are likely to increase (Dai, 2013). According to Wilhite (2000), droughts have different definitions and are categorized into four types, namely, meteorological drought, agricultural drought, hydrological drought, and socioeconomic drought, but this study focused mainly on the hydrological droughts. Hydrological drought is associated with an extended period with below average surface and subsurface water resources for established water uses of a given water resources management system (Mishra and Singh, 2010). Hydrological droughts depend on a variety of processes including the atmosphere and a host of other factors in the terrestrial part of the hydrological cycle that control the transportation of moisture (Mishra and Singh, 2010; Van Loon, 2013). Jung et al., (2010) and Van Loon, (2013) have indicated that the atmospheric processes that control hydrological droughts are linked to climate variability and change. In most cases the response of hydrological systems is closely associated with climatic conditions in that decrease in precipitation with rising temperatures, increases the potential evapotranspiration which leads to depletion of water and moisture storage (Vicente-Serrano and López-Moreno, 2005; Lorenzo-Lacruz et al., 2010).

Usually, propagation of drought is a process in which a deficit in precipitation subsequently results in a below normal in soil moisture, groundwater, surface, and subsurface water resources (Tallaksen and Van Lanen, 2004). The precipitation deficit will have various impacts depending on meteorological conditions, socioeconomic circumstances and ecosystem type (McVicar and Jupp, 1998; Senay et al., 2015). Even though drought is not region-specific, the most severe impacts of drought on population are seen in arid and semiarid regions where the available water resources are scarce even when under normal circumstances and the people have minimal adaptability choices (Masih et al., 2014). This calls for assessments of drought characteristics that will help to formulate effective management strategies specific to these regions that will help mostly in maintaining water scarcity.

Due to the fact that drought is a recurring phenomenon and is widespread in all climate zones, it is difficult to predict and monitor drought in large areas using conventional approaches. There have been no precise methods to measure drought, but the use of drought indicators and indices are the commonly used approaches to assess the effect of drought and define the drought characteristics. According to Hao and Singh (2015), drought indicators and indices are the variables describing the physical characteristics of drought such as intensity, severity, duration and spatial extent. World Meteorological Organisation and Global Water Partnership, (2016) defined indicators as variables or parameters used to describe drought conditions (e.g., streamflow, precipitation, temperature, soil moisture, etc.) while indices are typically computed numerical representations of drought severity, assessed using climatic or hydro-meteorological inputs. Some of the drought indices used are the Standardized Precipitation Index (SPI), the Standardized Precipitation Evapotranspiration Index (SPEI), the Palmer drought severity index (PDSI), Drought Severity Index (DSI), Soil Moisture Drought Index (SMDI) and Normalized Difference Vegetation Index (NDVI).

However, Hao and Singh (2015) have indicated that individual drought indicators and indices may not be sufficient for defining complex droughts events therefore it is important to combine multiple indicators and indices for capturing of various aspects of drought conditions for efficient monitoring of drought and early warning (Wilhite, 2005). Hence the use of multivariate drought index (SPEI) together with SPI for detecting and characterising various drought events over Botswana for this study is necessary. The Standardized Precipitation Index (SPI) is an index based on probability, developed to measure precipitation departures over time scales of choice (Mckee et al., 1993). The index uses only precipitation for computation therefore, it cannot include the temperature effect which influences the rate of evapotranspiration on quantification of droughts (Vicente-Serrano et al., 2010). But the Standardized Precipitation Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010), is able to include such an effect on drought quantification. SPEI is used to identify the drought severity associated with greater water demand due to evapotranspiration. Even though both indices are multiscalar but SPEI includes both rainfall and evaporation, allowing for the potential effects of temperature variability to be taken into account in the context of global warming.

Early warning and monitoring of drought are the major components of drought preparedness and management strategies (Wilhite and Glantz 1985). It is usually done using drought indicators and indices that are continuous functions of rainfall and other hydro-meteorological variables as mentioned above. The effectiveness of drought preparedness and other management strategies depends on timely information on the onset, progress and areal extent of the drought (Morid et al., 2006). Several countries, including Botswana however, have limited institutional and technological ability to monitor and mitigate the effects of drought. In addition, information on the drought onset and development is not readily accessible to agencies responsible for drought preparedness and mitigation. However, over the past years, the use of copula based models for the probabilistic characterizations of droughts have emerged as a method for improving the ability to address complexities of early warning and efficient monitoring of drought situations (Pontes et al., 2019). Probabilistic drought analysis using the copula method is an effective tool in multivariate distribution construction. Copulas use a nonlinear approach to establish the joint probability distribution of two or more related variables and are able to model the dependence structure between the random variables independent of their marginal distributions (Shiau, 2006). Apart from the development of joint probability distribution, copulas are able to establish the joint return periods. Accordingly, the joint probability analyses of drought characteristics can provide very valuable complementary criteria for developing policies governing decision-making in the realm of drought crisis management (Song and Singh, 2010; Montaseri et al., 2018).

According to Sivakumar and Wilhite (2002), effective drought management emphasizes the three-pillars: monitoring and early warning, risk and impact assessment and mitigation and response. However, the most commonly used approach to drought management has been reactive, focusing largely on crisis management, whereby the policy responses addressed immediate needs rather than a pro-active approach which entails preparedness, mitigation, prediction/early warning actions that could minimize potential impacts and lessen the need for government intervention in the future. In preparation for the likely recurrence of drought, drought-prone countries must develop a national drought policy and associated preparedness and mitigation plans aimed at risk reduction (Wilhite, 2019). Wilhite and Pulwarty (2018) have indicated that the crisis management approach to drought management increases vulnerability to future drought episodes by reducing self-reliance and increasing dependence on governments and donor organizations. Generally, the pro-active approach to drought management should be focused on steps developed and implemented before the initiation of a drought event rather than within the emergency framework (Rossi et al., 2005). Therefore a major aspect of the pro-active approach in drought mitigation should focus on improving the reliability of the water supply system to meet future demands under severe drought conditions (Knutson et al., 1998; Wilhite, 2000). However, Wilhite (2019) has indicated that it has been a challenging task for policymakers and natural resource managers throughout the world to adopt a more proactive approach to drought management even to this date. Botswana's drought response has also been ineffective, drought have been treated as an emergency and responded to through crisis-based programs that encourage the dependency of producers and communities on state aid and support (Davies et al., 2017) without incorporating methods that will withstand drought, and support water conflict prevention. According to Davies et al., (2017), the Rural Development Council of Botswana was resolved to set up a task team to conceptualize drought and its levels of severity with a view to contribute to the subsequent development of a National Drought Management Strategy since drought are unending and now seen as a 'normal' part of Botswana's climate. The persistence of a reactive and generalized response to drought means that neither response times nor risks have been reduced suggesting that additional input on this matter is necessary and it should emphasize on the implementation of the strategies. This is critical because a lack of preparedness means that drought continues to have severe consequences for the country as a whole.

Adoption of the three-pillar approach to drought can be useful in changing the approach to drought management (from reactive approach to pro-active approach) because they illustrate the importance of developing a comprehensive and effective drought monitoring and early warning system, to provide reliable and timely information to managers and other decision makers and linking the information derived from this system to vulnerability and impact assessments (Wilhite, 2019). Therefore this study carried out a probabilistic analysis of drought (hydrological) events using copulas which can play a critical role in the appropriate planning and management of water resources systems. This is an important element of drought early warning systems since it can provide useful information to the decision makers and other stakeholders. The information lies under the three pillars of drought management which Wilhite (2019) has indicated that exploring them (a new paradigm for drought risk management) would be most convenient for all drought-prone countries, Botswana included.

In this study, the three drought characteristics namely duration, severity and intensity are investigated, and it is shown how copulas can be used to build the correlating three-dimensional joint distribution and to compute the joint return periods. More precisely, drought characteristics were identified on SPI and SPEI at a 12-month timescale. The 12-month time scale was chosen to represent the hydrological drought. A longer temporal scale is favourable since it is most suited for monitoring of long term droughts than short temporal scales (e.g. meteorological and agricultural droughts) (Hayes et al., 1999).

1.2. Rationale of the study

"A single drought indicator may not be sufficient to characterize the complicated drought condition and its wide impacts. Thus the characterization of drought from a multivariate perspective is required to alleviate the inadequacy of drought characterization from a single aspect, which encompasses a multitude of cases".

1.3. Statement of problem

Semi-arid countries are well known for frequent and severe drought. Botswana is not exceptional. Therefore, Botswana as a semi-arid country with a relatively low and variable rainfall, has experienced frequent drought in the past over the entire country. Hence they have had significant impacts on the country's economic development, food security and human health for a long period since 1983. According to Davies et al., (2017), historically, the Government of Botswana has taken a reactive approach to dealing with drought crises but the approach is no longer seen appropriate since droughts are recurrent over the country, therefore this calls for the authorities to anticipate and prepare for droughts. According to Wilhite (2019), a key point of dealing with droughts involves the adoption of the three pillars of drought preparedness plan, which when implemented can help to mitigate the impacts of drought, through improved monitoring and early warning systems. Therefore a probabilistic analysis of drought events using copulas can be useful for providing a variety of information about drought (drought return period and joint probability) that can play a critical role in the appropriate planning and management of water resources systems.

1.4. Objectives

The study aims to analyse drought characteristics over Botswana using Standardized Precipitation Index (SPI) and Standardized Precipitation Evapotranspiration Index (SPEI) at a timescale of 12 months

The specific objectives are:

- To identify drought prone areas over the country.

- To evaluate the performance of the two climatic drought indices' ability to characterize the drought events in order to select the best index for the data (spatial variability).
- To determine the temporal variability of drought events from the selected index.
- To determine the recurrence time of drought with different duration, severity and intensity from historical data of 117 years (1901-2018) in the frame work of multivariate drought characterization using copula.

1.5. Research questions

The following research questions guided the study:

- What are the relationships between the duration, severity and intensity of drought over various parts of the country?
- What are the probabilities (risk of) of occurrence of various drought events of specified duration, severity, and/or intensity over different parts of the country? How are these informations used in water use and planning in the country?

1.6. Significance of the study

An objective of drought analysis is to manage the limited water resources available during drought events through enhancing drought preparedness, mitigation of its impacts with robust and relief policies to enhance the economic security. Accordingly, having the actual spatio-temporal information about the drought for both historical and future periods is highly important in view of the recurrent and severe drought over the country. The challenges posed by climate change effects have made it essential to analyse temporal and spatial variability of drought severity due to climate change particularly in semi-arid environments such as Botswana. This study carried out a multivariate analysis of hydrological drought based on the copula approach which evaluates drought more comprehensively as compared with the univariate analysis. The multivariate analysis using copulas will provide an essential information in drought prediction and decision making.

Chapter 2. Review of Literature

2.1. Background

In recent times a concern has grown worldwide that drought are increasing in frequency due to the changing climatic condition. Hence there has been an urge to carry out some investigations about the characteristics of drought but mostly via the drought indices, deterministic approaches and probabilistic theories. Examples of studies that have used drought indices for drought analysis includes that of Aaron-Morrison et al., (2016) who applied Standardized Precipitation Index (SPI) to study drought across the Southern Africa region and concluded that the region is prone to frequent droughts mostly due to the arid-semi arid environment. In Botswana drought characteristics has also been studied by Batisani (2010, 2012) who investigated the spatio-temporal-severity dynamics of drought in Botswana using the SPI. In another related study Tirivarombo and Oromeng (2018) also presented the spatial and temporal drought analysis in Botswana. The findings from these researches shows that SPI has the ability to detect and characterize drought. Edossa et al., (2014) and Vicente-Serrano et al., (2012) suggested the use of Standardized Precipitation Evapotranspiration Index (SPEI) for analysing drought, in particular for applications which involve future climate scenarios. Byakatonda et al., (2018a) used SPI and SPEI to investigate the characteristics of drought and its temporal patterns over Botswana at different timescales. The authors indicated that SPEI proves to be more effective in the characterization of droughts in semi-arid regions.

Examples of studies conducted for analysing drought using deterministic approach include the use of extreme dependency score that is mostly used in deterministic forecasts (e.g. Piechota, and Dracup, (1996)) and the use of stochastic models (e.g. Mishra et al., (2007) and Akyuz et al., (2012)). For probabilistic theories, several studies (Fernández and Salas, 1999; Shiau and Shen, 2001; Salas et al., 2005; Shiau et al., 2007; Mishra and Singh., 2009; Wong et al., 2013) were performed to examine the statistical properties of drought in the study of droughts but it has been realised that the researches focused mostly on univariate analyses based on well-defined techniques used in drought analysis. According to Chen et al., (2011), drought is a multi-attributable dependent random variables for which separate analysis of drought characteristic (duration, severity, frequency etc.) distributions are not able to show an association between them. A recommendable method for defining characteristics of drought, is to develop a joint distribution of drought variables. Several studies such as Shiau and Shen (2001) and Cancelliere and Salas (2010) suggested various approaches for investigating the joint distribution of drought characteristics but it has been very difficult to use them due to the advanced mathematical derivations used to fit parameters from the observed data (Shiau, 2006; Ma et al., 2013). As a result alternative approach based on copulas are developed. Salvadori and De Michele (2004), and Beguería et al., (2014) used the bivariate distribution of drought analysis and the return periods from the fixed (predetermined) marginal distributions of duration and severity to analyse drought. Although, several probabilistic theory studies were conducted globally to analyse drought, it has been realised that there has never been a single investigation on probabilistic characterization of droughts over Botswana. Hence the investigation of multivariate characterisation of hydrological drought using copulas will provide a probability-based definition of drought in Botswana which in turn will help in providing utile information for water resource planning and management by decision makers and other stakeholders in the water sector.

2.2. Rainfall and drought variabilities

Agriculture has been the backbone of Botswana's economy for many years; which is dependent on natural rainfall variability. Therefore, the failure of seasonal rainfall tend to affect individuals who depend on rain for their crops which indirectly affects the country's food production. The occurrence of low and erratic rainfall over the past decades across the country has contributed the occurrence of droughts. Low and variable rainfall, and associated droughts have historically been a major cause of famine across Southern Africa, animal deaths, and water shortages (Adaawen et al., 2019). The drought in 2015 caused the drying of the Thamalakane River supply water to the Okavango Delta. Hence the animals and people who were dependent on the water from the Okavango Delta were challenged by such situations and in the country's capital, Gaborone dam was down to nearly 20% of its capacity (Strzepek et al., 2011).

Byakatonda et al., (2018a) identified increasing and decreasing rainfall trends across the country in summer. The study area exhibited a decrease in summer rainfall of about 7.4 per cent in the northern, central and southern locations during the period of 1960 to 2014. The southwest (Tshane) and west (Ghanzi) parts of the country experienced a marginally increasing trends while the eastern (Francistown) had increasing trends. The winter rainfall trends across the country found to exhibit mixed trends. These results of trend identification in annual rainfall across the country are very important to drought analysis because drought is mainly dependent on multi-scale temporal, and spatial rainfall variation. For instance, the duration and intensity of rainfall in Botswana is strongly affected by the westerlies and easterlies from their climatological locations, shifting of the Inter Tropical Convergence Zone and the tropical cyclones from the Indian Ocean. While Bykatonda et al., (2018a, 2018b) have investigated rainfall variability and drought variability over Botswana, characterization based on probabilistic multivariate approach has never be conducted to the extent that support water resource planning and management.

2.3. Definition and types of droughts

Defining droughts is a complex task due to their variability in space and time as well as due to being region-specific and context-dependent. However, they are in general characterized by a prolonged moisture deficiency in relation to the historical average caused by reduced rainfall, resulting in water shortages for some type of activity or the environmental sector in a particular area (Wilhite et al., 2007). Drought results from a complex interchange between natural rainfall deficiencies or excessive evapotranspiration over varying time and area on one hand and the demands of human and environmental water use, on the other hand that may be exacerbated by ineffective water distribution, planning, and management. (Erfanian et al., 2017). According to White and Walcott (2009), it is important to differentiate between drought and concepts like aridity whereby a particular climatic region is characterized by a permanent feature of low rainfall and seasonality in which a region faces water scarcity as a regular part of the annual climate regime. Therefore, drought can occur in any climatic region (high as well as low rainfall areas) characteristics varying from one region to another.

The rainfall deficit can be in terms of the spatial-temporal distribution of drought, timing if they were sufficiently extreme to adversely affect plant production, water supply, wildlife and ultimately human livelihoods, and food security (Rahman, 2016). Therefore, drought results in different impacts depending on meteorological conditions, ecosystem type, and socioeconomic conditions. Even though, the predominant factor in drought occurrences is rainfall deficiency, there are many climate conditions, such as high temperatures, low relative humidity and strong winds that are linked with drought occurrences in many parts of the world and are said to greatly exacerbate the severity of drought events.

Wilhite and Glantz (1985) reviewed the concepts of droughts and its four major types: meteorological drought, agricultural drought, hydrological drought and socio-economic drought (Fig. 2.1). Meteorological drought occurs when the annual rainfall is less than average over a region for an extended period of time (month, season, or year) which may result in a region becoming dry. Agricultural drought mostly focuses on rainfall deficits, variations between the actual and potential evapotranspiration, and deficits in soil water. Continuing below average rainfall levels can result in meteorological drought leading to agricultural drought, which happens at a time when there is an insufficient soil moisture to meet the needs of a specific crop. A hydrological drought is associated with the impact of rainfall deficit on the surface, and subsurface water supplies based on flux and dam, river, and groundwater levels measurements. Socio-economic drought occurs when the physical water shortage starts to have impact on human production and daily life and the environment at large. It is basically considered as a consequence of the other drought types (meteorological, agricultural, and hydrological) (Wilhite, 2000). This indicate that different drought types are also related to the impacts.

According to Byun and Wilhite (1999), drought can be studied and classified into four categories which are (i) understanding the causes of drought under improved knowledge of the circulation of the atmosphere associated with drought occurrences, (ii) understanding of the drought parameters such as frequency and severity of drought as an approach to characterize the probability of occurrence of droughts events with various magnitudes, (iii) understanding of the drought effects and lastly (iv) focusing on the responses, mitigations, and preparedness strategies.

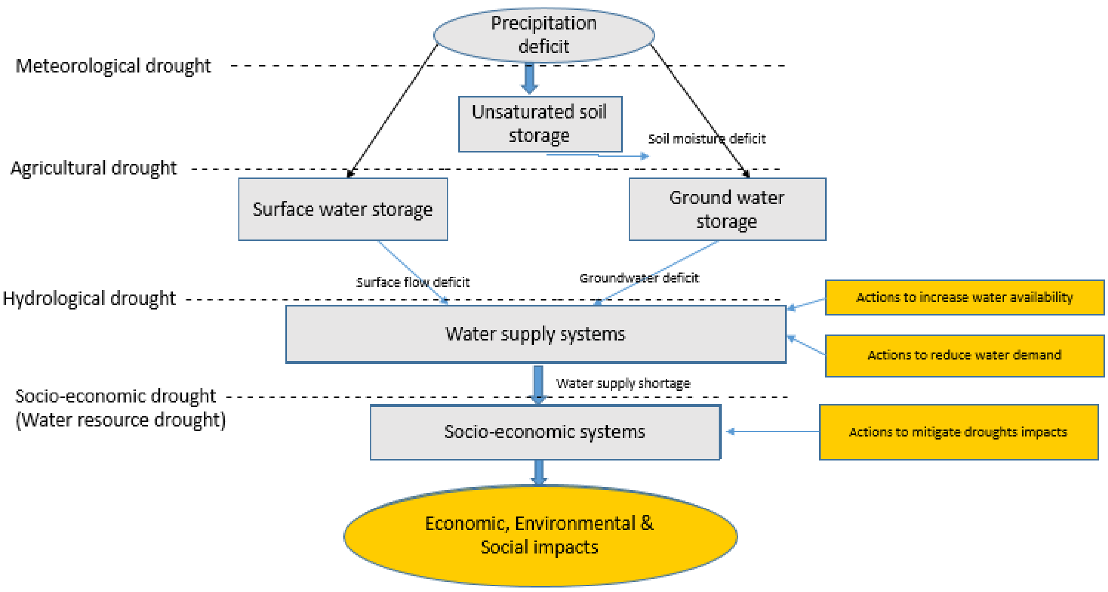

Fig.2. 1: Illustration of the drought definitions through the hydrological cycle (Adapted from Rossi et al., 2007).

2.4. Drought impacts and management

The Intergovernmental Panel on Climate Change (IPCC) report (IPCC, 2007), stated that drought events are expected to increase in many regions of the world in the 21st century. This projected increase is seen as a potential cause for impacts (social, economic, and environmental) which must be considered in preparations in responding to drought conditions (Vlachos, 1989).

Economic impacts include but not limited to:

- Reduction in production of animal and meat production;
- Reduction in traditional crop yield;
- Endangering fish life and other marine life;
- Water for animals may not be obtained and it may be costly;
- Defects affecting tourism;
- Unbalance between income and expenses;
- Industrial reduction; and
- Farm fires and forest fires.

Many of the environmental impacts include:

- Losses and, or destruction of fish species and livestock species;
- Lack of food, and drinking water for wildlife;
- Increased disease in wildlife due to decreased food and water intake;
- Damages to plant species;
- Concentrating wildlife to favourable habitat conditions and others migrate;
- Occurrences of diseases;
- Decreased levels of water in reservoirs, dams, lake, rivers;
- Losses of wetlands;
- Lack of drinking water;
- Deterioration in water quality and increased saltation; and
- Land degradation.

Lastly, some of the social impacts include:

- Unemployment increase;
- Reduced incomes;
- Immigration of people;
- Loss of human life;
- Health problems associated to low water flows and poor quality of water;
- Quality deterioration due to waste water; and

- Reduction in recreational areas/activities.

Developing and implementing effective national policies for mitigating the impacts of drought is required. The World Meteorological Organization (WMO, 2006) suggests that, for there to be significant reduction of negative drought impacts, it is also vital to develop technologies and methods to improve the drought characterisation. Often when drought events occur, focus is mostly based on the response and recovery from its impacts. But according to Wilhite (2000), management of drought should also involve the mitigation, preparedness, and prediction, and early warnings in order to make the significant reduction of the economic and environmental damages related to drought together with minimizing sufferings of people. Therefore, policy makers and researchers should consider both the protection and recovery concepts for managing the drought risks. Fig. 2.2 shows how drought can be seen as a manageable risk (Wilhite, 2000).

According to the cycle of disaster management, when a drought occurs, it is important to first assess the impacts contributing to the drought occurrence which mostly involves the estimation of costs and losses. Then follows the response that includes government and other stakeholders' interventions to help with the post-impacts of droughts. Most of the response efforts are usually made to save lives of people, minimise the damage properties and improve the post-disaster recovery process in general.

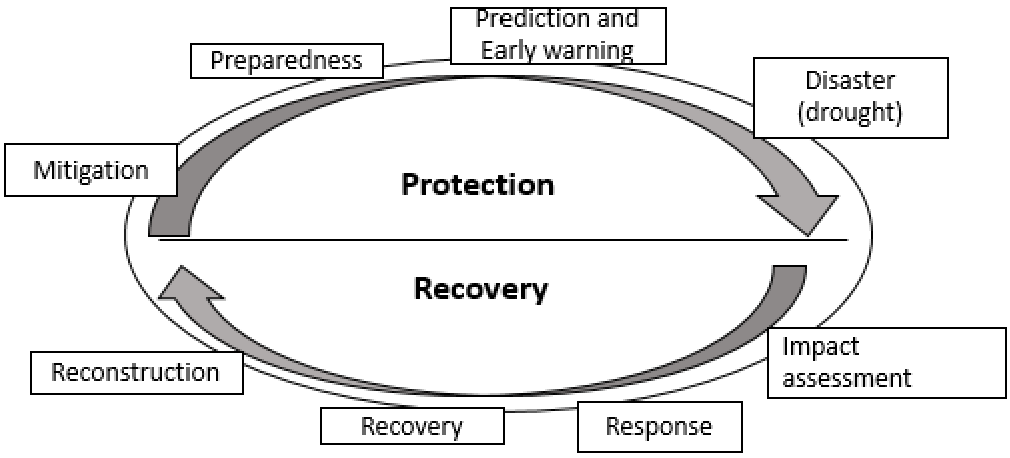

Fig.2. 2: The cycle of disaster management (taken from Wilhite (2000)).

The recovery and reconstruction processes involve the actions that bring back the critical life-support systems for people in the affected area and the processes are mostly directed to reduce the drought impacts and minimise the recovery time (Wilhite, 1997). Prior to the drought occurrences, it is vital to develop mitigation plans which should include programs, policies and actions that will work to reduce the risk that people may face during drought events together with their properties. Therefore when making mitigations plans, identification of the impacts related with the previous droughts should be considered in order to make an assessment on whether these impacts can recur from similar future drought events. Prediction of drought events provide decision and policy makers forecasts of the drought occurrences in form of probability of occurrence. Early warning, which depend on this information, involve the actions that can provide information that could be used to alert decision makers and other relevant stakeholders to respond and implement risk management options designed on past characteristics of similar drought events on timely manner.

The three pillars of drought management

Drought management planning process gives decision makers and stakeholders the opportunity to identify communities, sectors and regions vulnerable to drought and devise ways to mitigate impacts before they occur (Venton et al., 2019). Therefore Drought planning is an effective and economically efficient way to allocate resources to managing drought. According to Wilhite (2019), without a coordinated national drought policy plan that includes comprehensive monitoring, early warning and information delivery systems, vulnerability, and impact assessments, the identification and adoption of appropriate local-level mitigation and response measures aimed at risk reduction, nations will continue to respond to drought, as they have in the past. Therefore nations should adopt these three pillars of drought preparedness plan since they are a key point of dealing with droughts.

Early warning and information delivery systems- The goal of monitoring an early warning is to initiate early action to prevent a crisis situation (Wilhite, 2019). Ideally, therefore, affordable systems are required wherein relevant and understandable data flows between stakeholders at different levels, and between different sectors, in a timely manner. For effective drought monitoring and early warning it is suggested that the bottom-up approach to be employed, this include data collection from local sites which can be aggregated to grids and then to basins or districts (Davies et al., 2017).

Vulnerability, and impact assessments- Understanding who is vulnerable to what stressors, hazards and issues is a very important starting point in deciding how to adapt to climate and other hazards and reduce vulnerability (Sivakumar and Wilhite, 2002). According to Adger et al., (2007), vulnerability assessments are tools used to understand the possibility for harm to occur in human and ecological systems as a consequence to the effects of climate change. Therefore, a more holistic vulnerability assessment should include consultation with a variety of stakeholders from different sectors and levels, and should consider issues such as power, inequality, local knowledge, culture and gender.

Mitigation and response measures- Mitigation involve the short- and long-term actions, programs, or policies implemented in advance of drought that reduce the degree of risk to human life, property, and productive capacity (Davies et al., 2017). While on the other hand, response actions are those taken once an area is experiencing severe drought and are intended to address impacts and expedite recovery of the affected area. In drought management, it is advised to identify the mitigation actions that could be taken to lessen the risk associated with future drought events for each of the principal impact sectors. More emphasis should be made on mitigation actions over emergency response because the emergency responses does little to reduce risk and may increase vulnerability to drought through increased dependence on government or donor interventions.

2.5. Review of major drought indices

Several approaches have been used as tools for drought assessment and this include quantification of shortage of stream flow, decreased levels of water storage, measurement of lack of rainfall and drought indices (Keyantash and Dracup, 2002). Due to their complexity, droughts have been very difficult to quantify and therefore, there has never been a direct method to measure it. However, of these different methods, the drought indices are commonly used for assessment of drought (Keyantash and Dracup, 2002; Heim Jr, 2002; Morid et al., 2006; Barua, 2010). Drought indices are crucial aspects of monitoring and assessment of drought because they simplify complex interrelationships among many climates and other parameters related to climate (Tabari et al., 2012). Therefore they make easier communication of information about climate anomalies with regard to their spatial extent, duration, frequency and severity (Wilhite et al., 2000; Tabari, et al., 2012). Drought indices are primarily used to measure the effects of drought, and to evaluate the different characteristics of drought. There are several drought indices that can be used for monitoring and assessment of drought depending on various variables such as precipitation, soil moisture, and runoff. These include the Percent of normal (PN), Deciles method (DECILES), Palmer Drought Severity Index (PDSI), Normalized Difference Vegetation Index (NDVI), Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Drought Severity Index (DSI), Soil Moisture Drought Index (SMDI), Standardized Stream Flow Index (SFI), Soil Moisture Index (SSI), Effective Drought Index (EDI), Crop-Specific Drought Index (CSDI).

Drought indices based on precipitation including the SPI, are based on two assumptions: first being that the precipitation variability is greater than other variables such as potential evapotranspiration and temperature and lastly, other variables are stationary (Vicente-Serrano et al., 2010). The significance of these other variables in this situation is negligible, while drought is influenced by the temporal variability in precipitation. Some authors, however, have cautioned against deliberately neglecting the significance of temperature effects on drought conditions (e.g., Hu and Wilson, 2000 and Vicente-Serrano et al., 2011). Empirical studies have also shown that rising temperatures have a significant influence on the severity of drought (Vicente-Serrano et al., 2010). Evidence suggest, prolonged drought of 2015-2016 over Southern and Eastern Africa were exacerbated by the concurrent high temperatures (e.g., Mengistu Tsidu, 2016). Therefore, according to Vicente-Serrano et al., (2010), it is preferable to use drought indices that encompass temperature data in their formulation (such as PDSI, SPEI, etc.) particularly for applications that involve future climate scenarios.

The drought indices can be obtained from in-situ station data (Zargar et al., 2011) but in certain areas of Southern Africa, station data observed are short of sufficient spatial and temporal coverage while it is also difficult to obtain near-real-time observed data (Thenkabail et al., 2004). Drought indices may be classified into meteorological, agricultural and hydrological indices, if the typology of drought is investigated. Brief descriptions of the commonly used drought indexes are described in the following.

2.5.1. Role of indicators/indices on drought management

The most used drought management tools are known as the indicators. Drought indicators are variables or parameters used to describe the available water in soil or hydrologic systems (drought conditions) (World Meteorological Organisation and Global Water Partnership, 2016). Generally, drought indicators are described as a broad term to cover any parameters or indices that are used to characterize and quantify drought. They play a significant role in monitoring and defining drought which can be a single parameter (e.g., rainfall or streamflow at a particular gauging station) or an index combining many kinds of data. Different classification schemes have been used to group drought indicators. However, the common classification is according to drought type, e.g., precipitation- and temperature-based indicators for meteorological drought, soil moisture or vegetation stress indicators for agricultural drought, and indicators based on streamflow, reservoir or groundwater levels for hydrological drought (Zargar et al., 2011). According to Nagarajan (2009), drought indicators should be linked with drought management and impact reduction goals. Therefore, the performance of drought indicators should be considered; for instance, the degree of responsiveness or persistence desired in an indicator. Some water managers may prefer a drought indicator that responds quickly to short term anomalies, such as SPI-3 in order to take early action to reduce drought impacts while other water managers may prefer drought indicators with greater stability and persistence such as SPI-12, so as to avoid frequent invoking or revoking of drought response. For drought plan to be developed they also rely on indicators which will help in determining a final drought level for a particular region therefore it is important to recognize that drought indicators play a crucial role in helping the decision makers in selecting the thresholds.

2.5.2. Major drought indices

Palmer Drought Severity Index (PDSI)

The Palmer drought severity index (PDSI) established by Palmer (1965), was intended to assess and show the extent and severity of drought events and has been widely used for the assessment of meteorological and agricultural droughts (Pereira, 2009). PDSI estimates the departure of the moisture supply on the basis of the water balance equation of the supply and demand principle taking into account not only precipitation but also climate and hydrological properties like temperature, soil moisture and runoff. The index generally considers temperature along with precipitation for its measurements. PDSI can calculate the runoff, evapotranspiration, soil moisture, and recharge (basic terms of the water balance equation) if the above inputs are available. PDSI computation encompasses two layers of soil with each layer having the Available Water Content (AWC), but the AWC values are usually subjectively decided.

The popularity and wide application of PDSI in the field of drought monitoring may be based on the fact that it provides decision-makers with the analysis of recent weather abnormalities for a particular region, enabling them to compare current conditions with historical ones (Mika et al., 2005; Svoboda and Fuchs, 2016). Even though the PDSI is widely used, when calculating the PDSI for a single location, the fact that it uses a two layer soil model with a single soil

AWC parameter may be applicable when calculating the PDSI for a single location and therefore is not appropriate for calculating the PDSI for different locations (regions) where the soil is heterogeneous to space (spatially) (Narasimhan and Srinivasan, 2005).

Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI), developed by McKee (1993), is a common drought index used for the assessment and monitoring of drought according to their severity. SPI is calculated for any location in any region with a precipitation record based on the frequency of a drought at a given time scale. The index requires data about precipitation as an input, making it ideal for areas where data collection is not substantial. SPI's key advantage is that it can be calculated for various time scales, allowing it to describe different drought conditions thus reflecting the effect of drought on the available various water resources.

According to Svoboda and Fuchs (2016), soil moisture conditions, for example, respond to short-term precipitation anomalies, while soil water, stream flow and storage represent the long-term precipitation anomalies, and McKee et al., (1993) used these conditions when calculating the SPI for 3-, 6-, 12-, 24-, and 48-month time scales. For any location, the measurement of SPI is based on the long-term record of precipitation of a desired period. The long-term precipitation record is then fitted to a probability distribution, usually the gamma distribution that will be transformed into a normal distribution such that the mean SPI of the area and the period desired is zero (Edwards and McKee, 1997; Tigkas et al., 2013). The SPI values are therefore expressed in standard deviations for any drought event that a specific rainfall event diverges from the normalized average, with the positive SPI representing greater than the mean precipitation (precipitation excesses/wet events) and negative values representing less than mean precipitation (precipitation deficits/drought events) (Edwards and McKee, 1997; Tigkas et al., 2013).

Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI), established by Vicente-Serrano *et al*., (2010), is an enhanced drought index used to determine the severity of drought attributed by evapotranspiration which is associated with the higher water demand. Like to PDSI, the SPEI measures the demand for evapotranspiration due primarily to the fluctuations and trends in different climate variables besides precipitation. Nonetheless, the PDSI doesn’t have the multi-scalar character that is important both for determining drought in relation to different hydrological processes and for differentiating between different types of drought.

While on the other hand, SPEI incorporates PDSI's sensitivity to changes in evaporation demand, normally caused by fluctuations in temperature, with the ease of calculation and the multi-temporal design of SPI (Vicente-Serrano et al., 2012). The calculation of SPEI is the same as SPI but instead of using precipitation as an input, it uses climatic water balance as the inputs. According to Begueria et al., (2014), water balance compares the water availability (rainfall) with the atmospheric evaporative demand (evapotranspiration), hence can provide a more accurate measurement of drought severity than using rainfall measurements alone.

Surface Water Supply Index (SWSI)

The SWSI established by Shafer and Dezman (1982) was made to complement the PDSI thereby using precipitation, stream flow and storage of reservoir as input data. The index was designed to show the conditions of surface water and thus incorporates both climatological and hydrological features into a single index value (Svoboda and Fuchs, 2016).

Incorporation of the all the major components of water supply into a single index seems to be easy in calculation but it also has weaknesses:(i) with its unique calculation of each basins, comparison of SWSI values between basins is difficult (Doesken et al., 1991). Another disadvantage is that the whole SWSI algorithm for that basin would need to be improved to compensate for changes in the weight of each hydrological variable if there are changes in water control within a basin such as flow diversions.

Crop moisture index

The Crop Moisture Index (CMI) established by Palmer (1968) is used to monitor agricultural droughts. It is an index for monitoring short-term supply of moisture over regions which produce large crops. It is also based on the average temperatures and total rainfall of a Climate Division for each week together with the previous week values of the CMI (Palmer, 1968; Uang-aree et al., 2017). It is the sum of deficit in evapotranspiration and soil water recharge. The CMI is good for responding to changing short-term conditions rapidly but is weak at tracking of long-term drought. Another disadvantage of the CMI is that it starts and ends near zero in each growing season which may limit the index to be used for botanical annuals. More detailed discussion can be seen in Heim (2002); Mishra and Singh (2010); Svoboda and Fuchs (2016) on the drought indices.

2.7. Theoretical basis of marginal distribution and copula functions

2.7.1. Copula definition

A copula function is a joint multivariate probability distribution whereby the marginal distributions are coupled into multivariate distributions. Copulas were used to define the dependencies between random variables in the joint probability analysis in areas such as risk management, meteorology, finance and hydrology (Salvadori et al., 2007). Compared to coefficients of correlation which also measures the correlational strength, copulas are furthermore able to provide information about how the association differs across the distributions. Therefore, this makes it more useful in capturing the tail dependence of the random variables since it is able to reflect the extreme scenarios, which most times are not captured by simulating the marginal distributions (McNeil and Neslehov, 2009).

Based on the Theorem of Sklar (Sklar 1959), for any n random variables, $X_1, X_2, \dots, X_n$, having a joint cumulative distribution function:

$$F(x_1, x_2, \dots, x_n) = P(X_1 \leq x_1, X_2 \leq x_2, \dots, X_n \leq x_n) \qquad 2.\ 1$$

with cumulative distribution functions (marginal):

$$F_j(x) = P\left(X_j \leq x\right), \ \ j = 1,2, \dots, n, \qquad 2.2$$

then, a copula C exists, so that

$$F(x_1, x_2, \dots, x_n) = C[F_1(x_1), F_2(x_2), \dots, F_n(x_n)]. \qquad 2.3$$

$$= C(u_1, u_2, \dots, u_n)$$

where $F_j(x) = u_j$ for $j = 1,2, \dots, n$, with $U_j \sim U(0,1)$.

The marginal distribution is uniform over (0, 1). The theorem states that, if each $F_j(x)$ is continuous, then C is unique.

To obtain the probability density function c, of the copula distribution, the following equation can be used, when $F(\bullet)$ and $C(\bullet)$ are differentiable (Nelsen, 2006):

$$c(u_1, u_2, \dots, u_n) = \frac{\partial^n}{\partial u_1, \partial u_2, \dots \partial u_n} C(u_1, u_2, \dots, u_n). \qquad 2.\ 4$$

Sklar (1959), suggested the use of copula to understand and reveal the true nature of complex dependence between random variables. Therefore by the use of copulas, we are able to determine the relations between two or more random variables in order to produce a joint probability distribution. Copulas can determine the joint probability distribution of the related variables. This characteristic is very important in view of the fact that drought parameters such as duration, severity and intensity are correlated. This correlation undermines their joint distribution based on marginal distributions. However, copula takes into account this dependence and provides realistic joint probability distributions and return period of drought events. For example, Shiau (2006) investigated the conditional return periods of drought duration and severity made on a conditional probability distribution established by copulas while other authors used conditional probability in drought prediction.

2.7.2. Copula families

Copulas are categorized into several families, and these may include Elliptical (Normal and Student-t), Archimedean (Frank, Clayton, and Gumbel), which are the most applied copula types. These different copula families are used for modelling different dependence structures of the variables.

2.7.2.1. Meta-Elliptical Copulas

These are the elliptical distribution copulas. The major characteristic of the elliptical copula is its extension to arbitrary dimensions and is comparatively rich in parameters i.e., an *n*-dimensional copula has at least $n(n-1)/\ 2$ parameters. In addition, their restriction to symmetry of radials makes it a weakness as regards tail dependency. Normal or Gussian copula and t-copula are the elliptical copulas commonly used. The normal and Student-t copulas are expressed as (Chen et al., 2011):

(i) *Normal*

$$C_N(u;\Sigma) = \int_{-\infty}^{\phi-1(u_1)} \cdots \int_{-\infty}^{\phi-1(u_n)} \frac{1}{\sqrt{(2\pi)^n|\Sigma|}} exp\left(-\frac{1}{2}\boldsymbol{x}'\Sigma^{-1}\boldsymbol{x}\right) dx \qquad 2.5$$

where $\phi - 1$ is the quantile function of a standard normal distribution while $\sum$ is the correlation matrix

(ii) *Student-t*

$$C_t(u;\Sigma,v) = \int_{-\infty}^{t-1(u_1)} \cdots \int_{-\infty}^{t-1(u_n)} \frac{\Gamma\left(\frac{v+n}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{(\pi v)^n|\Sigma|}} \left(1+\frac{x'\Sigma^{-1}x}{v}\right)\frac{v+n}{2} dx \qquad 2.6$$

where t^{-1} is the quantile function of a standard univariate Student t_v function while v is the degrees of freedom.

Normal or Gaussian copulas are used in many real world problems, often used for financial modelling whereas t-copulas were mostly used for hydrological extremes like droughts and flood because they can characterize tails of the distribution. The normal distribution's dependence is modelled by means of a symmetric with definite positive matrix and its elements describes the dependence between different variables. The t-copula provides flexibility in the structure of tail dependency and covariance.

2.7.2.2. Archimedean Copulas

Archimedean copulas are in form of symmetric or asymmetric copulas. They are a copula class which allows for a wider range of dependence structures. The symmetric Archimedean copulas has one parameter for multi-variables which makes all the pairs of variables share the same dependency structure. That means the Archimedean copulas can only model n-1 dependence which indicate that they are not appropriate to model the dependence of more than three variables, if the different pairs show different degrees of dependency (Genest et al., 2007).

Archimedean copulas follows the algebraic form below:

$$C(u_1, u_2, \dots, u_n) = \psi\big(\psi^{-1}(u_1) + \psi^{-1}(u_2), + \cdots, + \psi^{-1}(u_n)\big) \qquad 2.\ 7$$

where ψ is the inverse of the generator (Nelsen, 2006) and

$$C_X(U_1, \dots, U_n) = \phi^{-1}(\phi(U_1) + \cdots + \phi(U_n))$$

where ϕ is the generator of the copula. Many copulas of Archimedean are used in bivariate cases and play an important role in areas such as risk analysis. The following are the commonly used Archimedean copulas:

(i) *(Clayton, 1978)*

$$\boldsymbol{\phi C(u) = u^{\theta C} - 1}$$

The asymmetric expression is

$$C(u_1, u_2, u_3, \dots, u_n) = \left(u_n{}^{-\theta_1} + \left(\left(u_1{}^{-\theta_3} + u_2{}^{-\theta_3} - 1\right)^{\frac{\theta_2}{\theta_3}} + u_3{}^{-\theta_2} - 1\right)^{\frac{\theta_1}{\theta_2}} - 1\right)^{\frac{-1}{\theta_1}} \qquad 2.8$$

where $0 \leq \theta_1 \leq \theta_2 \leq \theta_3$

The symmetric expression is given by

$$C(u_1, u_2, u_3, \dots, u_n) = \left(u_1{}^{-\theta} + u_2{}^{-\theta} + u_3{}^{-\theta} + u_n{}^{-\theta} - 3\right)^{\frac{-1}{\theta}} \qquad 2.\ 9$$

where $\theta \geq 0$

(ii) (Frank, 1979)

$\boldsymbol{\phi F(u) = \log\left(\frac{e^{\theta F u}-1}{e^{\theta F}-1}\right)}$

The asymmetric expression is given by

$$C(u_1, u_2, u_3, \dots, u_n) = \frac{-1}{\theta_1}\ln\left(1 + \frac{1}{e^{-\theta_1}-1}\left(e^{-\theta_1 u_n}\right) - 1\right).\left((1 - \frac{1}{(1-e^{-\theta_2})}.\left(1 - (1 - \frac{1}{1-e^{-\theta_3}}.(1 - e^{-\theta_3 u_1})(1 - e^{-\theta_3 u_2})\right)^{\frac{\theta_2}{\theta_3}}\right).\left(1 - e^{-\theta_2 u_3}\right))^{\theta_2} - 1)\right) \quad 2.10$$

where $0 \le \theta_1 \le \theta_2 \le \theta_3$

whereas the symmetric expression is

$$C(u_1, u_2, u_3, \dots, u_n) = \frac{-1}{\theta_1}\ln\left(1 + \frac{\prod_{i=1}^{n} e^{-\theta_1 u_1 - 1}}{\left(e^{-\theta_1}-1\right)^3}\right) \quad \text{Where} \quad \theta \neq 0 \quad 2.11$$

(iii) *(Gumbel, 1960)*

$\boldsymbol{\phi G(u) = (-\log u)^{\theta G}}$

The asymmetric expression is then given by

$$C(u_1, u_2, u_3, \dots, u_n) = \exp\left\{-\left[(-\ln u_n)^{\theta_1} + (((-\ln u_1)^{\theta_3} + (-\ln u_2)^{\theta_3})^{\theta_3} + (-\ln u_3)^{\theta_2})^{\frac{\theta_1}{\theta_2}}\right]^{\frac{1}{\theta_1}}\right\} \quad 2.12$$

where $1 \le \theta_1 \le \theta_2 \le \theta_3$

and the symmetric expression is subject to the condition that

$$C(u_1, u_2, u_3, \dots, u_n) = \exp\left(-\left[(-\ln u_1)^{\theta} + (-\ln u_2)^{\theta} + (-\ln u_3)^{\theta} + (-\ln u_n)^{\theta}\right]^{\frac{1}{\theta}}\right) \quad 2.13$$

under the condition $\theta \ge 1$

2.8. Parameter estimation methods and measures of goodness of fit

Copulas has some underlying functions which include the marginal cumulative functions and joint cumulative functions. Therefore to approximate the unknown parameters of the copula functions, it is ideal to specify how to estimate the margins and the joint separately (Ayantobo et al., 2019). The estimation precision should be the most considered factor when selecting the method of estimation. Several approaches are used for estimating copula parameters for a given data. These include method of moments, semiparametric maximum pseudo-likelihood (MPL) method, fully parametric maximum likelihood estimation (MLE) method, Inference Functions for Margins (IFM) method, the inversion of Kendall's tau estimator and the inversion of

Spearman’s rho estimator. MLE is the only method that will be described in detail since it is used in this study.

The Maximum Likelihood (ML) is an effective method to estimate parameters particularly when the data analysed is large enough and also if it has no trends of heteroscedasticity (Hastie et al., 2009). Given the observed data and also knowing the distribution family, ML will find the probability density function which is likely to produce the underlying data.

For example if y is vector of observed data and θ is the vector of the parameter, then $f(y|\theta)$ indicates a probability density function (unknown). Its probabilistic function is defined as $L_{\theta}(y) = f(y|\theta)$. According to this method the parameter vector‘s value, which maximizes the likelihood function is searched. That means when dealing with logarithms, the logarithm of the probabilistic function is being maximized rather than $L_{\theta}(y)$. The parameter values maximizing the $l_{\theta}(y) = \ln\big(L_{\theta}(y)\big)$ is called the maximum likelihood estimates:

$$\left\{\theta\,\widehat{MLE}\right\} \subseteq \quad \{\arg\max l_{\theta}(y)\}$$

According to Wong et al., (2010), maximum likelihood estimator is recommendable since it has the lowest mean square error compared with other estimators.

Another alternative for MLE methods, is the use of rank correlation measures from the observed data to estimate the copula parameters. Several methods can be used to calculate the degree of dependency between the variables, but the coefficient of rank correlation is the most useful measure of dependency, since it provides invariant measures of scale when fitting the copulas. The method correlates the data set ranks and not the values themselves therefore in the process smoothing out the presence of outliers (Hastie et al., 2009).

A goodness-of-fit test refers to testing the correspondence between the observed data and the fitted (assumed) model (Wong et al., 2010). The assessment of goodness of fit test is concerned with the testing precision of the sample generated from the theoretical Probability distribution Function (PDF). The goodness of fit test is necessary for the selection of an appropriate copula to properly model dependence among marginal distributions. Therefore, different models can be used to evaluate fitted copula models ' performance. The widely used goodness of fit tests are the Anderson-Darling test, Kolmogorov-Smirnov test, Chi-Square test, Akaike Information Criterion and Bayesian Information Criterion.

The Kolmogorov-Smirnov (KS) test is best used in measuring the highest discrepancy between the observed and the hypothesized distribution (Wang and Wang, 2010).

The Chi Square(C-S) statistics are widely used to evaluate categorical variables relationships (Zeng et al., 2015).

The Anderson-Darling (A-D) test checks the variations of the distribution in both tails. According to Zeng et al., (2015), the A-D test is based on Kolmogorov-Smirnov (K-S) test modification thereby giving the tails more weight than the K-S test. Moreover, in determining the critical values, the A-D test uses the specific distribution.

Akaike Information Criterion (AIC) is based on testing how well the data set suits the model without over-fitting it. AIC developed by Akaike (1974) is an approximation of a constant plus and the relative distance between the unknown true probabilistic function of the data and the model's fitted probabilistic function such that a lower AIC indicate that the model can be considered to be closer to the true value. Therefore the method is able to indicate how well a model works in contrast with other models available for a data set. It is given by

$$AIC = 2k - 2\log(\hat{L})$$

where k is the number of model parameters and $\hat{L}$ denotes the maximized likelihood for the model. Then the model with the minimum value of AIC is selected.

Bayesian Information Criterion (BIC) is also an information-dependent criteria based on the probabilistic function just like AIC which has different penalty functions for overfitting. BIC is defined as

$$BIC = -2\ln(\hat{L}) + k\ln(N)$$

where k is the number of model parameters and $\hat{L}$ denotes the maximised value of the likelihood function and N is the sample size. Then the model with the minimum value of BIC is selected. Since different copula functions can be used to describe various dependency structures, finding and applying the correct copula model which best suits the data is recommended. A goodness of fit test for multivariate distributions should then be applied immediately after estimating the parameters of the copulas.

Chapter 3. Materials and methods

3.1. Description of the study area

Botswana is a landlocked country located in the midpoint of the Southern African Plateau. The country shares borders with Namibia, South Africa, Zimbabwe and Zambia. It lies within the latitude 18-27°S and longitude ranges of 20-29°E respectively. The mean altitude above sea level is around 1000 m with a total land area of 582,000 km² consisting of around 2 million people (Statistics Botswana, 2015). The climate of Botswana is classified under the Koppen classification scheme as arid/semi-arid. This classification is due to semi-permanent subtropical anticyclones of southern Atlantic and the southwestern Indian Oceans which are linked to the widespread and recurrent subsidence over Southern Africa (Batisani, 2012).

Botswana is prone to uneven rainfall distribution which has two distinct seasons: dry season and wet season. The rainfall at seasonal scale is affected by the latitudinal shift of the Inter-tropical Convergence Zone that moves to south of equator during Austral summer and back to the northern hemisphere in winter (Mphale et al., 2013). The country has a mean annual rainfall of 400 mm, ranging from 250 mm as the lowest in the south western part to 650 mm per annum as the maximum rainfall in the northern part (Bhalotra, 1987). The amount of annual rainfall generally decreases from North to South. Botswana's rainfall is highly seasonal, about 95% of it occurs from October to April (Bhalotra, 1987). The months of December to February mostly record the highest rainfall annually while the winter months May to August hardly record any rainfall. The Southern Africa region is occasionally affected by the tropical cyclones coming from the Indian Ocean which usually brings moisture to the region. For example, tropical cyclone Leon-Eline in 2000 and tropical cyclone Dineo in 2017 brought massive rainfalls to most countries in the region (Howard et al., 2019). The low and highly variable rainfall in both time and space, makes the country to be susceptible to drought, and this is worsened by the high evaporation rates which are approximated to be about 2100 mm/annum (Moses, 2019). The mean daily temperatures range from an average of 5.5 ºC as the minimum temperature in winter to an average of 38 ºC as the maximum temperature in summer (Kgathi, 1999).

3.2. Data

Monthly rainfall and potential evapotranspiration data of a spatial resolution of 0.5 ° was extracted from the Climatic Research Unit Time Series (CRU TS) data archive over Botswana for the period of 1901-2018 to calculate the SPI and SPEI drought indices. The CRU TS data generally contains the monthly time-series of precipitation, temperature, Potential Evapotranspiration and other climate variables. The dataset is produced by the Climatic Research Unit in University of East Anglia, England and publicly accessible from http://www.cru.uea.ac.uk/. The monthly values are obtained by combining the existing climatology with the station anomalies that are spatially interpolated to a 0.5 x 0.5 degree grids covering the global land surface. CRU's rainfall and potential evapotranspiration data are mostly made for 80-100% of the land surface. According to Mitchell et al., (2005), the CRU database is reviewed for in-homogeneity in station records using incomplete and partly overlapping records by detecting in-homogeneities with opposing signs in different seasons and creating comparison series using neighbouring stations.

Although data from the hydro-meteorological station gauge records are regarded to be reliable and quite accurate, but the density of the station gauged network is not high enough to accurately describe the changes in rainfall and its spatial distribution. Hence the use of grid data sets may be considered a feasible complement to station gauge records (Bosilovich et al., 2008; Shi et al., 2017) because they are capable of providing critical information on measurements for wider regions, from local to regional scales. Nevertheless, it is not possible to fully disregard the unavoidable errors produced by the gridded datasets because they might not be as reliable as the rain gage records for a specific point and take account of significant uncertainties. Therefore it is often recommended to check the gridded data sets before they are implemented in water-related issues such as drought and flood assessment. However, several studies (Harris et al., 2013; Shi et al., 2017; Tirivarombo et al., 2018) have indicated that the CRU TS dataset has an overall of good performances in capturing hydro-meteorological characteristics of the globe, and that of the study area in particular. Moreover, the Department of Meteorological Services (DMS) of Botswana has datasets of climate variables at good number of stations but with varying temporal coverage. The longest period of records is from 1960-to present at very few stations. Therefore, as the study intended to cover a long historical period (1901 -2018), the use of gridded CRU TS data was seen as viable option.

3.3. Methodologies

Characterisation of drought parameters were evaluated by the SPI and SPEI method. Both indices detect and provide the magnitude of the drought severity. Therefore this study carried a comparative analysis to determine if potential evapotranspiration has an effect on drought indices. The n-month of each index is based on the accumulated total precipitation and evapotranspiration of the previous n months. In other words, a 12-month SPI/SPEI gives a comparison of accumulated precipitation and evapotranspiration over that specific 12-month period whereas a 1-month SPI/SPEI signifies conditions within a single month. The occurrence of drought happens when the index values are continuously negative and ends when the index values become positive. In this study, the beginning and end of drought event is defined when the index value is continuously lower than -0.5. The SPI was calculated using SPI Matlab codes and the same code was modified to calculate SPEI. The drought variables such as duration, severity and intensity of drought were calculated only from SPEI. Since SPI here is used for simple comparison with SPEI without subjecting it to further analysis such as determining drought variables, their marginal and copula distributions as well as return periods. Fig. 3.1 shows the sequence in which the different methodologies are applied for drought analysis.

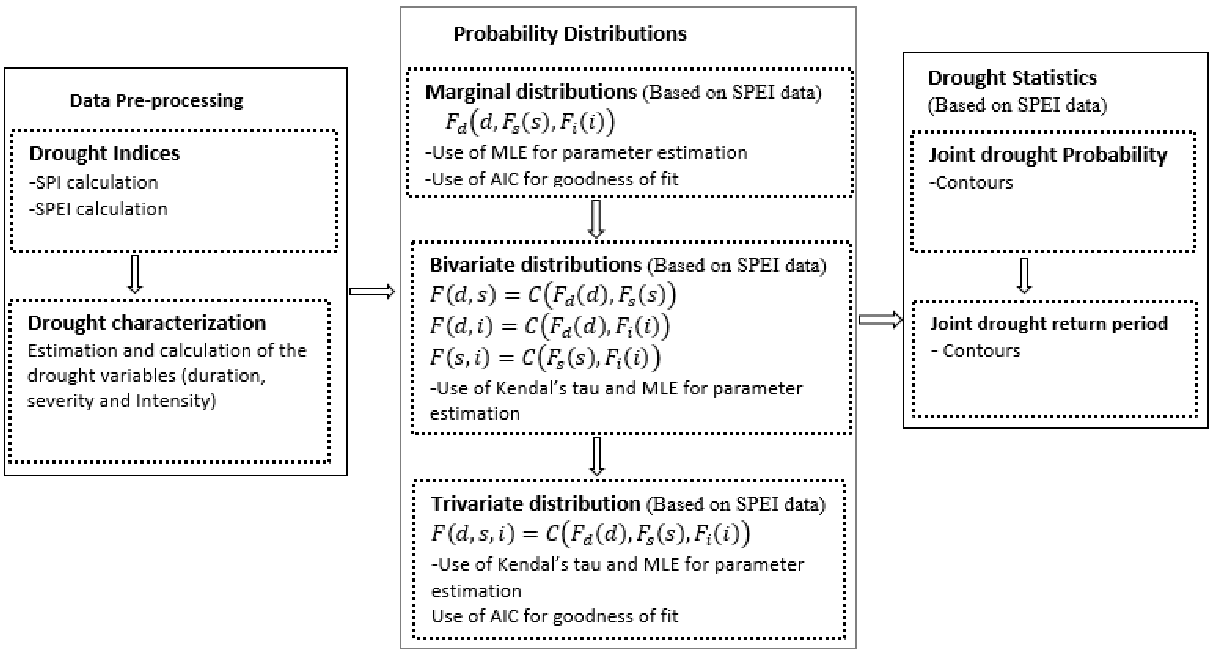

Fig.3 1: Sketch of the sequence of methodologies used in this study for drought analysis.

In the following sections, these methodologies are described in detail.

3.3.1. *SPI*

The SPI for any location (in this study, spatial grid) for a desired time period was determined from the long-term precipitation record by fitting it to a parametric statistical distribution (the gamma probability distribution). This was followed by the transformation of the distribution into a normal distribution, such that the mean SPI for the area and the desired time period is zero with variance of one (Mckee et al., 1993; Tigkas et al., 2013). Therefore, for any drought event, the SPI values are expressed in standard deviations that a specific rainfall event is different from a normalized average; positive SPI representing larger than mean precipitation (wet events) while negative values represent less than mean precipitation (Mckee et al., 1993; Tigkas et al., 2013).

The original SPI estimation suggested by Mckee et al., (1993) involves a probabilistic density function of cumulated precipitation which can be expressed as follows:

$$g(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \chi^{\alpha-1} e^{\frac{-x}{\beta}} \qquad 3.\ 1$$

where α and β are the shape and scale parameters respectively; $x > 0$ is the cumulative precipitation; and $\Gamma(\alpha)$ is the integral Gamma function defined as follows:

$$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1}\, e^{-y} dy \qquad 3.\ 2$$

The cumulative probability $G(x)$ can be estimated according to the following for any time scale i based on α and β:

$$G(x) = \int_0^{\infty} g(x)dx \qquad 3.\ 3$$

If q is the probability for no precipitation, then the observed cumulative probability of precipitation $H(x)$ is computed as:

$$H(x) = q + (1-q)G(x) \qquad 3.\ 4$$

If it is desired, the same formulas can be applied when using for other probability density functions instead of gamma.

The cumulative probabilistic distribution was then transformed into a standard normal distribution with a mean of zero and variance of one, thus resulting into the SPI value (Mckee et al., 1993). SPI therefore refers to the number of standard deviations from the mean at which an event takes place. This can be easily interpreted as the standard deviation as the division of a standardized precipitation and its long-term mean:

$$SPI = \frac{X_{ij}-X_{im}}{\sigma} \qquad 3.\ 5$$

where X_{ij} is the rainfall amount, X_{im} is the long-term mean and σ is the is the standard deviation

3.3.2. *SPEI*

The calculation of SPEI is based on the estimation of the potential evapotranspiration ($ET_{\circ}$) which is done based on an appropriate method (e.g., Hargreaves method, Thornthwaite method, Penman-Monteith method). The use of a particular method for estimation of potential evapotranspiration is not very significant for SPEI calculation therefore, the choice of the selected method should be made on consideration of the availability of data. For this analysis the Penman-Monteith method was used to estimate the PET. FAO (1998) recommended the use of Penman-Monteith as reference evapotranspiration, since it depends on the observed meteorological data, such as sunshine hours, wind speed, relative humidity and temperature hence it is able to capture the large magnitude of evapotranspiration. Several studies (Dehghanisanij et al., 2004; Kurc and Small, 2004) have found that the Penman-Monteith is more suitable for analysis in arid and semi-arid regions compared to the Thornthwaite method which is the original formulation method for SPEI calculation. According to some studies (e.g., Jensen et al., 1990), Thornthwaite method underestimates the potential evapotranspiration in arid and semiarid regions which means that the method could have not accurately estimated the evolution of potential evapotranspiration over the investigation study period. The Penman-Monteith method is based on energy balance principles and the transport of moisture such that it is able to take both thermal and aerodynamic factors into consideration making it one of the best approaches.

The total potential for evapotranspiration was calculated in this analysis using the Penman-Monteith equation of the University of East Anglia as part of the CRU data sets:

$$ET_{\circ} = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(es - ea)}{\Delta + \gamma(1 + 0.34U_2)} \qquad 3.6$$

where $ET_{\circ}$ indicating the potential evapotranspiration rate$(\mathrm{mm\ d^{-1}})$, G is the soil heat flux density MJ $\mathrm{m^{-2}\ day^{-1}}$, U_2 is the wind speed at 2 m height $(\mathrm{m\ s^{-1}})$, T is the mean daily air temperature at 2 m height (°C), Δ is the slope of vapour pressure curve (KPa $\mathrm{C^{-1}}$), es is the saturation vapour pressure (KPa), ea is the actual vapour pressure (KPa), R_n is the net radiation at the crop surface MJ $\mathrm{m^{-2}day^{-1}}$ and γ is the psychrometric constant (KPa $\mathrm{C^{-1}}$).

The monthly water balance based on the difference between the monthly rainfall and the monthly $ET_{\circ}$ is given by:

$Di = Pi - ET_{\circ}$ *3. 7*

where Pi is monthly total rainfall;

The calculated values of Di are tabulated at different time scales in the same manner as rainfall during the calculation of SPI.

The cumulative probability function is then given using the log-logistic distribution by:

$$f(D) = \frac{\beta}{\alpha}\left(\frac{D-\gamma}{\alpha}\right)\left(1 + \left(\frac{D-\gamma}{\alpha}\right)^{\beta}\right)^{-2} \quad 3.\ 8$$

and the probability density function is computed as

$$f(D) = \left[1 + \left(\frac{\alpha}{D-\gamma}\right)^{\beta}\right]^{-1} \quad 3.\ 9$$

where β,α and γ are shape, scale and origin parameters respectively where $\gamma > D < \infty$.

The standardization of the cumulative density function of the distribution to obtain the SPEI values is as follows:

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad 3.\ 10$$

$$W = \sqrt{-2ln(P)} \qquad for\ \ P \leq 0.5 \quad 3.\ 11$$

where P is the probability of exceeding the determined Di value and P= 1-$f(x)$.

The constants are C_0=2.515517, C_1=0.802853, C_2=0.010328, d_1=1.432788, d_2=0.18926, d_3=0.001308.

Using the obtained SPI and SPEI values, drought can be categorised into four (Table 3.1, which is adapted from McKee et al., 1993). However, in this study the first category is split into two categories namely normal (0 to -0.49) and intermittent drought (-0.5 to -0.99).

Table 3. 1: Classification of Drought based on SPI/SPEI.

SPI/SPEI	Drought category
0- to -0.49	Normal drought
-0.50 to -0.99	Intermittent drought
-1.00 to -1.49	Moderate drought
-1.50 to -1.99	Severe drought
≤ -2	Extreme drought

3.3.3. Determination of drought variables

Identifying the beginning and end of drought events is not easy, but by using tools such as drought indices, one can be able to identify the drought events and analyse their characteristics.

The individual hydrological drought events is identified by the 12-month SPEI and characterized based on duration, severity and intensity of the drought. The drought duration was considered as the length of time elapsed the index values are continuous negative and less than or equal to the truncation level. For this study the truncation level was -0.5. The drought severity was obtained as the cumulated index values during the drought duration while the drought intensity was determined as the ratio of drought severity to its duration. A threshold of drought index must always be defined for the determination of the drought duration (length of period) and drought severity (magnitude). Fig. 3.2 demonstrates the time series of SPEI and identification of drought duration and severity.

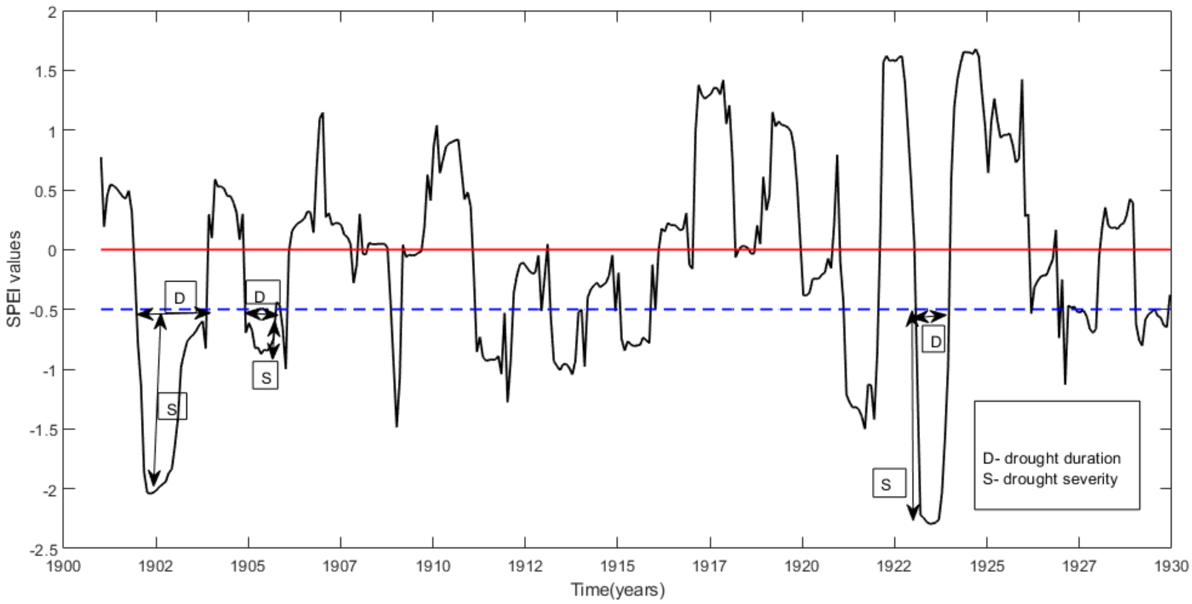

Fig.3 2: Characterization of drought events using duration and severity using SPEI.

3.3.4. *Delineation of homogeneous drought regimes using clustering*

One of the most common approaches to identifying homogeneous regions is clustering (Clarke, 2011). Clustering is used to separate the data into homogeneous groups with members having identical characteristics. This study used K-means clustering for selection of homogeneous regions across the country with similar drought characteristics based on SPEI data. K-means is one of unsupervised machine learning algorithms widely used for classification. According to Javadi et al., (2017), K-means clustering is one of the best method suited for determining geographical regions due to its ease of implementation and efficiency in application. The technique works by first determining the number of clusters to be formed, then setting the cluster centre which is the average value of all objects in the *m* cluster and finally determining the closest distance of each object with each cluster centre using the Euclidean distance (Hadi et al., 2018). K-means is able to produce K various clusters highest possible difference with a goal to reduce variability within clusters and to increase variability between clusters.

3.3.5. Marginal and copula based distributions

Assuming that all the drought characteristics are continuous, then various univariate cumulative distribution functions (CDFs) can be fitted to the distribution of the drought duration, severity and intensity of the observed drought events. Several studies (Shiau, 2006; Mirabbasi et al., 2012 and Zin et al., 2013) indicated that drought duration and severity have distributions that can be best described by exponential and gamma distributions, respectively. However, other researches have recommended that the analysis of marginal univariate distributions shouldn't be limited to these mentioned distributions since there is regional variation in suitability of these distributions (Yusof et al., 2013). Therefore a selection of best-fitting marginal distributions among large pool of distributions should be made based on suitable test statistics. The Objective selection of an appropriate marginal distribution for each dependent variable is important in developing appropriate bivariate / multivariate joint distribution of probability using copula. For this study the selection of the best-fit distribution was based on the Akaike information criterion (AIC). According to Zhang and Singh (2006), AIC is highly appropriate for use than other goodness-of-fit statistics. Six distributions namely Weibull, Exponential, Generalized Extreme Value, Gamma, Lognormal, and Generalized Pareto were tested to determine the best-fit marginal distribution for each drought variables.

Multivariate variable analysis of drought has a challenge when it comes to dealing with different types of distributions because the variables are highly correlated (Kwak et al., 2013). The copula function suggested by Sklar (1959) was therefore seen as an alternative in the consideration of the structure of dependency between the drought variables through the use of marginal distributions (Shiau, 2006: Song and Singh, 2010). Sklar (1959) used the copula to establish the association between multiple variable and also because of its ability to be used in any type of distributions. Generally, offers a way to explain the dependency structure of a given multivariate data, irrespective of their marginal probability distributions (see also Chapter 2, Section 2.6 for more details).

The Akaike information criterion (AIC) was again used to select the best-fitted copula function for this study. The copula class with lower values of AIC was selected and used to show the relationship between the drought variables (see also Chapter 2, Section 2.7).

The following nine copula groups were used for this analysis to identify the best fit copula to demonstrate dependence among the three drought variables; Normal, Student's t, Gumbel-Hougaard, Rotated Gumbel, Clayton, Rotated Clayton, Joe-Clayton, Frank, and Plackett copula. The chosen copulas belong to different families, which supports correlation of both positive and negative variables therefore they were selected to cater for incidences where there are both positive and negative correlation within the drought variables.

Since the variables duration, severity and intensity are not mutually independent, a multivariate formulation has to be created to construct their joint occurrence. Therefore a copula theory can be used for this purpose (e.g. Shiau, 2006). An approach focusing on conditional distributions is being pursued for this analysis. The joint probability distribution can help one to know the conditional probability of drought duration(Dd), or severity (Ds), and intensity (Di) exceeding a given threshold, $P^{\cap}{}_{DSI}(Dd \geq d \text{ } and \text{ } Ds \geq s \text{ } and \text{ } Di \geq i)$, $P^{\cup}{}_{DSI}(Dd \geq d \text{ } or \text{ } Ds \geq s \text{ } or \text{ } Di \geq i)$. The latter is less stringent and this kind of information can be useful for the design of drought contingency plans in water supply management systems (Shiau, 2006). The probability can be estimated in terms of copulas but could not be attained with separate drought duration and severity analysis. Following Shiau (2006), the trivariate non-exceedance probabilities can be estimated by

$$
\begin{aligned}
P_{DSI}{}^{\cap} &= P(Dd \geq d \cap Ds \geq s \cap Di \geq i) \\
&= 1 - F_D(d) - F_S(s) - F_I(i) + F_{DS}(d,s) + F_{DI}(d,i) + F_{IS}(i,s) - F_{DSI}(d,s,i) \\
&= 1 - F_D(d) - F_S(s) - F_I(i) + C_{DS}(d,s) + C_{DI}(d,i) + C_{IS}(i,s) - C_{DSI}(d,s,i) \qquad 3.\ 12
\end{aligned}
$$

$$
\begin{aligned}
P_{DSI}{}^{\cup} &= P(Dd \geq d \cup Ds \geq s \cup Di \geq i) \\
&= 1 - F_{DSI}(d,s,i) \\
&= 1 - C_{DSI}(d,s,i) \qquad 3.\ 13
\end{aligned}
$$

where $\mathrm{P_{DSI}}^{\cap}$ denotes the joint probability of occurrence of duration and severity and intensity while $\mathrm{P_{DSI}}^{\cup}$ indicates the joint probability of occurrence of duration or severity or intensity. $\mathrm{F_d}$, F_s, $\mathrm{F_i}$, $\mathrm{C_{ds}}$, $\mathrm{C_{di}}$, $\mathrm{C_{is}}$, $\mathrm{C_{dsi}}$ are mariginal and copula distributions (see also Chapter 2).

After determination of the probabilities of different drought events, they can then be used to determine the return time of such events. For this study copula functions are used to overcome the overestimation and underestimation of risk associated with droughts. According to Serinaldi et al., (2009), drought return periods are particularly important, as they can provide critical information on the proper use of water in drought conditions. The return period of drought events must be estimated with a knowledge of the possible drought inter-arrival time determined from the observed droughts events. The inter-arrival time is known as the period between the start of a drought event and the start of the next drought (Shiau, 2006). Shiau (2006) calculated the drought's return period with severity and duration and droughts which are separately greater than or equal to certain rates. Assuming that drought events occur separately, the return period of a critical drought events may be derived as:

$$T_D = \frac{E(L)}{1-F_D(d)} \qquad T_S = \frac{E(L)}{1-F_S(s)} \qquad T_I = \frac{E(L)}{1-F_I(i)} \tag{3. 14}$$

where T_D, T_S, T_I are return periods for droughts with D, S, I greater than or equal to certain values $(\mathrm{d, s, i})$, respectively; $F_D(\cdot)$, $F_S(\cdot)$, $F_I(\cdot)$ are duration, severity and intensity CDFs; $E(L)$ is the expected inter-arrival time.

However, according to Shiau (2003), the return period that takes into account multiple variables is more recommendable in drought assessments. Shiau (2006) extended the separate return periods to joint return periods of drought with specified two or three parameters of drought events (e.g., duration and severity, duration and intensity, severity and intensity or all of them). Therefore, in this study the joint return period of drought events characterized by duration, severity and intensity are determined. Shiau (2006), defined the joint return period definitions for the drought events based on copula as follows for bivariate and trivarate conditions:

for bivariate drought characterization Eqn. 3.15 is used:

$$T_{And}(DS) = \frac{E(L)}{P(D \geq d, S \geq s)} = \frac{E(L)}{1 - F_D(d) - F_S(s) + F_{(d,s)}}$$

$$\frac{E(L)}{1-F_D(d)-F_S(s)+C[F_D(d),F_S(s)]} \tag{3. 15}$$

The same equation was used by replacing *S* with *I* or *D* with *S* to determine $T_{And}(DI)$ and $T_{And}(SI)$.

for trivariate description, the following equation was used;

$$T_{And}(DSI) = \frac{E(L)}{P(D \geq d, S \geq s, I \geq i)} = \frac{E(L)}{1-F_D(d)-F_S(s)-F_I(i)+F_{DS}(d,s)+F_{DI}(d,i)+F_{IS}(i,s)-F_{DSI}(d,s,i)}$$

$$= \frac{E(L)}{1-F_D(d)-F_S(s)-F_I(i)+F_{DS}(d,s)+F_{DI}(d,i)+F_{IS}(i,s)-C[F_D(d),F_S(s),F_I(i)]} \tag{3.16}$$

The computer codes for all analysis are written in Matlab programming language.

Chapter 4. Results and discussions

4.1. Homogeneous drought regimes and fidelity of the drought indices

Fig. 4.1 shows the results of clustering based on time series of the 12-month time scale SPEI. A set of seven clusters with similar drought characteristics were obtained from the SPEI data over Botswana. The drought sub regions in Botswana can be largely classified as- north eastern region (region 1), central region (region 2), south-western (region 3), western region (region 4), south-eastern region (region 5), eastern region (region 6) and north-western region (region 7).

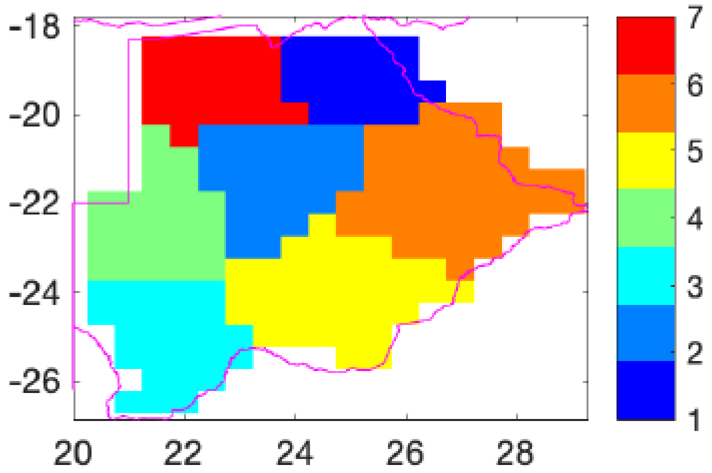

Fig.4. 1: Homogeneous drought zones in Botswana based on K-means clustering.

It was observed that rainfall patterns across the study area varies by region, and by season. Fig. 4.2 depicts the average monthly rainfall magnitude specific to Botswana. The regions delineated in Fig. 4.1 depicts the distinct climatic regions in Botswana.

It is noticeable that high rainfall magnitudes were obtained during a period from November-March which is known as the rainy months. In these rainy months, the northern part of Botswana recorded the highest rainfall magnitudes which indicate that region 1 and 7 are the wet regions across the study area. Both regions recorded average monthly rainfall of about 80-140 mm for the season. The south-eastern, the eastern and the central regions also recorded high rainfall magnitude but it was lower than the northern part (around 80-90 mm). Relatively lower rainfall magnitudes (around 40-80 mm) were evident in the south-western part and the western part.

It was observed that from April-August, (winter season) the rainfall magnitude were lower than the preceding months (January-March) across the whole country with rainfall magnitudes less than 20 mm. Although the season is dry, the month of April showed a slightly high rainfall magnitudes (around 40-60 mm) than other months which indicate that there is an occurrence of late summer rainfall conditions across the country. Although the amount of rainfall was lower, the northern area experienced the highest rainfall magnitudes during the season. The months of September and October were perceived as the pre-rainy season across the study area as they marked the end of the low rainfall season. A gradual increase in rainfall (around 40-60 mm) was observed from northern to southern and eastern to western across the whole country.

Overall, regime 1, generally referred as the Chobe region, represents a usually fairly wet Botswana area annual mean rainfall of more than 600 mm. Regime 2 presents the central part of the country which falls somewhere between the two extreme regimes on the east and west of Botswana. The region experiences annual mean rainfall of 350-450 mm. Regime 3 represents the arid/ dessert region, found in the extreme south-west of Botswana and receives rainfall less than an average of 250 mm per annual. Regime 4 represents semi-arid area found at the Kgalagadi Basin in the Western Part of Botswana and has a mean annual rainfall of 250mm-400 mm. Regime 5 has mean annual rainfall of 400-550 mm. Regime 6 receives an average annual rainfall of 350 mm-550 mm. Regime 7 usually known as the Okavango delta region is also a relatively wet region with average annual rainfall of 600 mm. The country's rainfall climatology presented in this study is consistent with that of Moses (2019)'s findings in terms of distribution, which also indicated that the country's rainfall onset and cessation are from November to March, with the highest rainfall amounts recorded at the northern parts of the country. He also indicated that the lowest amount of rainfall was found at the south-western part of the country.

Generally, homogenous drought regimes 1 and 7 are wetter than the other regimes for the period under study, this could be attributed to the reason that the northern part of Botswana receives majority of its rainfall as the ITCZ shifts to the south in austral summers. Then follows regime 5 and this is confirmed by Moses (2019), who indicated that southeast Botswana is the secondary maximum after the northern area in terms of rainfall accumulations. On the other hand, the south west and western parts are characterized by low rainfall. The rainy season in Botswana occurs in austral summer therefore the country particularly receives rainfall from November to March while from April to August is normally dry.

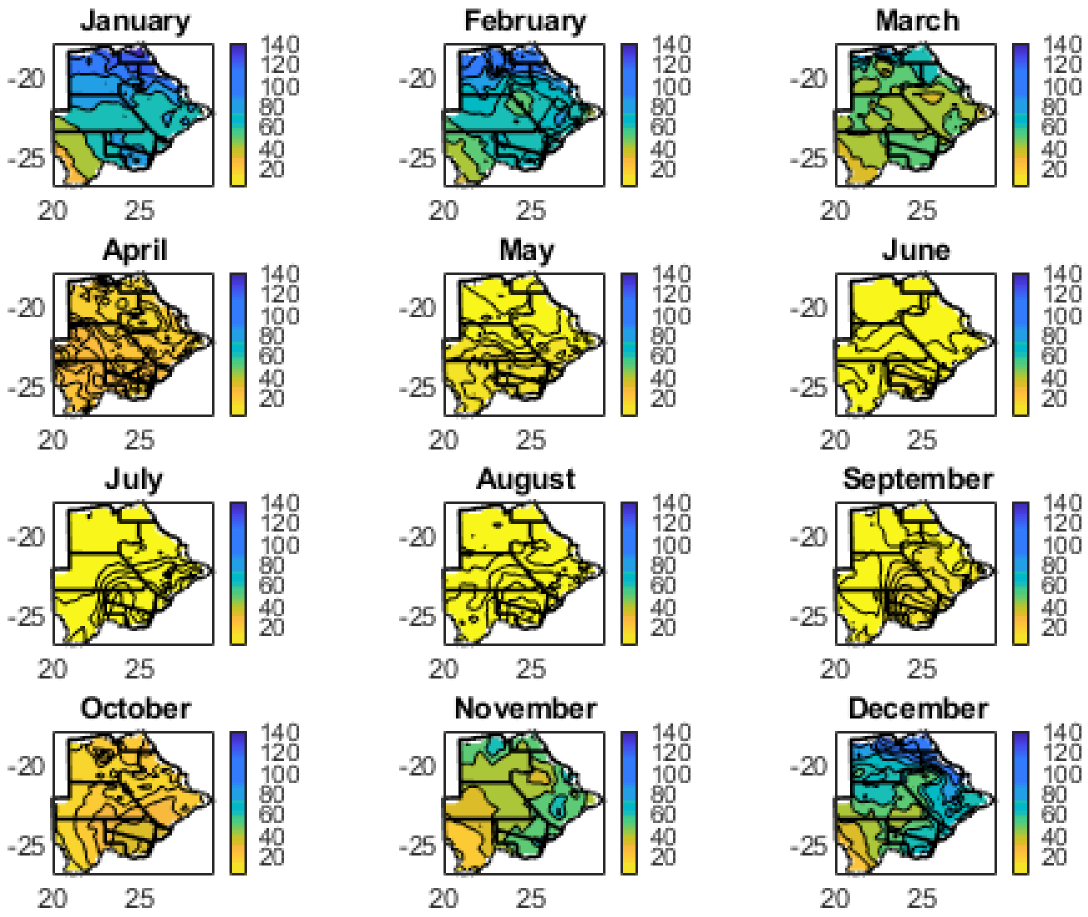

Fig.4. 2: Average monthly rainfall of Botswana during 1901-2018 determined from CRU rainfall.

Figs. 4.3 and 4.4 show the mean monthly averages of SPI and SPEI over Botswana respectively. The results indicated that both SPI and SPEI are consistent with each other in detecting the spatial variation of drought events over eastern parts of Botswana. However, the two indices differ from each other over western half of Botswana which covers much of Kalahari Desert areas. Western Botswana is generally dry receiving annual rainfall less than 250 mm per annum. As a result, SPI, which depends purely on rainfall detects low areal extent of drought over this region as compared to SPEI which indicates more frequent and severe droughts during the last 118 years. The SPEI is more consistent with the climatology of rainfall and temperature over Botswana. Moreover, this finding is consistent with other studies that have reported SPEI is suitable for semiarid and arid regions (Vicente-Serrano et al., 2014; Beguería et al., 2014 and Byakatonda, and Parida, 2018b). Another difference is that SPEI is able to identify more droughts in the severe to moderate categories over wider areas in the country than SPI does. Low rainfall magnitudes over the south west and western regions correspond with the severe drought experienced over the regions. In contrast, frequent and severe drought over the north western region which receives large amount of rainfall over the country could be attributed to the high temperatures which lead to high evapotranspiration rates. Vicente-Serrano et al., (2014) and Um et al., (2020) indicated that the severity of drought has risen over the past decades as a result of increased demand for atmospheric evaporation as a result of temperature increases.

The climatology of SPI and SPEI indices implies the accumulated mean condition over the 11 months preceding current month plus the current month. This means that each of monthly mean indices comprises of six rainy (warm) months and 6 dry (cold) months. As a result, the difference between monthly climatologies of the indices arises because of the difference in which month's data from 1901 (i.e., beginning of the time series) and/or 2018 (i.e., end of the time series in the analysis) are included in the monthly means. In principle, the impacts of such difference should be minor on the monthly mean due to averaging over large data of 117 years versus a single "outlier" implying insignificant difference between monthly climatology. In this regard, SPEI is more consistent than SPI between monthly climatology where each of the monthly climatology shows the same prominent wet and dry eastern and western Botswana respectively. Again, this confirms SPEI is more robust over SPI in capturing observed drought events over Botswana and this is consistent with Byakatonda et al., (2018c)'s findings which indicated that SPEI was identified to be more robust in drought monitoring across Botswana. In contrast, for SPI, most of the severe drought were observed during the summer months (January, February, March, and September) where rainfall is available although in a small spatial extent. Moreover SPI was able to identify the eastern part as a drought prone area during the winter months (May, June, July and August). Therefore, both indices detected severe drought better in the eastern part of the country.

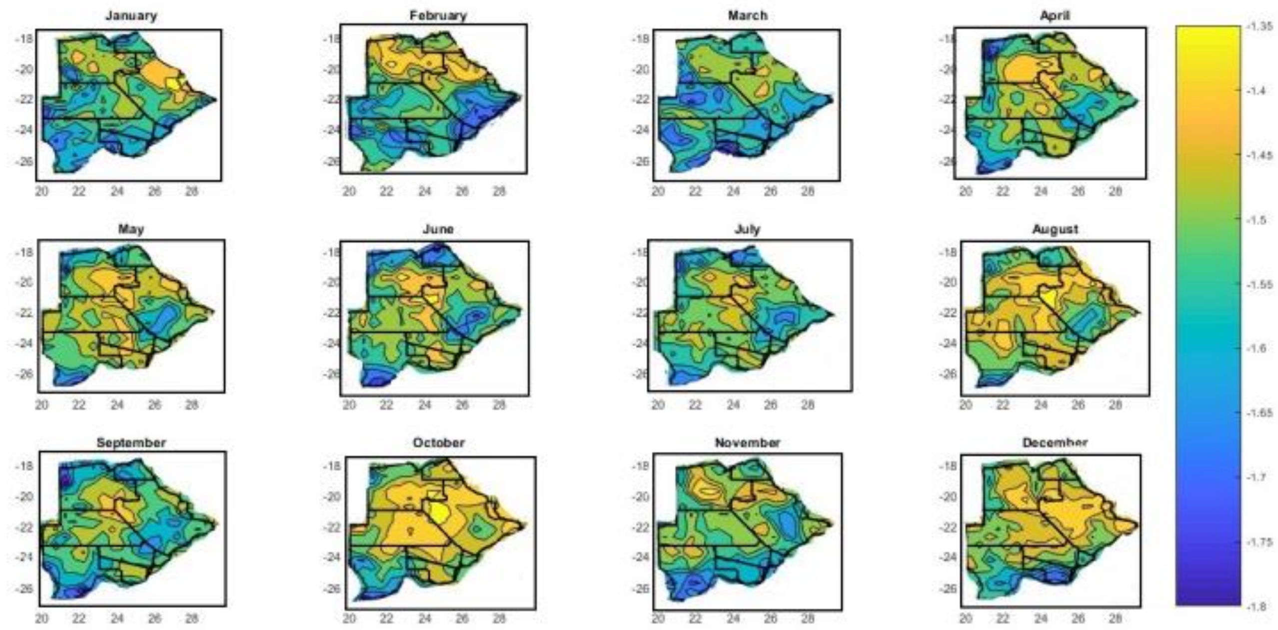

Fig.4. 3: Historical monthly mean of 12-month SPI for the period of 1901-2018 over Botswana.

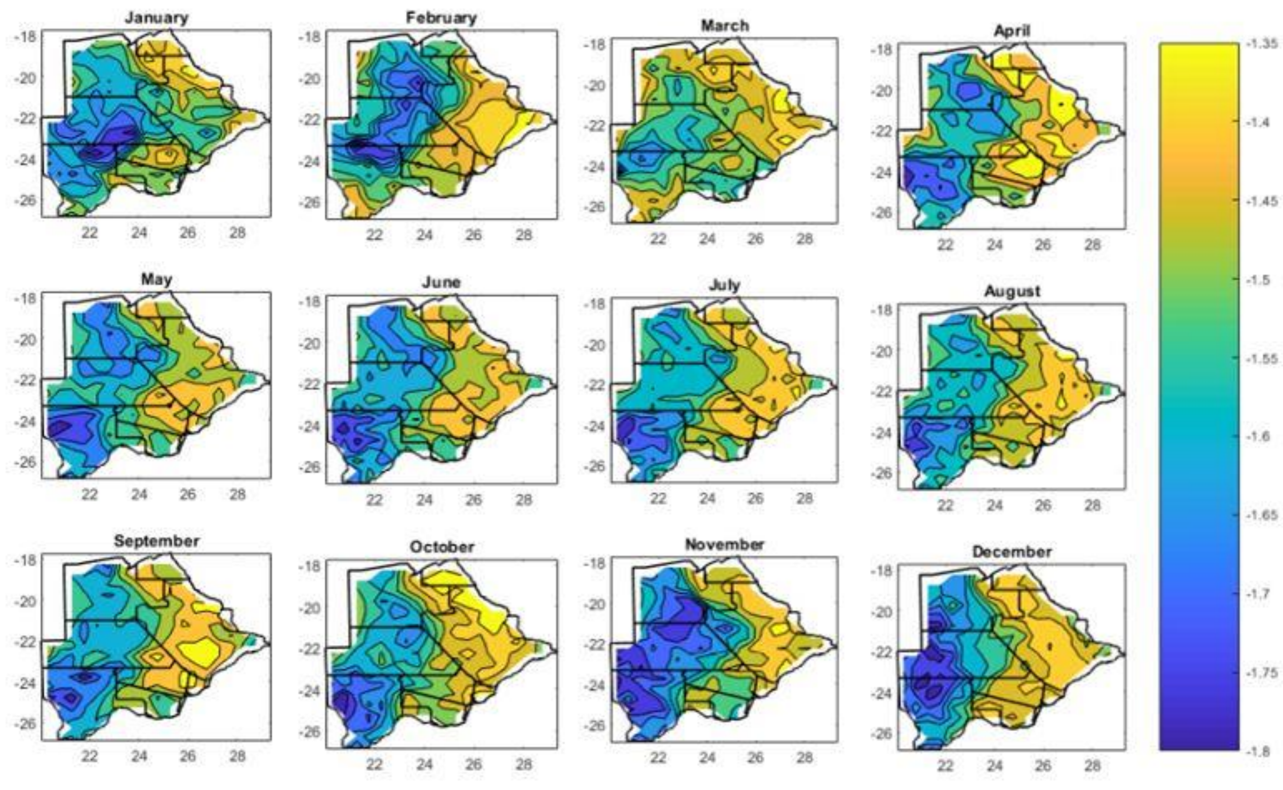

Fig.4. 4: Historical monthly mean of 12-month SPEI for the period of 1901-2018 over Botswana.

4.2. Trends of SPEI and areal extent of drought

Fig.4.5 shows the 12-month SPEI monthly time series estimated for clusters 1-7. SPEI recorded the following most severe drought events; -2.79 (1994), -2.96 (1994), -3.00 (1945 and 1992), -3.00 (1994), -2.97 (1992), -2.43 (1992) and -3.00 (1947) for regions 1-7 respectively. In the north eastern region at region 1 where the influence of the Inter Tropical Convergence Zone stands out, 7 extreme drought events were recorded. It was observed that the region was susceptible to moderate to severe drought, and this agrees with Byakatonda et al., (2020) findings that the northern locations over the country are more susceptible to moderate droughts. Severe and frequent drought was detected across the entire region but the most felt drought events were recorded in 1912, 1915-1916, 1947, 1965, 1967, 1982 and 1994. The time prior to 1965 was found to be cooler and the drought events were not frequent. The longest recorded drought in the region was registered between 1988-1992 and 1993-1995. This region is known as one of the potential areas for rain-fed agriculture, but the drought event affected it which hampered the efforts of improving the food security situation over the country (Statistics Botswana, 2017). Another most damaging drought event was recorded between 2001/03 and 2005. Then followed the 2015 drought event which mostly affected the agricultural activities and the highest cattle and goat mortality were recorded during the period (Statistics Botswana, 2017). This drought event coincides with the 2015/16 El Niño which affected the Southern African continent.

In the central region at region 2, 9 extreme drought events were registered, but in general the region is much wetter than region 1. This is indicated by the occurrence of the wet periods during the study's first two decades. The most felt drought events recorded over the region were in 1933, 1944, 1947, 1964/65, and 1992. The longest drought on record over the region (2) was found in 1981-1987. This is one of the severe hydrological drought events that affected most of the African continent which caused a huge socio-economic and environmental impacts across the region (Richard et al., 2001). The recent 2015/16 drought event region was not severe over the region. In the south-western region at region 3 which borders the Kalahari Desert, equally most drought events recorded at region 2 were also detected. The longest drought of 1981-1987 at region 2 started here earlier in 1978 and ended in 1985. This finding is in agreement with Davies et al., (2017) who indicated that this severe drought of 1978-1985/88 affected the whole country at large. But most severe drought found over this region was in 1945.

In the western region at region 4, 11 extreme drought events were recorded. The region was found to be most prone to frequent moderate-severe drought events. The longest drought of the 1980s, started in 1982 and ended in 1984. The severe and frequent drought across the region could be attributed to the increasing trends of aridity over the region as indicated by Byakatonda and Parida (2018c). In the south-eastern region at region 5, 7 extreme drought events were recorded in the years 1941, 1944, 1949, 1964/65, 1961/62 and 1964. The 1982-1986 drought was recorded in the region as the longest in duration while the 1992 was the severe drought event. The most recent drought of 2015/16 was detected in this region. This agrees with Byakatonda et al., (2018c) who detected severe drought events of 2015/16 across the region. According to Statistics Botswana (2015), the south eastern region was the most affected region which recorded the highest drought severity compared to other regions during the period of this drought event. The impacts of the drought was intense over the region, which also resulted in the highest livestock mortalities and the lowest inflow in the supplying reservoirs which lead to an increase water demand due to the inadequate rainfall over the previous years.

The eastern region recorded at region 6, recorded 7 extreme drought in the following years; 1941, 1945, 1947, 1965, 1972, 1983 and 1991. The first decade of the study period recorded the wet spell and it was observed that the region was cool in general. The longest 1980s drought event was also detected over the region and it started from 1982 and ended in 1987. Severe drought was also recorded in 1965. The 2015/16 drought event was recorded as moderate in this region. In the north-western region at region 7, 9 extreme drought events were recorded and it was observed that the region was susceptible to moderate to severe drought. The longest recorded drought over the region was found in 1981-1987 but was interrupted in 1984 and 1986 by relatively above normal rainfall. This drought event affected the activities over the region especially the tourism sector (Byakatonda et al., 2018c). The region was faced by shortage of water, high livestock and wildlife mortalities due to the drying of the Okavango delta which is the main water source around the region (Statistics Botswana, 2017). Although the region receives the highest rainfall, frequent and severe drought were observed, which might be because of the high temperature experienced by the region. According to Moses and Hambira (2018), the Okavango delta region loses 98 % of water through evapotranspiration which might translate to the occurrence of frequent and severe drought over the region. Vicente-Serrano et al., (2014) indicated that a higher atmospheric evaporative demand is linked with an increased severity of climatic drought, which may decrease the surface water resources over an area. It shows that SPEI has shown an increased severity of drought relative to SPI, which demonstrates the necessity of including evaporation in the determination of severity of drought under the conditions of global warming (Vicente-Serrano et al., 2014; Byakatonda et al., 2018c).

According to Statistics Botswana (2017), the country was declared as drought stricken in the following years: 1981-1987; 1991-1999; 2001-2005; 2007-2008; 2011-2013; and 2014-2015 which most of them were also detected by SPEI. Most of these drought occurrences coincided with the 1963-1964 El Niño years, 1965-1966, 1979-1980, 1982-1983, 1987-1988, 1991-1992, 2002-2003, 2009-2010, and 2015/16. According to Nicholson et al. (2001), rainfall over Botswana is reduced during El Niño events which could mean that El Niño has an effect on the droughts over the country. According to Moalafhi et al., (2018), a deficit in rainfall over the coming seasons in the country is mainly due to these persistent El Niño conditions. This also agrees with Vicente-Serrano et al., (2011); and Byakatonda et al., (2020) findings that confirmed the ENSO's influence on severe drought occurrence.

It was observed that for all the regions, the first 50 years of the study period was mostly dominated by mild to moderate droughts and the severity of drought across the country started to increase starting from 1960 to the present time and the period is affected by moderate to severe drought with some incidences of extreme drought. In the early and late 1980s, droughts predominated primarily in 1982-1983 and 1986-1987 and were most severe in 1991-1993, 1997-1998 and 2015/16. Generally, Botswana had been found vulnerable to two drought categories, namely moderate and severe droughts and moderate drought is the most dominating category and this is in line with Batisani (2011)'s findings indicating that Botswana was more prone to moderate droughts.

Drought over Botswana could be attributed to the evolving weather patterns due to excessive heat build-up on the surface of the earth, meteorological changes resulting in decreased rainfall, and decreased cloud coverage, all resulting in higher evaporation rates. However, anthropogenic activities such as deforestation, overgrazing and poor cropping practices that reduce soil moisture content, and inadequate soil management strategies that lead to soil degradation can worsen the resulting effects of drought. Considering that most of the surface water supplies in Botswana are typically sustained by rainfall, insufficient rainfall could be the major cause of drought.

Fig. 4.6 shows the percentage of drought area across the country which indicated that the country is prone to moderate to severe drought. It was observed that throughout the decades, moderate drought was most prevalent across the country with the percentage of drought area (PDAs) ranging from 5 to 60 %. PDAs greater than 50 % were recorded in 1911-1918, 1960-1967, and 1970. Drought event with a longer duration was recorded during 1982-1989.

Incidences of severe and extreme drought events were detected with higher PDAs ranging from 50- 99 %.

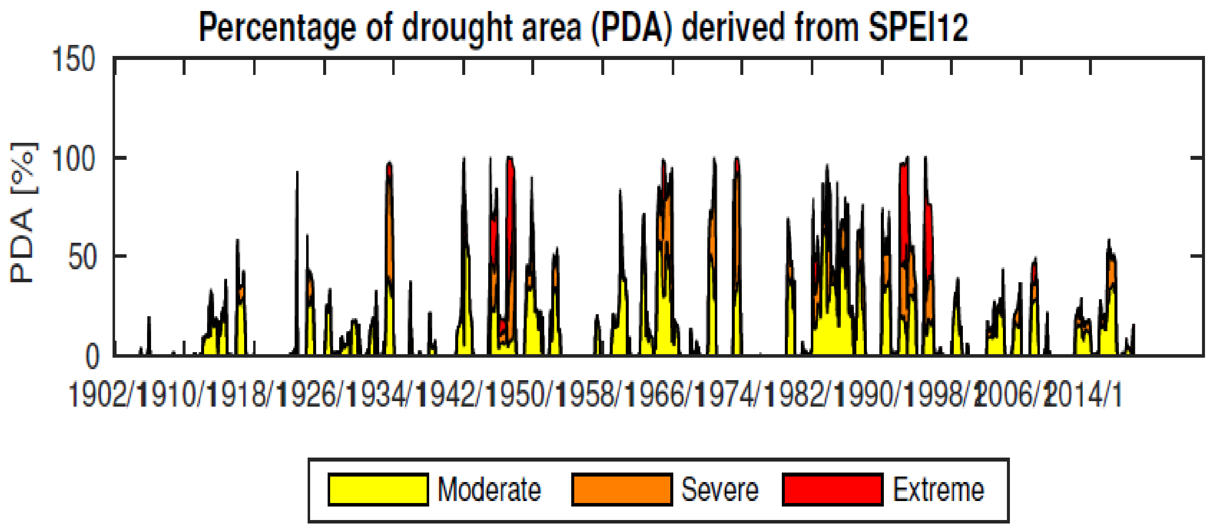

Fig. 4.6: The percentage of the drought occurrence over Botswana for SPEI-12 during the period 1901-2018.

4.3. Climatology of drought variables

Fig. 4.7a-c shows the statistics of the duration, severity and intensity of all the drought events recorded during the period 1901–2018 for all the seven regions (clusters) across Botswana. The results indicate that large number of drought events recorded in the seven regimes had a short duration while less number of drought events had longer duration. This shows that as the duration of drought increases the number of drought events tend to decrease. Throughout this period, it was observed that, region 5 has drought of longer duration, followed by region 7, region 1 and region 6. According to the results, the eastern parts of the country have recorded large number of droughts with longer duration than over the other parts of the country.

On the other hand, it was observed that large number of drought registered over the seven drought regions had a high severity while less number of drought events had low severity. It reflects that number of drought events increased with the increasing severity. Regime 6 has drought of higher severity, followed by region 3, region 5, and region 1. Region representing the eastern part of the country are characterized by drought of higher severity than those droughts occurring over the central and western Botswana.

Intensity exhibited a similar trend as the severity, large number of drought events recorded in the seven regions had a high intensity. Region 5 has drought of higher intensity, followed by region 3, region 6, and region 4. Regions representing the eastern and western parts of the country are characterized by drought of higher intensity than those droughts occurring over the central and northern parts of Botswana. The large number of drought observed in the eastern and southern regions could be attributed to the recently increased temperatures over the regions which are linked with the increased evaporative demand. Since drought are recognised as important challenges in water resources planning and management, therefore characterizing its variables and their interdependence over individual regimes could be very useful in drought preparedness and mitigation.

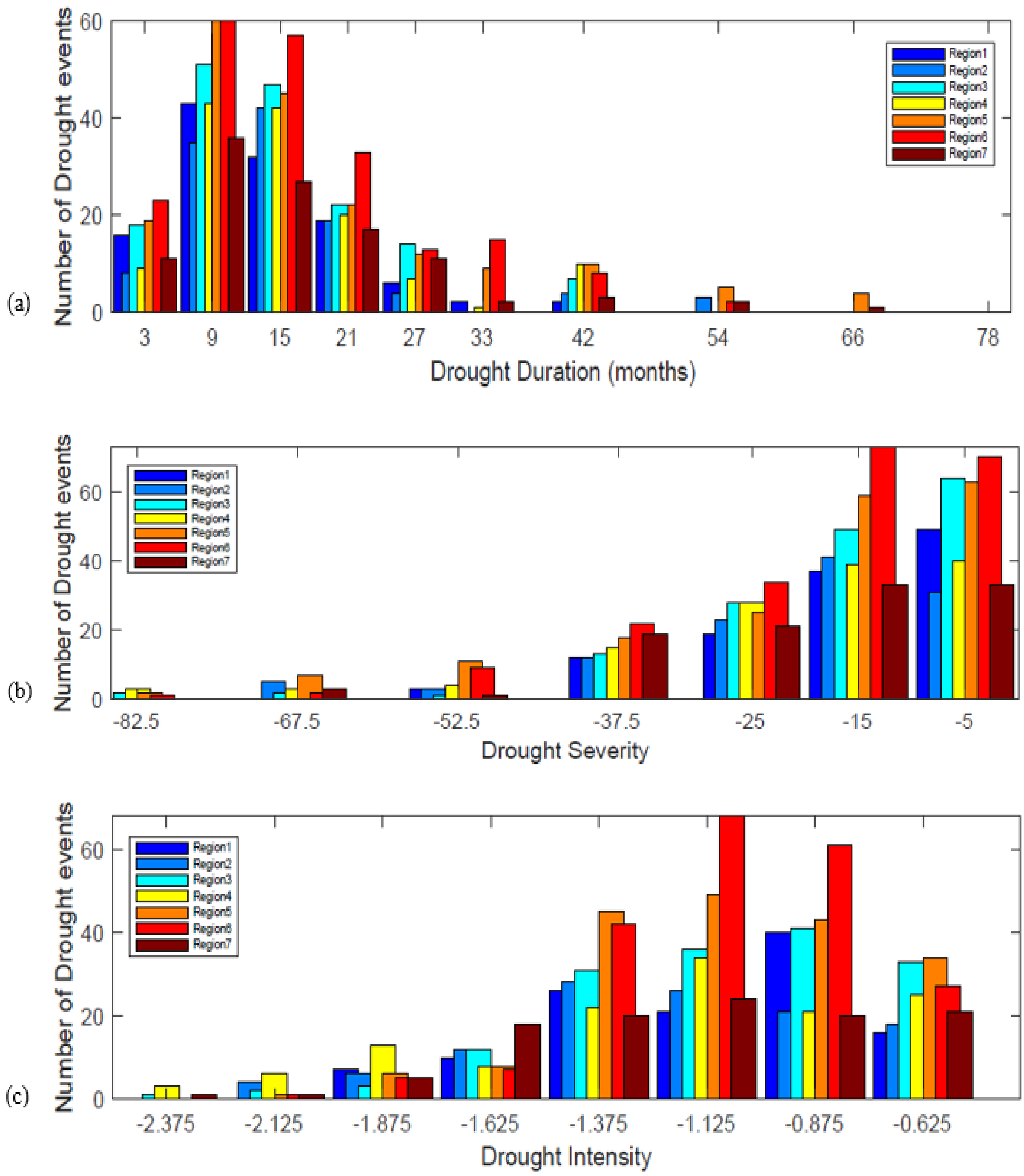

Fig. 4.7: Frequency of drought (a) duration, (b) severity and (c) and intensity.

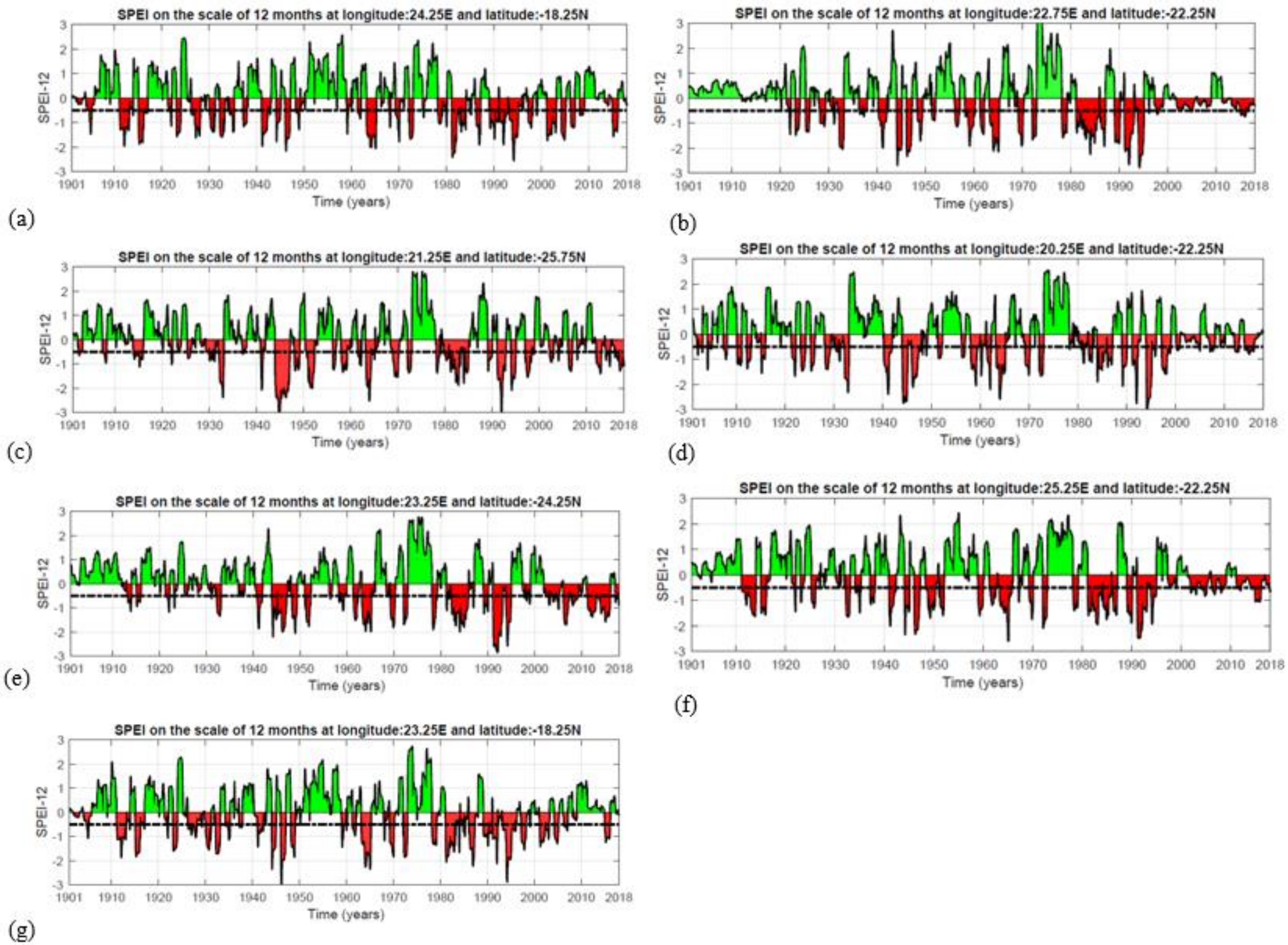

Fig.4. 5: Historical SPEI time series for randomly selected grid in (a) region 1 to (g) region 7 during the period 1901–2018 over Botswana.

4.4. Marginal and copula distributions of drought variables

4.4.1. *Estimation of marginal distributions*

The marginal distribution for duration, severity and intensity of drought was established based on the lowest values of AIC. The analysis of the goodness of fit tests indicated that the drought duration was best distributed with the Generalized Extreme Value distribution while the drought severity and intensity were both best distributed with Weibull distribution. Fig. 4.8-4.10 compares the empirical and computed marginal distributions of the duration, severity and intensity of drought. It was observed that the empirical and theoretical CDFs fit well with all the marginal distributions.

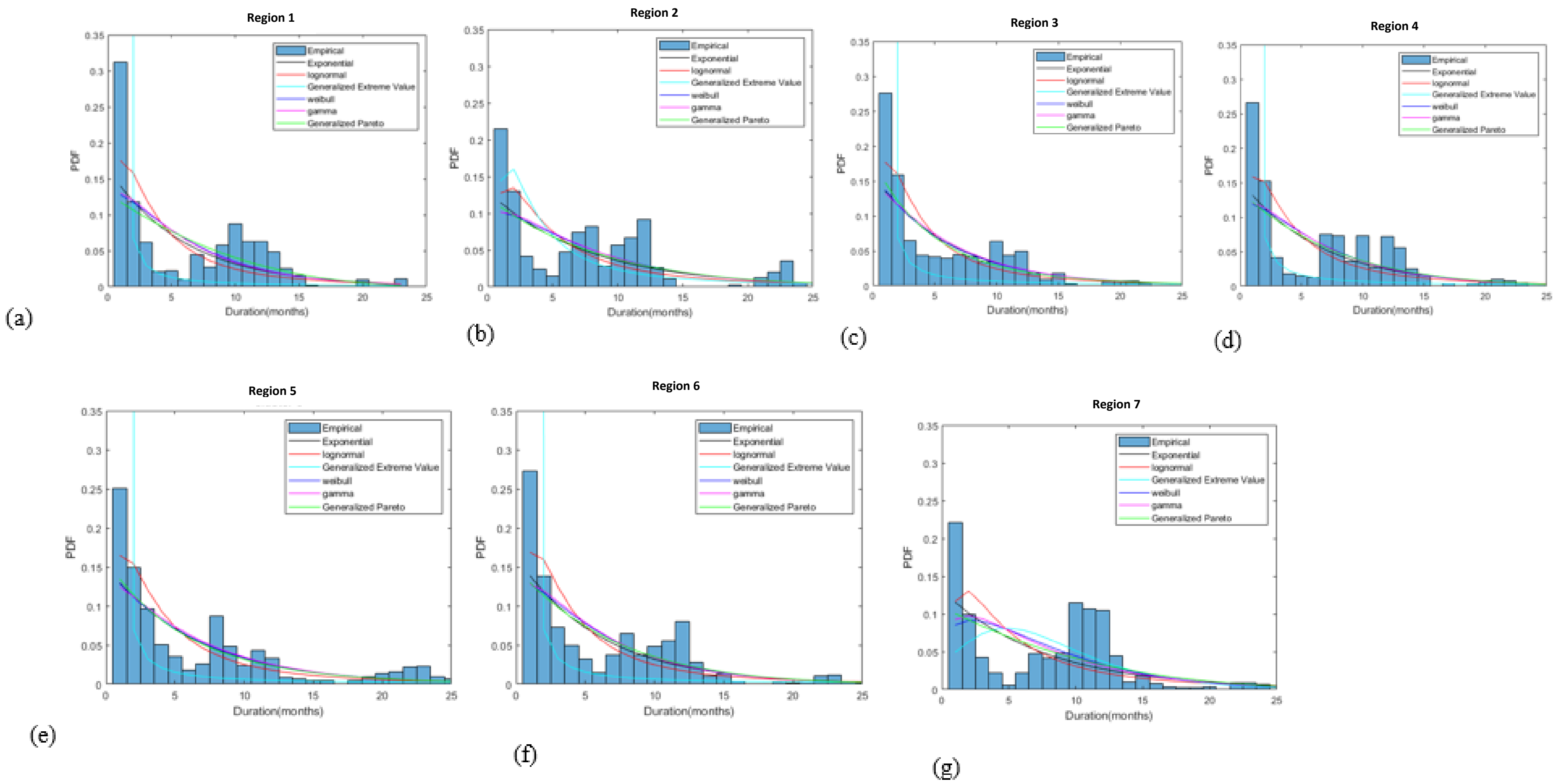

Fig. 4. 8: Marginal distribution fitting for drought duration for Exponential, Lognormal, Generalized Extreme Value, Weibull, Gamma and Generalized Pareto distributions in region 1(a)- region 7 (g) as shown in the legend.

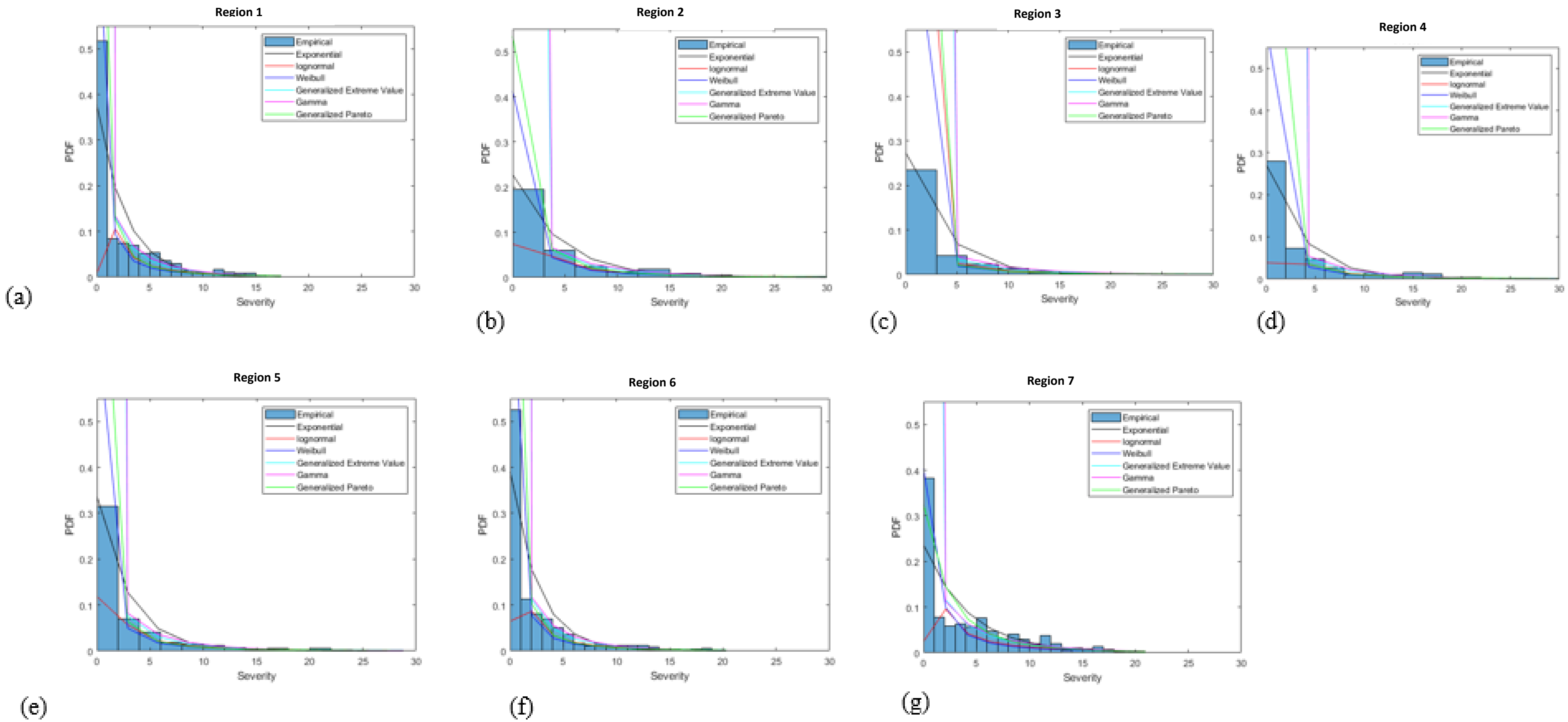

Fig. 4. 9: Marginal distribution fitting for drought severity for Exponential, Lognormal, Generalized Extreme Value, Weibull, Gamma and Generalized Pareto distributions in region 1(a)- region 7 (g) as shown in the legend.

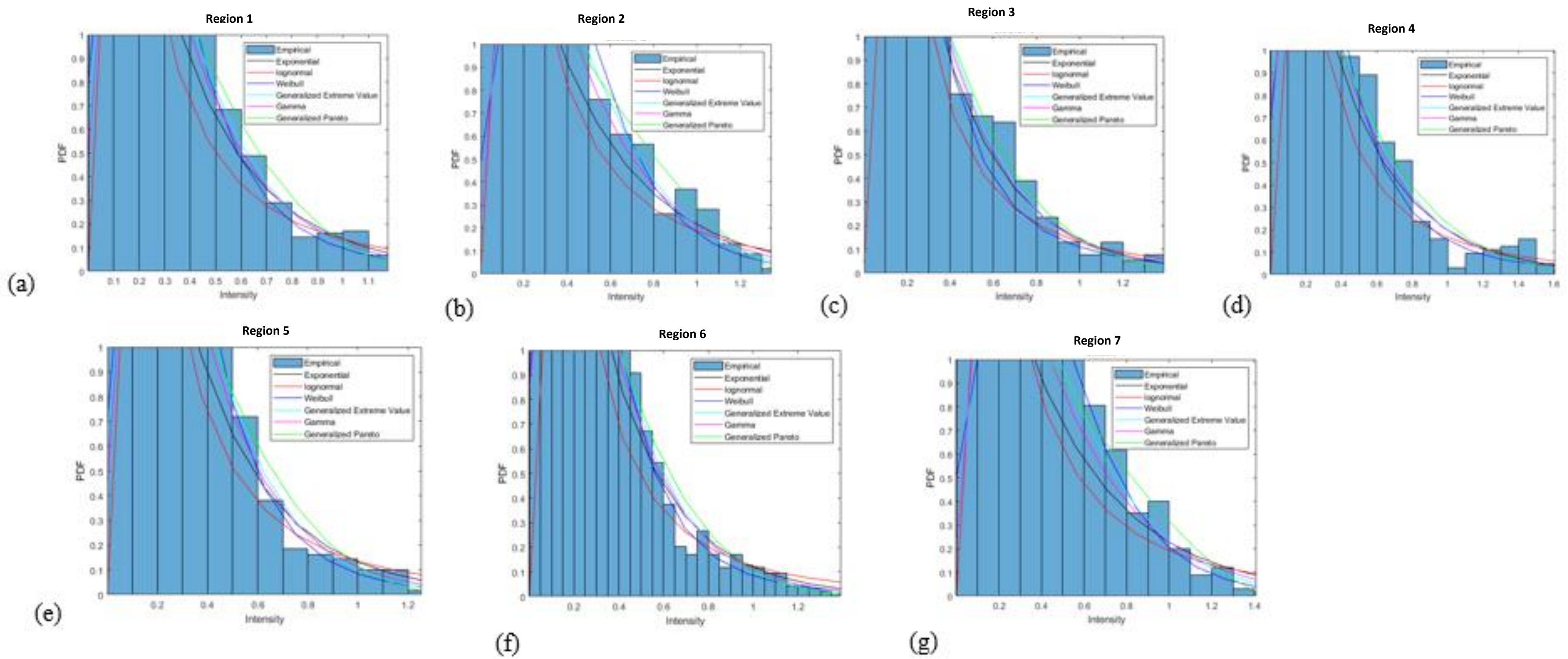

Fig. 4. 10: Marginal distribution fitting for drought intensity for Exponential, Lognormal, Generalized Extreme Value, Weibull, Gamma and Generalized Pareto distributions in region 1(a)- region 7 (g) as indicated in the legend.

4.4.2. *Selection of best fitting copula to joint distribution of drought variables*

After the selection of the optimal marginal distributions for drought duration, severity and intensity, the distributions were used to determine the most suitable distribution of copula. Nine copula distributions, namely Normal, Student's t, Gumbel-Hougaard, Rotated Gumbel, Clayton, Rotated Clayton, Joe-Clayton, Frank, and Plackett copula distributions were evaluated in this study to find the best fit copula distribution that shows the dependence amongst the three drought variables for each region in the study area. The association between drought duration, severity and intensity was measured using the Kendall's tau and Pearson correlation coefficient to statistically confirm the dependency structure and the corresponding copula distribution parameters. A positive association was observed from all the variables. Duration and severity had the highest correlation compared to others pairs. The results for Kendall's coefficient (τ) for the seven clusters are can be seen in Table 4.3. The obtained parameters were used with the suggested copula distributions to check the best-fitted trivariate copula family in modelling the dependence amongst the drought variables. The most appropriate copula functions were determined using the lowest values of AIC in regard to the likelihood function of the copula function and also the univariate marginal distribution (Zhang and Singh, 2006). The estimation of copula parameters was done using the MLE method which is the common and reliable statistical method (Ma et al., 2013). It was observed that for drought duration and severity marginals, the Normal copula distribution had the smallest values of AIC in comparison to other copula families across the clusters. While on the other hand, Clayton copula distribution was considered as the best copula for the marginal distribution of drought severity and intensity across all the regions.

Table 4.3: Correlation coefficients of drought variables

Region	Variables	Kendall's coefficient (τ)	Pearson's coefficient
1	Duration and Severity	0.542	0.612
	Duration and Intensity	0.447	0.585
	Intensity and Severity	0.304	0.411
2	Duration and Severity	0.654	0.723
	Duration and Intensity	0.510	0.648
	Intensity and Severity	0.309	0.565
3	Duration and Severity	0.621	0.706
	Duration and Intensity	0.582	0.761
	Intensity and Severity	0.423	0.768

4	Duration and Severity	0.569	0.698
	Duration and Intensity	0.477	0.640
	Severity and Intensity	0.377	0.485
5	Duration and Severity	0.528	0.686
	Duration and Intensity	0.481	0.617
	Intensity and Severity	0.334	0.354
6	Duration and Severity	0.492	0.643
	Duration and Intensity	0.440	0.580
	Intensity and Severity	0.231	0.393
7	Duration and Severity	0.598	0.764
	Duration and Intensity	0.497	0.632
	Intensity and Severity	0.324	0.443

4.4.3. *Bivariate and trivariate return periods of drought*

To study the appropriateness of applying the bivariate and trivariate copula for the three drought variables, the selected best copulas were used to determine the value of joint probabilities of drought events for any duration or severity or intensity. Normal copula functions were used to estimate the trivariate joint probabilities for the drought duration while Clayton copula functions were used for the drought severity and intensity in the seven clusters using Eqn. 3.21. Fig. 4.11-4.17 show the probability map of the bivariate and trivariate drought return periods (T_{And} (DSI)) for region 1 to region 7. The data points superimposed to the contours indicates the historical individual drought events observed within the study period.

For region 1, most of the historical drought events recorded had short duration, high severity and intensity under both bivariate and trivariate drought characterization. Moreover, the return periods were also observed to be short for most drought events (ranges from 4-15 years). It was observed that large number of drought events were found under bivariate (*D* Vs *I*) characterization than in trivariate characterisation. For both bivariate and trivariate characterization, less number of drought events were recorded with longer return periods and longer duration. Furthermore drought events with longer duration, higher intensity and severity were observed to have longer drought return periods, i.e. the trivariate return periods increased as the values of the drought variables (*DSI*) increased. For example, using Fig. 4.11b, for drought events with severity index (*S*) of -48.5 and duration (*D*) of 36.6 months, resulted in a return period of 100 years, while in Fig. 4.11c for given drought events with the same duration of 36.6 months and intensity (*I*) of -0.97 resulted in 100 years. Moreover for the trivariate characterization (Fig. 4.11d), given drought events with D = 36.6, S = -48.5 and I= -0.97 resulted in a return period of 200 years.

For region 2, large number of drought events over the region were also of short duration, high severity, high intensity and short return periods for both bivariate and trivariate drought characterization. On the other hand, less number of drought events were recorded with longer return periods and longer duration. The majority of the historical drought events recorded the return periods of 15 years under both bivariate and trivariate drought cases. In region 3, most of the historical drought events recorded had short duration, high severity and intensity under both bivariate and trivariate drought characterization. For instance, from Fig. 4.13b, the same drought events with S = -48.5 and D =36.6 months, resulted in a return period of 30 years, while in Fig. 4.13c for given drought events of the same D = 36.6 months and I= -0.97 also resulted in 30 years return period. Moreover for the trivariate characterization (Fig. 4.13d), drought events with D = 36.6, s = -48.5 and I= -1.07 resulted in a return period of 30 years.

For region 4, there were also large numbers of short drought duration, low severity and intensity under both bivariate and trivariate drought characterization. The majority of historical drought events recorded return periods ranging from 8-35 years under both bivariate and trivariate drought cases. For example, given drought events with D = 36.6, S = -48.5 and I= -1.08 resulted in a return period of 40 years. There were also large numbers of short drought duration, low severity and intensity in both bivariate and trivariate drought characterization for region 5. For example drought events with severity index of -48.5 and duration of 36.6 months, the return periods were recorded as 15 years over region 5, while in Fig. 4.15c for given drought events of the same D = 36.6 months and intensity I= -1.08 also resulted in 15 years return period. The trivariate characterization (Fig. 4.15d) given drought events with D = 36.6, s = -48.5 and I= -1.07 resulted in a return period of 15 years. In region 6, using Fig. 4.16b, drought events with S = -48.5 and D =36.6 months resulted in a return period of 15 years, while in Fig.4.16c for given drought events of the same D = 36.6 months and I=-0.97 resulted in 15 years. While for trivariate characterization (Fig. 4.16d), drought events with D = 36.6, S = -48.5 and I= -1.07 resulted in a return period of 15 years. Region 7 on the other hand registered return period of 20 years for bivariate (D Vs S), while 15 years for (D Vs I), and 20 years for trivariate case.

Generally, most of the historical drought events over both homogenous drought regions have short duration, high severity, high intensity and short return periods in both bivariate and trivariate drought characterization. However, there is a large number of drought events with shorter return period (in years) over regime 1, followed by 3, 4 and 7 than over the other three regimes represented by regime 2, 5 and 6. Such findings regarding the drought return periods can be useful for risk evaluation of drought mitigation and tactical planning on the water resource under severe and extreme drought conditions across the study area. Since the impact caused by a drought event may vary according to its duration and severity, bivariate/trivariate analyses can represent the exceptionality of drought events as the correlation between droughts characteristics are proportional to its damage potential, i.e., the negative impacts associated with a short but extremely severe drought may be stronger than another longer but less severe drought (Pontes et al., 2020).The drought return periods can be used as part of early warning and information systems thereby reducing vulnerability and enhancing people's response capabilities (Wilhite et al., 2014). According to Wilhite and Svoboda, (2000), an effective early warning systems should give a foundation for an effectual drought mitigation plan due to the slow starting characteristics of the drought. For this reason, it is important to provide relevant and reliable drought information based on different drought variables for overall drought characterisation. Therefore, drought preparedness planning is recommended to be an accepted tool which should be applied by governments to reduce the risks to future drought events.

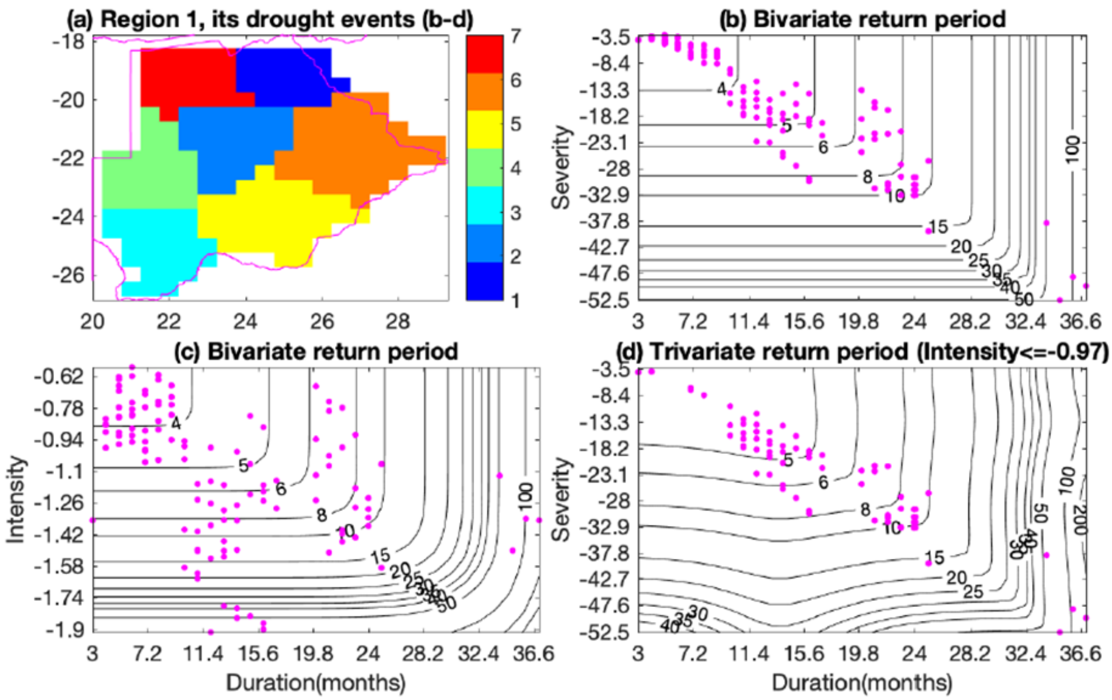

Fig.4.11: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 1 during 1901–2018.

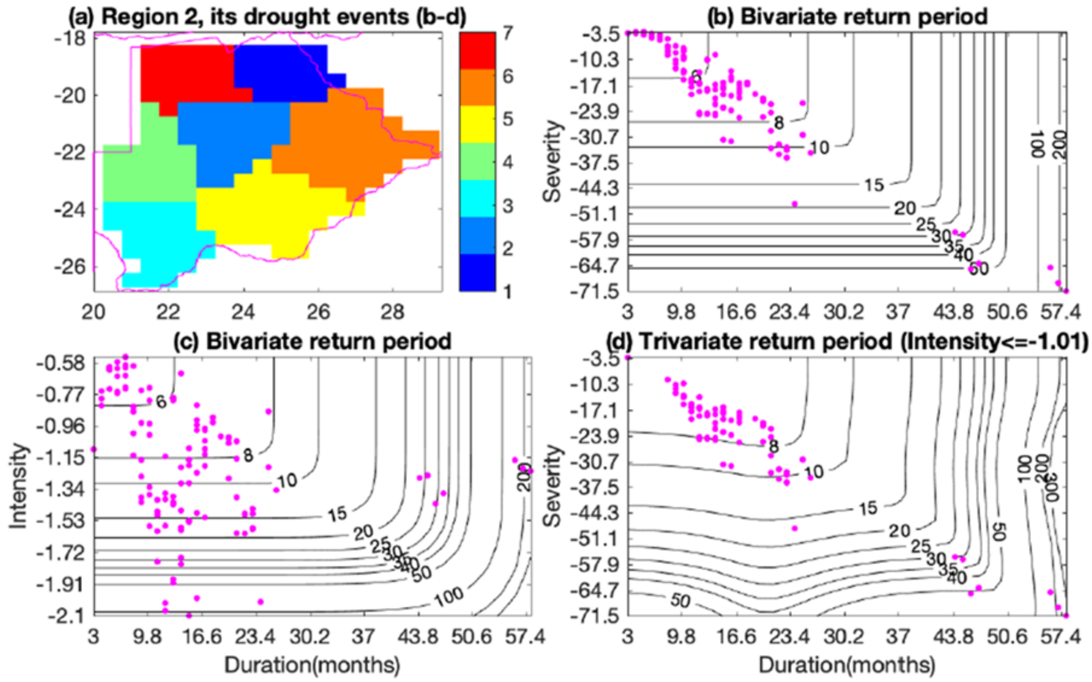

Fig.4.12: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 2 during 1901–2018.

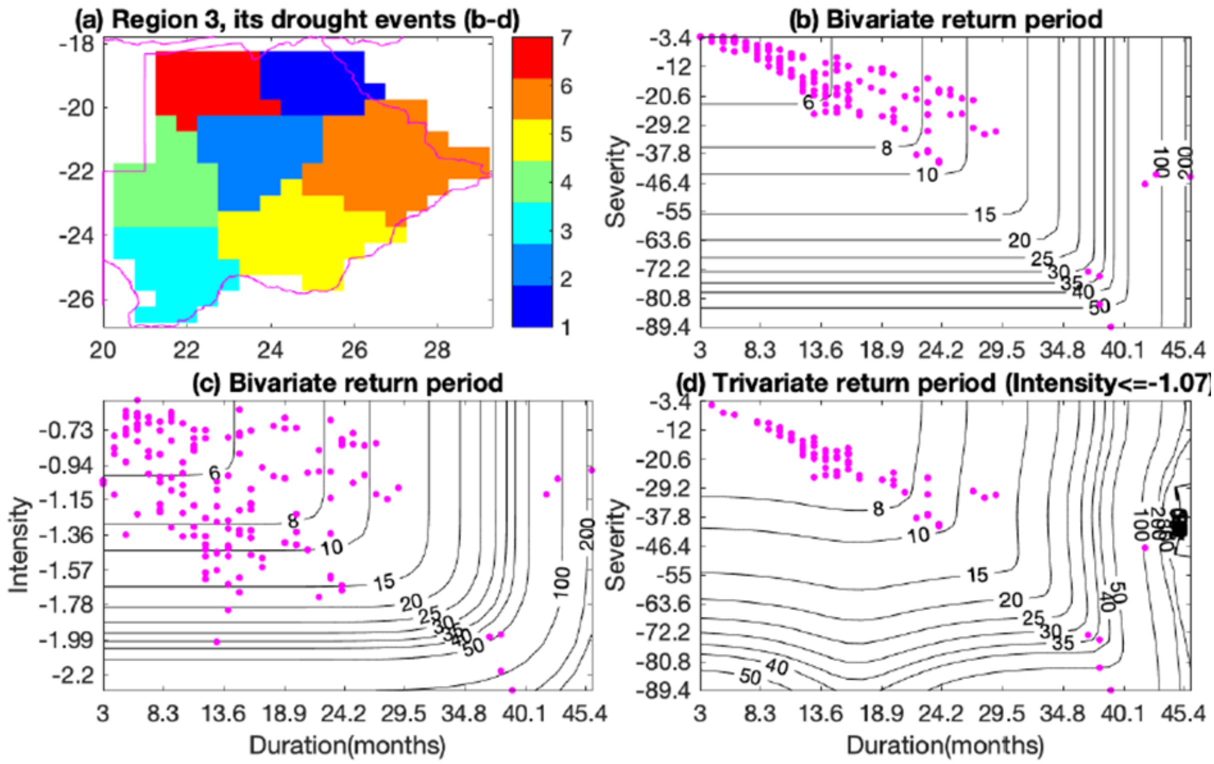

Fig.4.13: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 3 during 1901–2018.

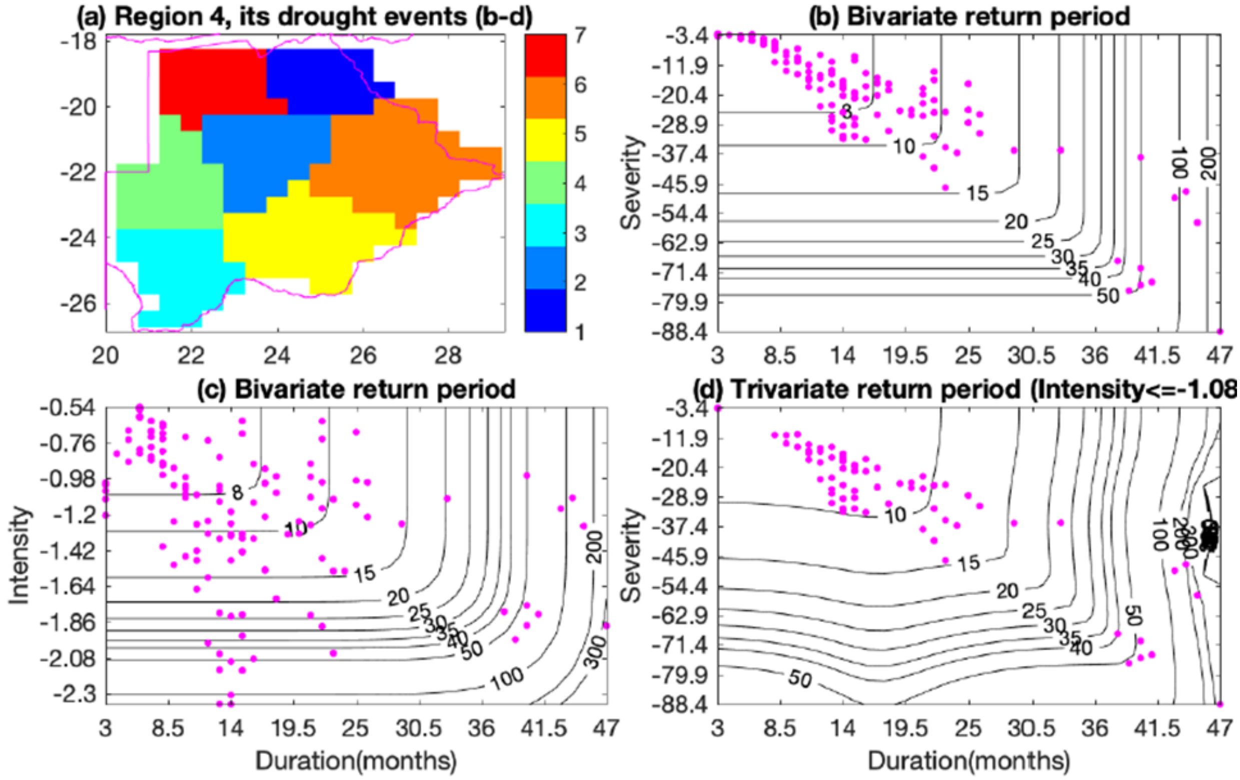

Fig.4.14: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 4 during 1901–2018.

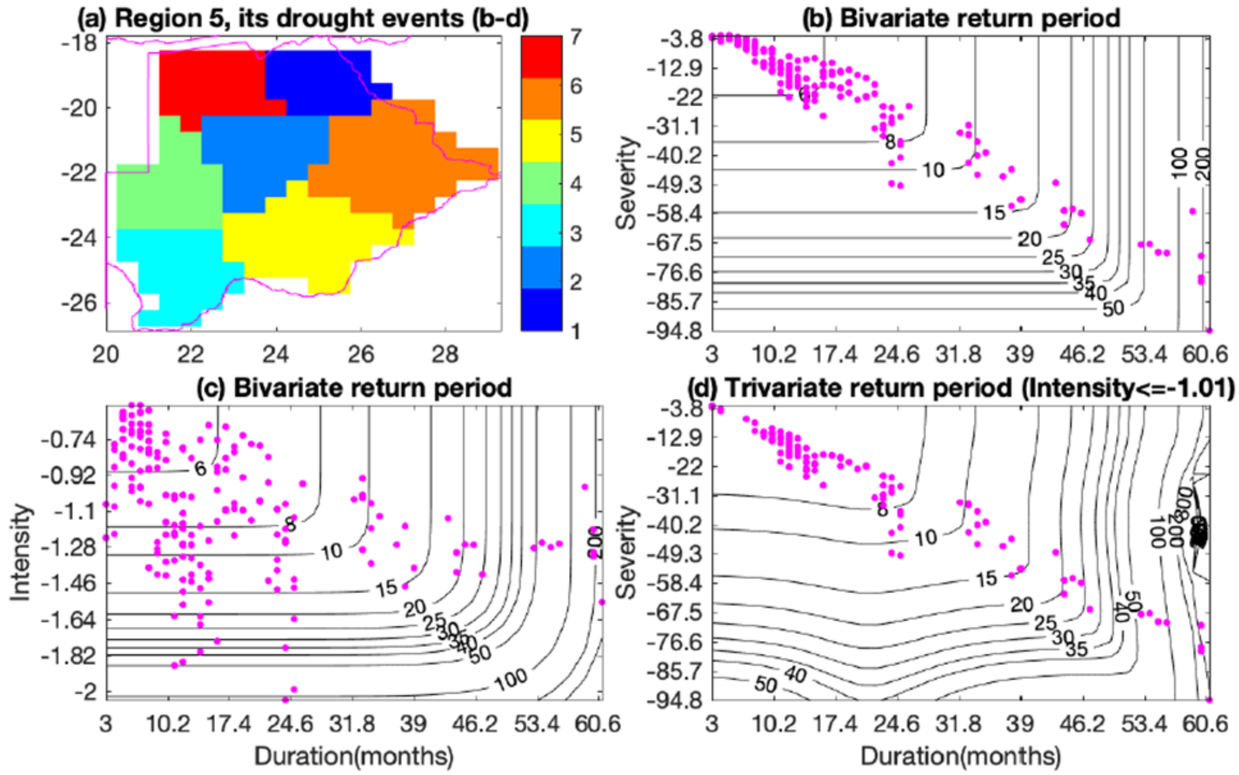

Fig.4.15: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 5 during 1901–2018.

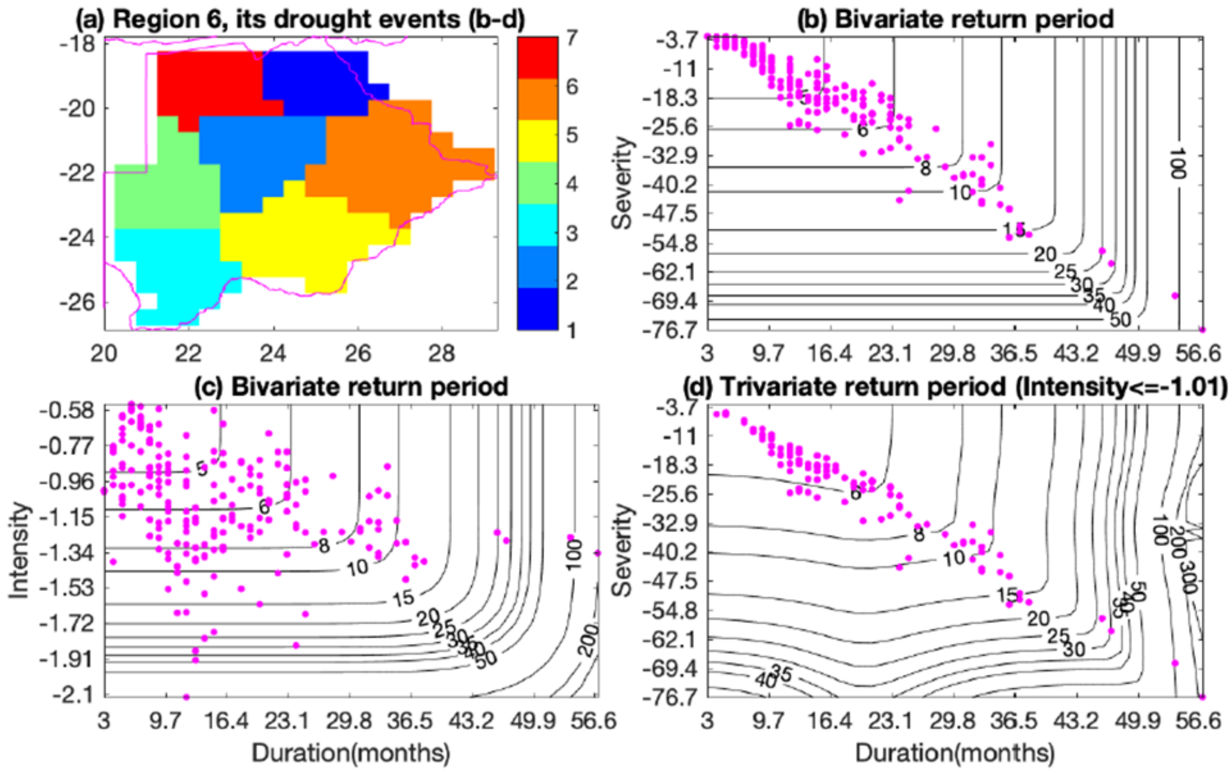

Fig.4.16: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 6 during 1901–2018.

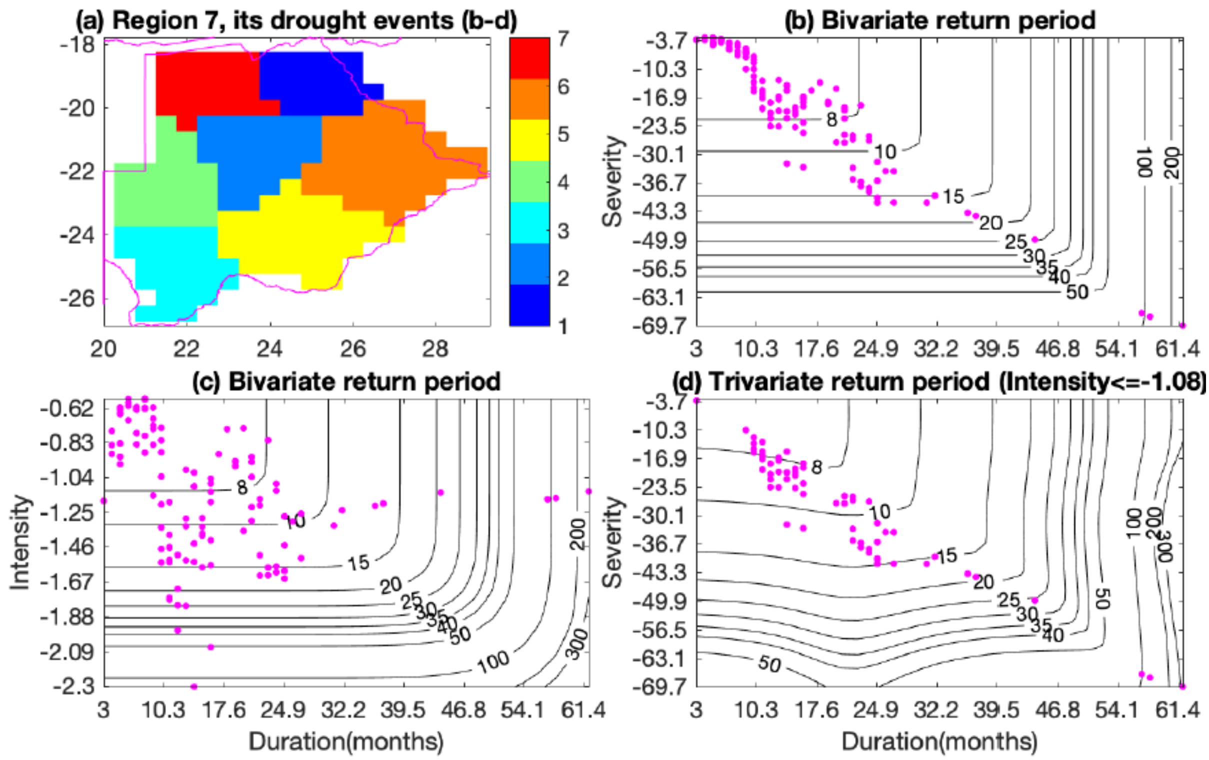

Fig 4.17: Joint bivariate and trivariate return periods for drought duration, severity, and intensity in region 7 during 1901–2018.

4.4.4. *Potential drought risk to hydrological systems within their life times*

Fig. 4.18 shows the drought risk map for hydrological system with a design lifetime of 10 years based on bivariate and trivariate joint distribution of drought duration, severity and intensity for the seven regions under consideration; $P^{\cup}{}_{DSI}(Dd \geq d \; or \; Ds \geq s \; or \; Di \geq i)$. The black and magenta dots superimposed on contours represent the historical drought events observed within the study period at different locations and periods. The different colours in the contours are the risk of drought occurrences (%) within the next 10 years. As observed from the figure, drought events with short duration and high severity had high probability of occurrence while drought events with longer duration and high severity showed a low chance of occurrence. Intensity of similar range were used to demonstrate this for the seven regions during the study period.

For example, in region 1, considering drought events with an intensity of 1.24, four drought events were found. The drought event of 1911-1913 with duration (*D*) of 20 months and severity index (*S*) of -25 was found, and had a high probability (70-80 %) of recurring in the next 10 years. Another drought event of 1991-1993, with *D*=24 months and *S*=30 was found to have a probability of 60-70% to recur. In region 2, two drought events with intensity of 1.27 were found within the same region. The drought of 1931-1933 found at the longitude and latitude of 22.25,-20.75, with *D*=25 and *S*= 30; has a risk of reoccurrence of 60-70%. The drought event of 1981-1986 found at the longitude and latitude of 22.25,-21.25, with *D*= 55 and *S*= -70 had a low chance of recurring (0-10%). In region 3, intensity of 1.37 was selected, and a drought event of 1982-1986 was found at the longitude and latitude of 23.75,-22.75. The drought event had a duration of 48 months and severity index of -66, and it was found that its risk of occurrence was at 0-10%. In region 4, two drought events (1940-1942 and 1982-1986) were recorded at the longitude and latitude of 21.25, -20.75 and 21.75, 21.25 respectively under an intensity of 1.26. The first drought event had a probability of 60-70 % to recur in the next 10 while the second one had 0-10% chance of recurring.

For region 5, an intensity of 1.20 was selected, and a drought event of 1984-1986 was found at longitude and latitude of 26.25, -23.75. The drought event had duration of 22 months and severity index of -31, and it was found that its chance of recurring in the next 10 years was between 60-70 percent. In region 6, eight drought events with a selected intensity of 1.22 were found within the same region. The first four drought events had a probability of 70-80% and the estimated values of duration and severity ranged from 20-28 months and -30-(-22) respectively. Another three drought events were found to have a risk of occurrence of 60-70%, and the estimated values of duration and severity ranged from 30-35 months and -40-(-32) respectively. The last drought event had 20-30% risk of occurrence in the next 10 years and it had a duration of 45 months and severity index of -58. For region 7, three drought events with intensity of 1.20 were found within the same region. The drought of 1940-1942 found at the longitude and latitude of 21.25,-19.25, with *D*=22 and *S*= 28; has a recurrence of 60-70%. The drought event of 1981-1984 found at the longitude and latitude of 21.25,-19.75, with *D*= 38 and *S*= -42 had 40-50% chance of recurring. The last drought event was found at the longitude and latitude of 21.75, -19.25 during 1981-1984. It was found that the probability of the same drought to recur was also between 40-50 %.

The risk of occurrence of drought events with longer duration and high severity is low across all the regions generally. However, region 3, 4 and 6 recorded large number of drought events with longer duration and low severity than other the regions. It was observed that, drought events with low intensities had a high chance of occurring while high intensity drought events showed low chance of occurrence (Fig. 4.19). The figure indicates that there was a small number of drought events recoded with a low chance of recurring in the next 10 years for an intensity ranging from 1.8-2.11.

The drought risk maps are able to provide information on the risk of drought occurrence hence able to provide sufficient information on the potential risk involved with severe and extreme drought conditions under the seven regions across the study area. Therefore this can be used in risk assessment of water management activities in Botswana.

Botswana currently faces multiple problems when it comes to drought mitigation. Therefore the biggest challenge is to persuade the policy and decision makers that mitigation measures are more cost-efficient than post-impact aid or relief programmes which are usually the attempts that are done when faced by drought events. Therefore the society would be better positioned to deal with the detrimental consequences of drought in the most successful way by proactively preparing for drought. The process of coping with drought during the disaster management can only be effective if sufficient information about drought could be readily available to enhance preparedness and mitigation impacts.

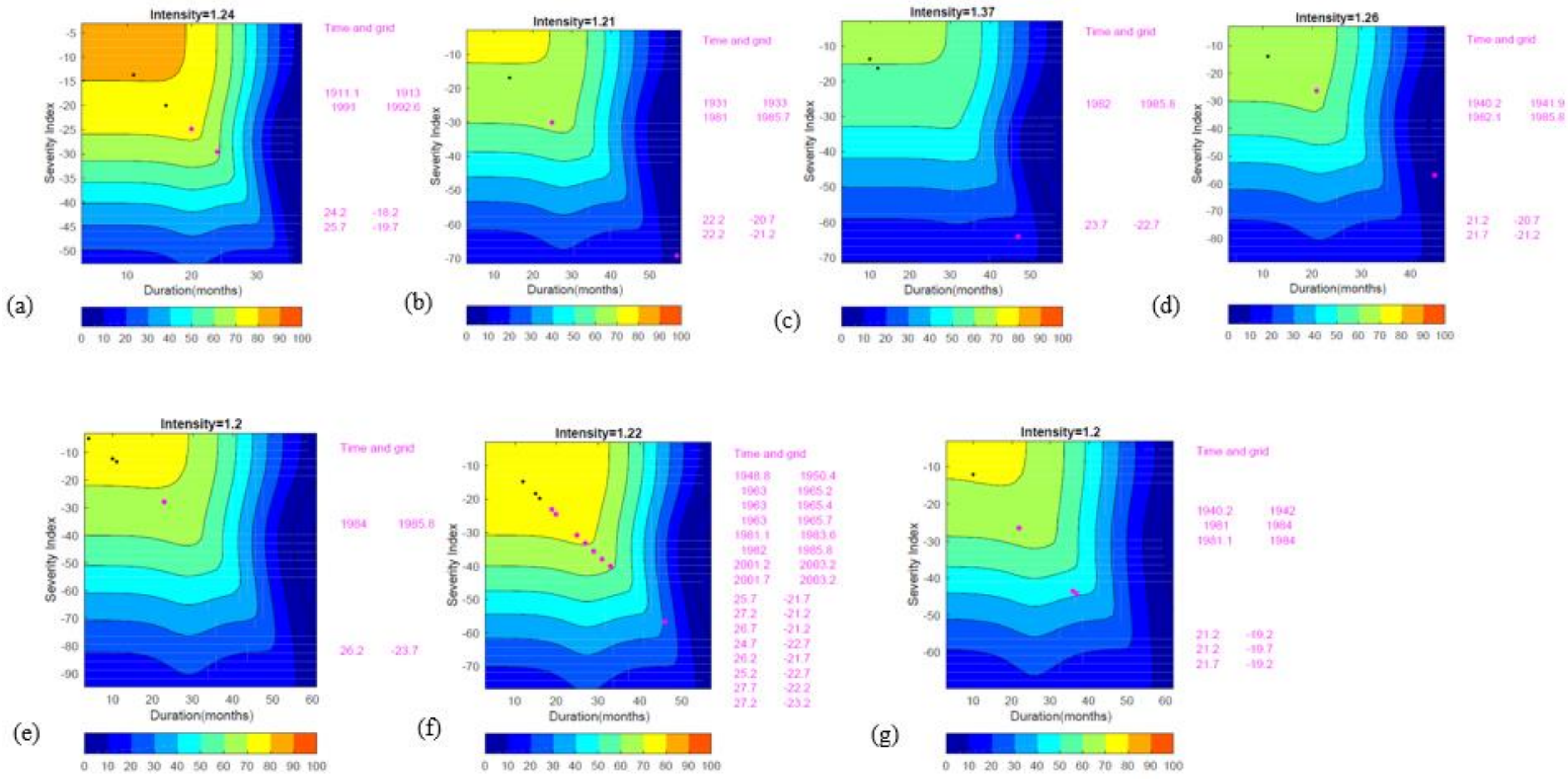

Fig. 4.18: Drought risk map for hydrological system with a design lifetime of 10 years based on trivariate joint distribution of drought duration, severity and intensity between 1.2 to 1.37 for region 1 (a) to region 7 (g).

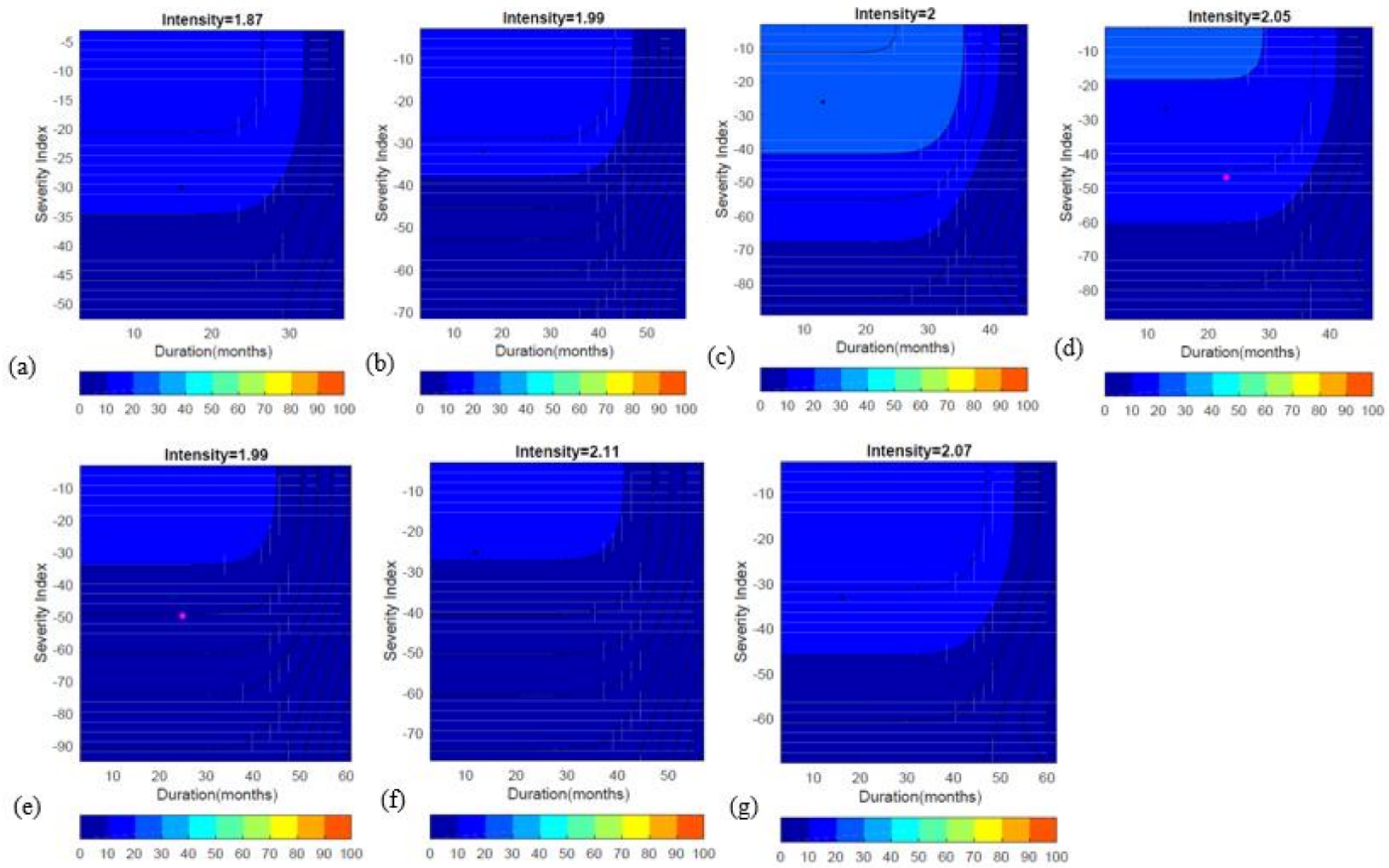

Fig. 4.19: Drought risk map for hydrological system with a design lifetime of 10 years based on trivariate joint distribution of drought duration, severity and intensity between 1.87 to 2.11 for region 1 (a) to region 7 (g)

Chapter 5. Summary of findings and conclusions

This study has characterized hydrological droughts in Botswana together with their spatial distribution using SPI-12 and SPEI-12 for a period from 1901 to 2018. Seven homogeneous regions were identified, each representing the north-eastern region (region 1), central region (region 2), south-western (region 3), western region (region 4), south-eastern region (region 5), eastern region (region 6) and north-western region (region 7) of Botswana. Each region portrayed the distinct climatic regions, with similar drought characteristics in Botswana. This is the first detailed study across Botswana that adopted the trivariate copulas to investigate the probabilistic relationships between the drought variables in the longest period of 1901 to 2018. The following conclusions can be drawn from this study.

Overall, both the SPI and SPEI identified the spatial drought variability. But SPEI recorded more severe and moderate droughts during the study period, and this reflects that temperature intensify the rates of potential evapotranspiration, thus raising the evaporative water demand which normally leads to water deficits. The country has been subjected to the increasing aridity caused by a substantial increase in temperature. Even though drought variability has been mainly been influenced by rainfall deficiency, the severity of drought has been aggravated by increased evaporative demand. Therefore, SPEI has been recognised to be more robust in monitoring of drought across Botswana. The northern, western and the south western parts of Botswana which are at the outskirts of the Kalahari desert, were more susceptible to severe drought but in general the country is susceptible to both moderate and severe droughts. However, the eastern and southern region recorded large number of droughts with higher intensities than that of droughts occurring over the northern and central regions. The most felt historical drought events were found in 1912-1915, 1933, 1944-1947, 1965-1967, 1982-1986, 1992-1995 and 2015. Most of the drought events coincided with the El Niño events which indicated that ENSO has influence on the drought evolutions over Botswana. Therefore the relationship between the drought occurrence and ENSO need to be investigated further in order to enable other ways of predicting droughts.

Furthermore, in assessment of the performance of nine copula distributions (namely, Normal, Student’s t, Gumbel-Hougaard, Rotated Gumbel, Clayton, Rotated Clayton, Joe-Clayton, Frank, and Plackett copula) and severity, Normal copula did best in modelling joint dependence structure of drought duration and severity while Clayton copula distribution was seen as the best-fitting copula model for the drought severity and intensity across the regions. The bivariate and trivariate drought characterization indicated that most of the historical drought events over homogenous drought regimes in Botswana have short duration, low severity, low intensity and short return period, with drought regimes 1, 3, 4 and 7 having longer drought return periods than the other three zones (2,5 and 6). In assessment of drought risk probability, it was observed that there is a low risk of occurrence of drought events with longer duration and high severity across all the regions in Botswana. However, large number of drought events with longer duration and low severity were recorded at region 3, 4 and 6 than other regions (1, 2, 5 and 7). According to the findings of this study, droughts in Botswana have short return periods, therefore are expected to continue recurring across the country. Due to this, it is necessary to develop proactive drought management plans to mitigate impacts of drought. Therefore proactive drought plans should consider using probabilistic characterization using copulas because they will enable a scientific identification of drought recurrence, which can be used as a preparation tool for the mitigation of future droughts. The analysis presented here can inform decision-makers as to which areas are more susceptible to the occurrence of future droughts.

Copulas are seen as useful tools in providing probability information of droughts, which can be used in long-term planning for development of effective strategies. Since drought events are viewed as crucial problems in water resources planning and management, probabilistic characterization (estimated bi/trivatiate return periods and drought risk maps in this study) is very essential, primarily in evaluating the water supply capability and the needed supplementary water resources during severe and extreme drought conditions for a given water supply system. Consequently, further emphasis should be focused on predicting and managing drought in the future, and more efforts are necessary to ensure normal water supply and development activities during times of drought. Drought is a climatic phenomenon that cannot be avoided but an attempt to intervene and prepare for them can be made to mitigate its impacts and to develop more resilient ecosystems that will help in improving water productivity. A potentially useful extension of this research is to relate the analysis with agricultural production planning, by developing a shared understanding with stakeholders and other partners on the kind of agricultural impact that is required to improve livelihoods which at the end can be used in developing risk reducing strategies for farmers.

The following recommendations can be made based on the key findings:

To strengthen early warning systems, a collaborative framework for early warning system need to be developed to enable easy flow of information across different scale and levels, from national levels all the way to community and household levels and vice-versa.

Discussions with different stakeholders such as the communities, civil society organisations, research institutions, academia, NGOs, and the private sectors should be made in order to know how they can and want to assist in the Drought Management Strategies because currently not all stakeholders have been involved, since Tadesse, (2016) has highlighted the importance of multi-stakeholder involvement and processes to manage drought.

Involvement of media by the Government of Botswana to communicate early warnings, disseminating information on government or non-government support programmes, advertising stakeholder engagements, promoting dialogue and providing tips for communities to adapt more effectively to drought can contribute to reducing the impacts of drought.

Implementing principles of integrated water resource management (IWRM) to reduce pressure on water resources and development of policies to encourage rain-water harvesting to increase availability of water which on the other hand can reduce the exposure of vulnerable agricultural communities to drought risks.

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