



Addis Ababa University
College of Social Science, Arts, and Humanities
Department of Geography & Environmental Studies

**Drought Incidence, Modeling and Prediction in Bilate River
Watershed, Central Rift Valley of Ethiopia**

By
Ashenafi Burka Wakene

**A Dissertation Submitted for the Partial Fulfillment of the Requirement for the
Degree of Doctor of Philosophy in Geography and Environmental Management
(Environment and Natural Resources Management)**

Addis Ababa University
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DECLARATION

I hereby declare that the dissertation titled “Drought Incidence, Modeling and Prediction in Bilate River Watershed, Central Rift Valley of Ethiopia” has been carried out by me under the guidance of Prof. Woldemalak Bewket and Dr. Birhanu Biazin as part of a PhD programme in Geography and Environmental Management. I further declare that this work has not been submitted to any other University or Institution for the award of any degree and all sources of material used for this dissertation have been duly acknowledged.

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This dissertation has been submitted for examination with my approval as University supervisor.

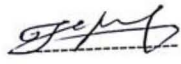
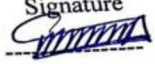
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DISSERTATION APPROVAL

This is to certify that the dissertation prepared by Ashenafi Burka titled: “Drought incidence, Modeling, and Prediction in the Central Rift Valley of Ethiopia” submitted for the partial fulfillment of the requirement for the Degree of Doctor of Philosophy in Geography and Environmental Management (Environment and Natural Resources Management) complies with the regulations of the University and meets the accepted standards concerning originality and quality.

Signed by the Examining Committee:		05/09/2025
Chairman, Examining Committee	Signature 	Date 21/08/2025
External Examiner	Signature _____	Date _____
Internal Examiner	Signature 	Date 08/09/2025
Advisor	Signature 	Date 27/9/25

DEDICATION

To my beloved mother, Marege Areda, whose love, sacrifices, and wisdom contributed to the making of the person I am now. Even though you departed this life a few years ago, your spirit continues to be my guide. This dissertation is the culmination of your never-fading belief in me, and your memory accompanies me every step of the journey.

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LIST OF ORIGINAL PUBLICATIONS

The following original research publications and the last manuscript served as the foundation for this PhD dissertation.

Ashenafi Burka, Birhanu Biazin, and Woldeamlak Bewket (2023), Drought characterization using different indices, theory of run and trend analysis in Bilate river watershed, rift valley of Ethiopia. *Front. Environ. Sci.* 11:1098113. DOI: 10.3389/fenvs.2023.1098113.

Ashenafi Burka, Birhanu Biazin & Woldeamlak Bewket (2024) Spatial drought occurrences and distribution using VCI, TCI, VHI, and Google Earth Engine in Bilate River Watershed, Rift Valley of Ethiopia, *Geomatics, Natural Hazards and Risk*, 15:1, 2377672, DOI: 10.1080/19475705.2024.2377672.

Ashenafi Burka, Birhanu Biazin & Woldeamlak Bewket (2024) Drought susceptibility modeling with geospatial techniques and AHP model: a case of Bilate River Watershed, Central Rift Valley of Ethiopia, *Geocarto International*, 39:1, 2395319, DOI:10.1080/10106049.2024.2395319.

Ashenafi Burka, Birhanu Biazin & Woldeamlak Bewket (2025). Future Drought Projection in Bilate River Watershed, Central Rift Valley of Ethiopia: insight from the state-of-the-art Global Climate Models

ABSTRACT

Drought poses extreme risks to semi-arid regions like Ethiopia's Central Rift Valley, which includes the Bilate River Watershed (BRW). This PhD research presents a comprehensive assessment of the dynamics of drought in the BRW using historical analysis, spatial observation, susceptibility modeling, and future climatic projections. Past meteorological droughts (1981-2019) were first explained with multiple indices (SPI, SPEI, RDI, eRDI, scPDSI) for seven stations. Correlation and Fleiss' kappa analyses revealed that SPI and SPEI at 6- and 9-month timescales performed best, identifying major droughts (e.g., 1984/85, 1999/2000, 2002/3, 2009). Theory of Runs showed increased severity in the southern BRW and increased frequency in other areas. The Mann-Kendall tests confirmed a significant increasing trend in drought conditions at Hossana and Wulbareg station within the watershed. Satellite remote sensing (Google Earth Engine, MODIS) was utilized to analyze spatial drought patterns (2000-2022) using VCI, TCI, and VHI for the May-October period. The VHI identified 2002, 2009, 2015, and 2022 as years of severe drought with extensive coverage (up to 70% area), primarily affecting southern, central, and southwestern parts. Spatial autocorrelation (Moran's I) confirmed high drought clustering, especially in severe years, with frequency analysis identifying the southern BRW as being most vulnerable. Building upon the observed patterns, an integrated model for drought susceptibility was developed using geospatial technique and Analytic Hierarchy Process (AHP) based on fifteen climatic, hydrological, soil, vegetation, topographic, water index, and socio-economic variables. AHP identified rainfall, temperature, evapotranspiration, and soil moisture as the major drivers. The model identified that 70.2% and 23.2% of the watershed fell in moderate and severe susceptibility categories, respectively, grouped together in the central and southern parts. ROC analysis validation (AUC = 0.701) showed adequate model performance. Then, using the SPEI index and bias-corrected CMIP6 simulations (SSP2-4.5, SSP5-8.5), drought projections for the twenty-first century (2015–2100) were produced. The frequency, intensity, and length of droughts increased dramatically during the 21st century, according to higher-level statistical calculations. This was especially true under the high-emission scenario SSP5-8.5, with peak intensity predicted in the middle of the century (2045-2054). These changes suggest drier conditions will be emerging during the period from the mid-2060s to the late-2080s, alongside the potential enhancement of multi-year drought cycles and increased extremes. Power spectral analysis suggested the potential enhancement of multi-year drought cycles (3.75-7.5 years) under high emission scenario. EOF analysis showed high spatially coherent drought pattern alongside persistent secondary spatial contrast. Analysis of the return period indicated that SSP5-8.5 had more extremes and greater variability. The consistent identification of spatial vulnerabilities, the confirmation of historical trends in some stations, and the alarming future projections demand proactive, and spatially targeted drought risk management and adaptation strategies. Overall, this research presents multidimensional evidence and concludes that the BRW faces significantly intense drought risks, highlighting the need for immediate and focused efforts to enhance watershed resilience.

Keywords: Drought Indices, Trend Analysis, GEE, Modeling, Spatial Autocorrelation, CMIP6 Projections, Bilate River Watershed, Rift Valley of Ethiopia

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ABBREVIATIONS AND ACRONYMS

AHP	Analytic Hierarchy Process
BRW	Bilate River watershed
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
CHIRTS	Climate Hazards Center Infrared Temperature with Stations
CMIP6	Coupled Model Intercomparison Project Phase 6.
DSM	Drought Susceptibility Model
EOF	Empirical Orthogonal Function
eRDI	enhanced Reconnaissance Drought Index
GCMs:	Global Climate Models
GEE	Google Earth Engine
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
PSA	Power Spectral Analysis
RDI	Reconnaissance Drought Index
RVLB	Rift Valley Lakes Basin
scPDSI	Self-Calibrated Palmer Drought Severity Index
SDF	Spatial Drought Frequency
SPEI	Standardized Precipitation Evapotranspiration Index
SPI	Standardized Precipitation Index
SSPs	Shared Socioeconomic Pathways
TCI	Temperature Condition Index
ToR	Theory of run
USGS	United States Geological Survey
VCi	Vegetation Condition Index
VHI	Vegetation Health Index

CHAPTER ONE

INTRODUCTION

1.1. Background

Drought is a natural and complex phenomenon that is a prolonged period of subnormal precipitation resulting in water shortages, which may have significant effects on ecosystems, economies, and human societies (Tareke and Awoke, 2022; Nandgude et al., 2023). Throughout history, civilization has been afflicted by the complicated natural disaster known as drought (Kim and Jehanzaib, 2020). A significant obstacle to accomplishing the Sustainable Development Goals of the UN, particularly Goal 2: Zero Hunger, is drought (Mansoor et al., 2022). Droughts can happen anywhere, at any time of year, and can differ from one country or region to another based on terrain (Ndayiragije and Li, 2022).

According to Mishra and Singh (2010) and Lemma et al. (2022), droughts are frequently classified as meteorological, agricultural, hydrological, and socioeconomic droughts. Meteorological drought is to a precipitation deficit and agricultural drought is about crop production impacts. Hydrological drought is reduced water availability in rivers, lakes and reservoirs; socio-economic drought consequences of disruption of societies and economies. Irregular precipitation patterns, and climate variability are the main climate factors that contribute to drought and are usually made worse by climate change. These factors are usually followed by an increase in the frequency and intensity of drought events (Nandgude et al., 2023; Cook et al., 2020). There is no doubt that the earth's climate system is warming, and extremes will likely become more frequent and intense in many places (Field and Barros, 2014; Hanadé Houmma et al., 2022 ; Ayugi et al., 2022). Hence, the world's attention has been focused on the overall rise in drought occurrences (Ma et al., 2022). Because of climate change and global warming, this situation becomes increasingly complicated (Mansoor et al., 2022).

Drought incidents have harmed human well-being, the environment, and the economy worldwide over the past few decades (Hagenlocher et al., 2019; Xu et al., 2024) and it is the most devastating natural disasters in the world (Ndayiragije and Li, 2022). It is without a doubt one of the most difficult and dynamic disasters to manage (Mansoor et al., 2022). Because of its intricate

relationships to agriculture, hydrology, meteorology, society, and the economy, drought is a persistent natural phenomenon that is difficult to define (Choukri et al., 2023). Despite lengthy dry spells characterized by below average precipitation, drought is characterized by severe water shortages with negative effects on ecosystems, the economy and human societies. Drought ranks close to the top of the hydroclimatic hazards when taking into account the effects on the environment, society, and economy (El Kenawy et al., 2023; Safdar et al., 2023; Nandgude et al., 2023).

Drought has impacted numerous countries worldwide and has long been a part of the environment (Mansoor et al., 2022). As cited by Shiferaw et al., (2014) approximately 410 significant drought occurrences occurred worldwide between 1980 and 2008, impacting over 53.5 million people annually (Lottering et al., 2021). Estimates of the yearly global economic losses resulting from droughts range from USD 6 to USD 8 billion, which is significantly more than the losses resulting from other natural disasters (Ma et al., 2022). Moreover, in its most recent report, released in 2022, the IPCC predicts that, primarily in poorer nations, an additional 2.5 million people would experience droughts over the next 30 years (Hanadé Houmma et al., 2022). Hence, compared to other natural catastrophes, drought is a chronic calamity that happens frequently worldwide and is not as quickly managed or mitigated (Wang et al., 2021).

In Africa, where most people depend on rain-fed agriculture, drought is a big problem as well, but it has had an especially detrimental economic impact on the agricultural sectors. Sub-Saharan Africa and the Indian subcontinent are predicted to suffer the most severe droughts due to their heightened vulnerability to climate change, which will affect their food security (Mansoor et al., 2022). Drought-induced severe water shortages, made worse by crop failure, pose a threat to millions of people's livelihoods. For instance, developing nations account for the majority of the world's undernourished population (Mansoor et al., 2022). Despite making up only 5% of all natural catastrophes, droughts can result in over 30% of all disaster-related damages (Mansoor et al., 2022).

The majority of African communities' lack access to alternate water sources, such groundwater, and are heavily reliant on rainfall. Drought may not yet affect nearby river basins and groundwater supplies, but a lack of precipitation can have detrimental consequences (Van Loon et al., 2016a). There have been more severe droughts in Africa during the past three decades that have a series

impact (Kassaye et al., 2021). Besides, drought events in the Greater Horn of Africa (GHA) are becoming more frequent and severe due to changes in the global climate (Ndayiragije and Li, 2022). Among other African regions, East Africa is primarily affected by drought. For instance, a disastrous drought in 1984 killed over 450,000 people in Ethiopia and Sudan (Kassaye et al., 2021).

More frequent drought events have been reported in Ethiopia during the last century (Haile et al., 2022). In Ethiopia, drought happens in different parts of the country throughout different seasons when seasonal rainfall falls by roughly 30 to 50 percent (Mera, 2018). Ethiopia is considered to be an East African nation that frequently experiences drought (Kourouma et al., 2022). Since the majority of Ethiopians rely on rainfed farming, the agriculture sector is particularly impacted more than the other sectors (Degefie et al., 2019). According to CSA (2014), approximately 49% of Ethiopia's GDP (gross domestic product), over 80% of its foreign exchange earnings, and 80% of its workforce are employed in agriculture, which is the mainstay of the country's economy (Suryabhagavan, 2017).

In recent decades, Ethiopia has seen a number of terrible, severe drought disasters (Tareke and Awoke, 2022). Drought exacerbates poverty and food insecurity by having a detrimental impact on livelihoods, output, lives, health, assets, and infrastructure (Shiferaw et al., 2014). Given the dependence of Ethiopia on agriculture, periodic droughts have a significant role in influencing the country's economy and the living standards of the majority of its agrarian population (Lemma et al., 2022). While Ethiopia is known as the "Water Tower of Africa" due to its abundant water resources, it is also considered one of the most drought-prone countries in the Horn of Africa (Gebrehiwot et al., 2011). Furthermore, Ethiopia witnessed an increase in drought patterns, which has highly impacted livelihood and food security (Kourouma et al., 2022).

For instance, during the 2002–2003 drought, the nation had a complete blackout for one day per week for almost four months, which was believed to have cost the nation between 10 and 15 percent of its GDP at the time (Degefu and Bewket, 2015). Ethiopia is therefore thought to be among the most climate-extreme vulnerable countries, and agriculture is a significant industry in its economy (Rettie et al., 2023). For instance, Ethiopia's Rift Valley drought negatively impact agricultural output, decreasing the crop availability and increasing livestock loss, potentially making many homes unable to sustain adequate food security. Therefore, regulation of their impacts is needed, and effective regulation and a hard community will make this possible. When

climate change is factored into the decision process as well, proactive stakeholder involvement and policy are the methods employed to cope with drought. This makes exhaustive and multi-dimensional information about drought's past, present, and future significant.

The process of analyzing drought's frequency, length, spatial extent, and effects using a drought index such as the SPEI is known as drought characterization. According to Ndayiragije and Li (2022), drought indicators are essential for detecting, monitoring, and planning for drought events. Drought indices are typically used for drought evaluation because they can convert vast volumes of data into quantitative information needed for several purposes, including accurate drought forecasts (Choukri et al., 2023). They are numerical depictions of the intensity of drought that are calculated based on hydro-meteorological or climate factors (Nandgude et al., 2023). It is required for the timely alert of decision-makers and stakeholders by early warning systems as well as to formulate effective drought preparedness strategies, mitigation plans, and response schemes. Several drought indices that make use of various climatic and meteorological factors have been created over time (Nandgude et al., 2023). Some were created to combat a particular kind of drought, while others were created for a particularly specific region (Yihdego et al., 2019).

The fact that drought indexes are used so widely over the world is evidence of their value (Ndayiragije and Li, 2022). Numerous drought indices have been created to define, quantify, and track occurrences of droughts; nevertheless, each of these has strengths as well as limitations (Mishra and Singh, 2010). For instance, the SPEI is sensitive to evapotranspiration estimation, and the SPI is easy to compute and employs precipitation as an input for all time periods and parameters (Choukri et al., 2023; Nandgude et al., 2023). They function as a list of drought indicators that are essential for figuring out the scope, length, and spatial aspects of drought events when paired with other monitoring data and models. Other indications are necessary to determine the severity of the drought, even though precipitation makes up the majority of many drought indices (Yihdego et al., 2019). A common drought index in many applications, the PDSI calculates the water balance equation to determine the moisture availability in the research area (Nandgude et al., 2023). Like the PDSI, the SPEI uses a simple water balance calculation based on the Thornthwaite model to evaluate potential evapotranspiration (Yihdego et al., 2019).

No single drought characterizing method can be applied to all situations, since drought is a multifaceted, complex, and heterogeneous phenomenon with multiple kinds and causes different

impacts in different situations. However, the most suitable method depends on the local climate, the nature of the droughts being characterized, the application purpose, and the data availability. It is better to be engaged in a comparative analysis of the relevant drought indices for a given watershed or area based on their accuracy in detecting historical drought incidents in the watershed. This framework of process helps in determining the most appropriate drought characterization method to suit the individual set of characteristics and needs of the watershed without a one-size-fits-all strategy through comparison of results for information about how to tailor the drought monitoring strategy according to the distinctiveness of the watershed.

Predicting drought is crucial for effective water resource management, disaster prevention, and impact reduction (Zhang et al., 2023). One of the primary methods for assessing historical and future variations in climatic extremes and understanding the influence of climate change on drought is the Global Climate Model (Behzadi et al., 2024). General circulation models (GCMs) allow for the simulation and projection of future climate scenarios (Li et al., 2021). These models serve as essential tools for analyzing climate systems, offering insights into climate variability and extremes. Many regions currently rely on GCMs to investigate potential shifts in climatic extremes (Supharatid & Nafung, 2021). Understanding both historical and anticipated drought patterns is fundamental for effective adaptation and mitigation strategies (Ma et al., 2022). Moreover, developing timely early warning systems and mitigation programs depends on a clear comprehension of expected drought trends (Xu et al., 2024).

To enable the comprehensive analysis of future climate change impacts, vulnerabilities, adaptation, and mitigation, the climate change research community created a set of new scenarios known as the Shared Socioeconomic Pathways (SSPs) (Kim et al., 2021; Behzadi et al., 2024). The sixth IPCC evaluation report uses the most recent SSP scenario, which breaks them down into five paths and takes into account both the current notion of the RCP scenario as well as future socioeconomic developments and measures to mitigate climate change (An et al., 2022). SSPs are scenarios used by GCMs in their most recent iteration to estimate climate change (Colín-García et al., 2024). Numerous factors, including population, economic growth, education, urbanization, and the rate of technology advancement, are included in SSP scenarios, which depict how socioeconomic forces will impact the entire world (Behzadi et al., 2024; An et al., 2022). The most significant advantage of SSP is that it helps policymakers develop future coping mechanisms by

precisely analyzing the linkages between climate change and human activity by taking into account a variety of aspects connected to future human activities (Ahn et al., 2023).

SSP scenarios are incorporated into CMIP6 predictions. It is essential to use these updated scenarios in order to improve comprehension of the effects of climate change (Abduljaleel et al., 2024). According AR6, the extent and severity of the effects of climate change are more severe than those anticipated by previous assessments (Feyissa et al., 2023). The CMIP6, a cutting-edge climate model experiment presently underway by the World Climate Research Programme (WCRP), provides the most recent climate modeling data for these kinds of studies (Feyissa et al., 2023). Recent and future climate data of CMIP's Phase 3 (CMIP3) and Phase 5 (CMIP5) were evaluated in the fourth and fifth assessment reports (AR4 and AR5) of the IPCC, respectively (Shafiei et al., 2023). In addition, the sixth phase of the CMIP's new multi-model data sets (CMIP6) is currently available, as reported by Carvalho et al. (2022). The CMIP6 models have been greatly enhanced, leading to updated microphysics parameterizations, more complex deep convective schemes, greater spatial and vertical resolutions, and modified ocean ice models (Shafiei et al., 2023). In CMIP6, a new set of emissions and land-use scenarios were taken into account under the shared socioeconomic pathways (SSPs), which are new aspects of societal development (Behzadi et al., 2024).

Global climate models (GCMs) project potential climate changes for various paths of greenhouse gas emissions (Salehie et al., 2022). To better understand climate change, the majority of GCMs have been created by the Climate Model Intercomparison Project (CMIP) (Shrestha et al., 2020). Our understanding of Earth's climate system and how trustworthy the projections in the future regarding climate change are dramatically improved due to the CMIP6 (Coupled Model Intercomparison Project Phase 6) dataset, an enormous collection of climate model simulations and predictions. Therefore, climate change-driven research on drought is essential with the growing population of the world in the twenty-first century (Badji et al., 2023). CMIP3 and CMIP5 model ensembles were created based on data from multiple GCMs and originated from the fourth and fifth assessment reports of the IPCC, respectively (Shrestha et al., 2020). Future climate projections are provided by the GCMs of the most recent phase of the CMIP6 for several SSPs (Salehie et al., 2022). Consistent drought modeling under plausible shared socioeconomic

representative concentration pathways is essential for properly controlling future drought risk in agricultural settings (Ngwenya and Simatele, 2024).

1.2. Statement of the Problem

Ethiopia's water resources, agriculture, and food security are all impacted by drought and climate change (Gobie et al., 2024). Besides, the migration of the productive part of the community will increase as the frequency of drought occurrence increases (Bewket et al., 2015). Therefore, severe drought in the past centuries and consequently, the household will become less drought-resistant in Ethiopia (Tareke and Awoke, 2022). For instance, Ethiopia suffered from drought at the most (39% of all afflicted) within East Africa, which accounted for more than 70% of all affected persons between 1964 and 2006 (Shiferaw et al., 2014). However, the spatial and temporal distribution of drought in Ethiopia was different in the last fifty years and the rift valley is one of the most frequently drought-affected areas (Mera, 2018). Drought is a frequent and unavoidable occurrence in Ethiopia (Gebrehiwot et al., 2011; Dufera et al., 2023).

The Bilate watershed is part of the rift valley lakes basin (RVLB), especially vulnerable to climate extremes since its economy is primarily based on agriculture, which has a low ability for adaptation (Tekle, 2015). The agricultural industry is arguably one of the most impacted by weather extreme (drought) and climate regime changes (Mansoor et al., 2022). In the Bilate watershed, there are an estimated 2.4 million people who depend on agriculture (Orke and Li, 2022). Besides, Ethiopia's highest rural population density, reaching 500 persons/km², is found in the Bilate River Watershed according to CSA in 2013 (Wodaje et al., 2016). The Bilate River serves as a major source of food, drinking water, irrigation water, wildlife, animal grazing, and a disposal site for human and agricultural waste (Hussen et al., 2018). Extreme droughts can undermine the food security of thousands of households since they are dependent on these resources for survival. Hence, drought inevitably has a dramatic environmental impact in the Bilate River watershed area, including an increase in soil degradation and loss of vegetation cover. Besides, rapid population growth puts greater pressure on limited and vulnerable land resources and encourages unsustainable resource use, which harms the ecosystem (Shiferaw et al., 2014).

The majority of research on Ethiopia's drought characterization have shortcomings, such as using only precipitation, not temperature, to calculate the drought index or only examining a small area

or a brief time frame (Morsy et al., 2022). For instance, most of the research that has been done in Ethiopia, including Bilate River watershed, is dependent on a single drought indicator for characterization that lacks comprehensive information. For example, Morsy et al. (2022) used the SPEI at 4- and 8-month timescales, while Mohammed and Yimam (2021) used the Reconnaissance Drought Index (RDI). Lemma et al. (2022) combined the Effective Drought Index (EDI) with SPI, whereas Suryabhagavan (2017) used the SPI on a variety of time scales. Furthermore, Kourouma et al. (2022) used SPI and SPEI to define drought conditions throughout Ethiopia, and Dufera et al. (2023) used both SPI and SPEI in Ethiopia's Oromia area.

Likewise, Suryabhagavan, (2017) used SPI once more for temporal drought characteristics such as drought magnitude (DM) and drought intensity (DI) over Ethiopia, while Legesse and Suryabhagavan (2014) used SPI along with NDVI and WRSI to assess the pattern and severity of agricultural drought in the East Shoa zone, Bayissa (2018) examines the features of past drought occurrences in the Upper Blue Nile basin by comparing six drought indices, including SPI, Gebrehiwot et al., (2011) applied SPI and VCI to evaluate the spatial and temporal characteristics of meteorological and vegetative drought in Tigray, Gidey et al., (2018) compared six drought indices including SPI to identify the main factors that cause drought in Raya and its environment, El Kenawy et al., (2016) applied SPI to assess the drought patterns over Ethiopia from 1960 to 2013.

Specifically, at Bilate watershed, Moloro (2018) used SPI, Engdaw et al. (2022) used SPI and RDI, Haile et al. (2022) used SPEI at different time scales, and Orke and Li (2021) used SPI, RDI, and SDI (Stream flow Index) for drought characterization in the watershed. However, no single drought index can fully describe the complex nature of drought, hence, this approach is insufficient. Because all forms of droughts, climatic regimes, and drought-affected sectors cannot be explained or applied by a single index or indicator (WMO and GWP, 2016). Moreover, many of the drought indices were created to address issues in particular climates, and all of them are appropriate everywhere (Yihdego et al., 2019; Tareke and Awoke, 2022). As a result, before applying the indices to a specific area of study, they should be examined to determine which is the best. By addressing this gap and employing a suite of indices, it would be possible to develop a more nuanced understanding of drought conditions. For the reason that, proper planning and management of our water resources, environment, and ecosystems depend on accurate drought

assessment (Mishra et al., 2015). Therefore, there is a need to research local and sectoral drought indices because the effects of the drought are primarily sectoral and local in scope (Ahopelto et al., 2023).

Furthermore, the current lack of explicit spatial drought information significantly hinders effective drought management in BRW. Most studies have resorted to interpolating point data to create spatial drought maps, which may not accurately reflect the variability of drought conditions across the watershed. By developing more precise spatial representations of drought, a study can identify vulnerable areas and prioritize resource allocation and intervention. Therefore, higher spatial coverage resolution, which can assist fill in the gaps of in situ data and are regularly updated to enable near real-time studies, is one benefit of employing remotely sensed data (Yihdego et al., 2019).

Remote sensing data can be used to monitor changes in land cover and vegetation health to assess drought (Nandgude et al., 2023). Remote sensing provides a variety of high-resolution earth observations that include geographical, temporal, and radiometric measures as earth observation technologies continue to develop quickly (Nandgude et al., 2023). In addition to climate, human activity also affects actual and typical water availability in a catchment (Van Loon et al., 2016b). The severity and duration of drought occurrences can be inferred from a number of factors, including temperature, wind, precipitation, soil moisture, stream flow, evapotranspiration, relative humidity, and vegetation health (Nandgude et al., 2023). Apart from climate change, anthropogenic activities also have a significant impact on drought occurrences (Kim and Jehanzaib, 2020). Hence, drought modeling using various factors offers a comprehensive approach to understanding and characterizing drought beyond traditional indices is imperative. This approach's ability to incorporate many environmental, climatic, and socioeconomic elements is one of its main benefits. The ability of drought modeling is more precisely identify at-risk locations is a major advantage. However, the literature on drought modeling in the Bilate River Watershed is seriously lacking.

Now that the danger of climate change and variability is widely recognized, droughts are predicted to happen more frequently (Mansoor et al., 2022). Then, a major potential for progress is the lack of future drought risk evaluations utilizing recent projected climate model data. Future drought scenarios can be predicted with the aid of climate projections, which enables the creation of long-

term plans to lessen possible effects. By filling this knowledge gap, a research can offer insightful information that enables local populations and policymakers to put adaptive measures into place, lowering susceptibility and improving the Bilate River watershed's overall readiness and mitigation for drought.

The term "drought mitigation and preparedness" describes the proactive measures typically taken by governments and societies to lessen possible vulnerabilities in the environment, economy, and society (Ndayiragije and Li, 2022). Moreover, climate change is predicted to increase the frequency and duration of droughts, which might have a major effect on global food production (Kassaye et al., 2021). Despite the great degree of uncertainty surrounding future developments, risk assessments are necessary to comprehend and eventually lower the likelihood of adverse effects related to droughts (Hagenlocher et al., 2019). Hence, future drought risk analysis is necessary using the climate model's projection output. The ability of global climate model output to replicate local climate conditions and by downscaling approaches is one of the most basic features of climate change research (Balcha et al., 2023).

Several studies have utilized global and regional climate models to assess climate change impacts in the Bilate River watershed like Edamo et al., (2022) , Orke and Li, (2022) , Gisha Kuma et al, (2022) , Orke and Shanka, (2025), and Hussen et al., (2018) . For instance, Orke and Li, (2022) assess the impact of climate change on water availability, Hussen, et al., (2018) used bias corrected climate model data to simulate crop water requirements under different climate scenarios, Orke and Shanka, (2025) used climate model data to simulate flood occurrences and map flood inundation areas under future climate scenarios, Kuma et al., (2022) uses climate projections data under RCP4.5 and RCP8.5 to assess changes in hydrometeorological variables and drought characteristics, and Edamo et al, (2022) also used climate models are used to examine the dynamics of hydrological extremes in the scenario of climate change with the highest emissions.. However, none of the above studies utilize the state-of-the-art CMIP6 data with SSP to project future drought.

Overall, the comprehensive lack of drought information unique to the watershed in question creates a substantial research vacuum that impedes efficient management and evaluation techniques. The effectiveness of various drought indices in precisely describing drought conditions is still not well understood. Additionally, there aren't many thorough studies that examine long-term drought patterns and variability using the most recent CMIP6 datasets particularly in BRW.

Filling in these gaps will improve the development of the watershed drought preparedness plan. The combined information from several data sources such as drought indices, remote sensing and drought modeling could give a comprehensive knowledge of drought information about the watershed. A Drought Management Plan (DMP), which calls for several drought indices and thresholds, is a well-liked method for proactive drought risk management (Ahopelto et al., 2023). Therefore, accurate drought monitoring, forecasts, and thorough evaluations are critical to making informed decisions (Kim and Jehanzaib, 2020).

Thus, by thoroughly examining drought using suitable drought indices, mapping spatial drought patterns using cloud computing platforms Google Earth Engine (GEE), and incorporating biophysical and socioeconomic data into drought modeling, this research contributes significantly to this study area. It also does future drought risk assessments in producing a multi-dimensional and comprehensive drought information. The knowledge gained from this study helps policymakers in creating strategies to improve drought preparedness and resilience against climate change and variability by offering practical advice. In the end, this study advances our collective understanding and opens the door to well-informed decision-making that tackles the problems caused by drought and promotes sustainable development.

1.3. Objectives of the Study

1.3.1. General Objective

The general objective of the research was to assess drought conditions in the watershed by combining remote sensing technologies, advanced modeling tools, and drought indices in order to comprehend temporal and spatial patterns of drought, evaluate drought susceptibility, and predict future drought events using climate projections for sustainable management of the watershed.

1.3.2. Specific Objectives

1. To assess various drought indices and choose the most appropriate one, and characterize the drought conditions in the watershed.
2. To enhance the mapping of drought distribution and occurrences in space by utilizing Google Earth Engine (GEE) and indices based on remote sensing.
3. To identify and model the elements influencing the watershed's vulnerability to drought.
4. To predict future drought risk by using the CMIP6 projections under SSPs

1.4. Research Questions

The following important research questions were attempted to be answer in this research in light of the above indicated study objectives:

1. How can drought conditions in the watershed be successfully described using various drought indices?
2. How might spatial mapping of drought occurrences and distribution be improved by GEE and indices based on remote sensing?
3. What are the watershed's drought susceptibility variables, and how can these be accurately modeled?
4. What information about future drought scenarios may be collected from CMIP6 projections?

1.5. Significance of the Study

This study is very significant since it uses advanced techniques like modeling tools, remote sensing, and drought indices to give a thorough picture of the drought conditions in the watershed. The study's integration of these advance methodologies improves our capacity to describe temporal and spatial drought patterns, modeling, and pinpoint risk indicators. For effective management of water resources, particularly in areas where water shortage presents major obstacles, such insights are essential. Additionally, the study advances the field of drought analysis and prediction by providing new uses for resources like Google Earth Engine, AHP modeling, and CMIP6 predictions in drought research within the study area.

Stakeholders, like policymakers and managers of the resources, will benefit from this research. Understanding and being able to predict future droughts allows decision-makers to have the information required for the formulation of mitigation and adaptation strategies. In general, this study contributes to the well-being of communities that depend on these ecosystems through the provision of critical knowledge gaps in drought characterization and prediction. It also encourages resistance to the effects of climate change and support sustainable management in the watershed.

1.6. Limitations of the Study

This research is limited by its lack of inclusion of socioeconomic conditions of drought and their effects on the local population, though it contains interesting information regarding the environmental impacts of drought in the watershed. "Socio-economic drought" defines the relationship between the physical event of drought and the economic activities or social circumstances affected by it, for example, livelihood, agriculture, and water resources. The research gives prominence mainly to biophysical considerations through a consideration of drought indices, remote sensing, and models at the expense of drought in terms of influencing community resilience, economic stability, and human health. This means there is an area of void regarding how residents in the watershed are adapting or coping with difficulties resulting from the drought. Furthermore, more precise spatial drought information may have been obtained if MODIS had been replaced with a high-resolution satellite image, such as a sentinel image.

1.7. Methodological Framework

This PhD research includes three fundamental concepts: characterization, modeling, and prediction of drought. Employing a combination of in-situ measurement and satellite sensor technology, the research makes an extensive assessment of drought temporality and spatiality, enabling intensive examination into its evolving behaviors among different spatial aspects and intervals. In fact, employment of the Google Earth Engine (GEE) cloud computing platform made spatial representation of drought particularly feasible, including for medium-resolution applications. The second core theme aims at drought modeling through the Analytic Hierarchy Process (AHP) model to integrate both biophysical and socioeconomic factors. The approach enables precise identification of drought-prone areas in the BRW, offering critical information on vulnerabilities and informing mitigation measures. Finally, the research addresses future drought predictions, applying CMIP6 data alongside shared socioeconomic pathway scenarios in order to predict the frequency, magnitude, and characteristics of future occurrences of drought. The predicting methodology serves to enhance readiness strategy through highlighting potential risk under multiple pathways of climate change. A compact depiction of the methodological approach adopted throughout the course of this PhD work is provided as presented on Figure 1.1 below, consolidating the systematic framework and analytic process of this research.

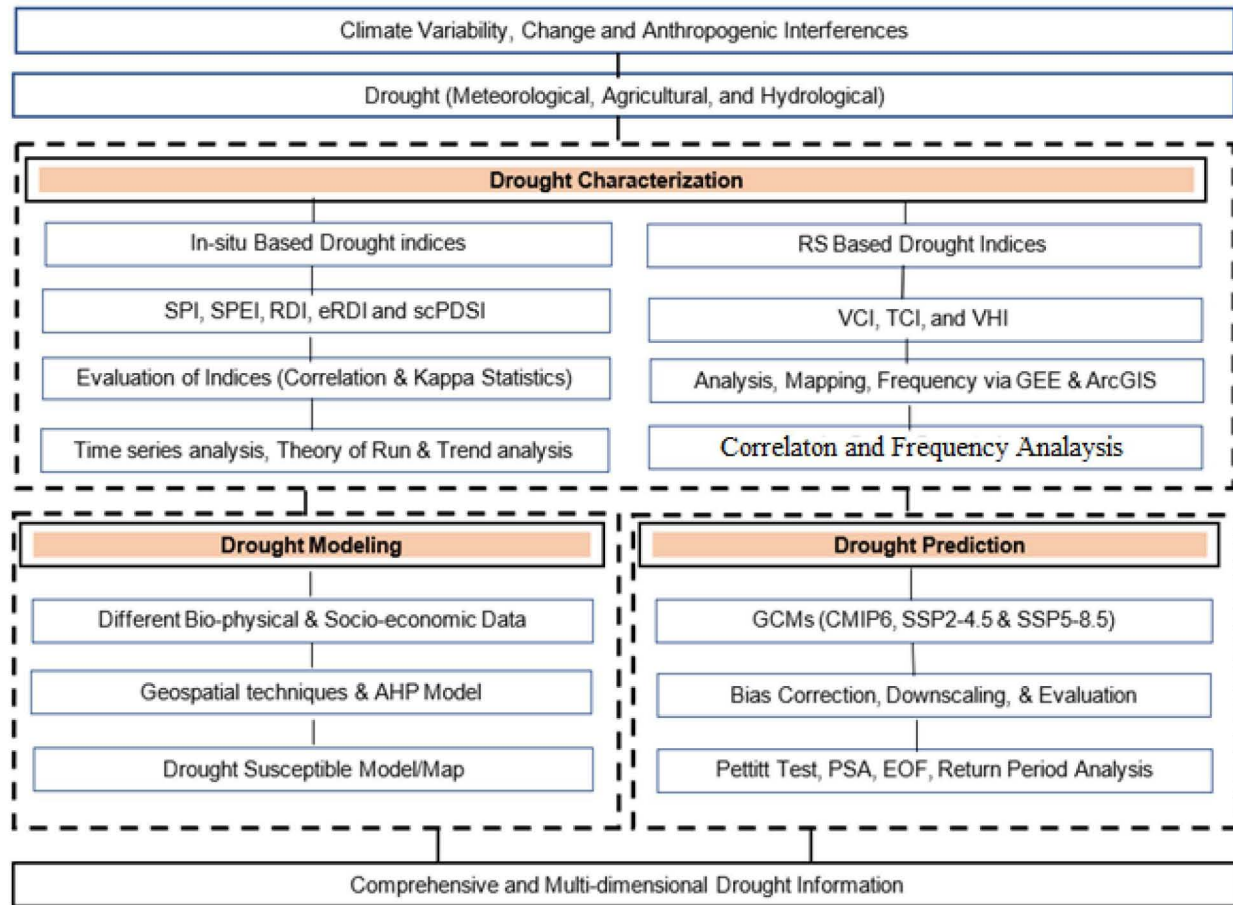


Figure 1.1: Methodological approach followed by this PhD research and its three major themes.

1.8 Study Area Description

Bilate river watershed is located in the South-Western Escarpment of the Main Ethiopian Rift Valley region (Figure 1.2). Geographically, it is located $6^{\circ}32'40''$ to $8^{\circ}09'29''$ N and $37^{\circ}46'11''$ to $38^{\circ}18'43''$ E. The area of the watershed is about 5324 Km². The watershed is confined to Abiyata and Shala lakes from the east, Omo Gibe basin from the west, and Lake Abaya and Chamo from the South. The North and Northeastern part of the watershed has steep slopes and the center and the south part has gentle slopes. The altitude of the watershed ranges from 1116 to 3373 m a.s.l. The watershed has a bimodal rainfall characteristic with a short and main rainy season. The watershed receives annual average rainfall that ranges from 1068.79 to 1276.68mm at lower altitude (example, at Bilate station) and higher altitude of the watershed (example, Wulbareg station), respectively (Figure 1.2 and 1.3). Bilate river is the main river of the watershed that drains into lake Abaya with its tributaries (Figure 1.5A and 1.5B). The Bilate river watershed covers parts

of the densely populated and drought-vulnerable areas in the country such as Hadiya, Kembata, Wolayta, Alaba, Silte zones and Gurage zone within the southern administration region.

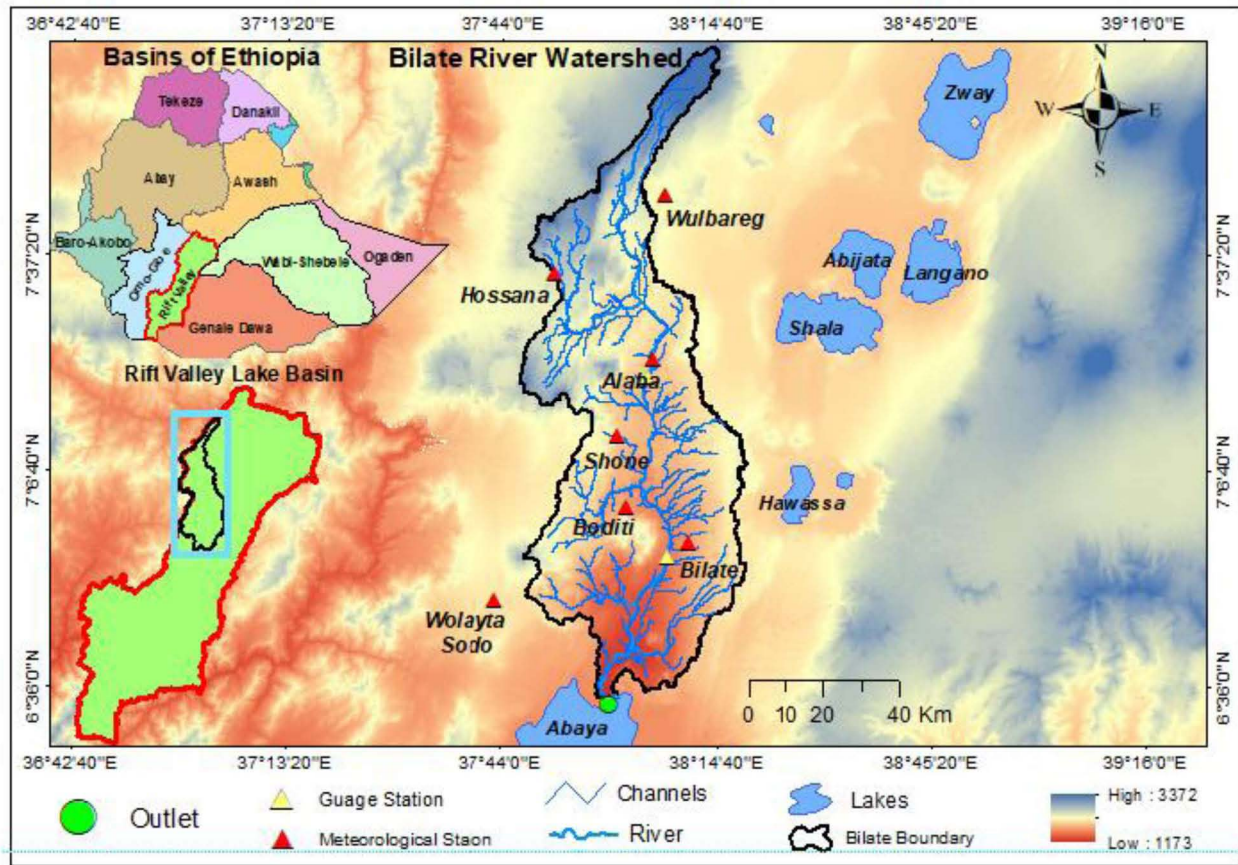


Figure 1.2: Location of Bilate river watershed within the rift valley Lake Basin of Ethiopia.

Bilate watershed is characterized by mixed cultivation and supports irrigation to grow commercial plants such as tobacco, vegetables and maize (Orke and Li, 2021). Agriculture is the dominant economic activity, particularly, in the highlands which receive relatively higher amount of rainfall, rain-fed cereal crop production, mixed farming and agroforestry-based perennial crop production are the main livelihoods of the inhabitants (Tesfamariam et al, 2019). According to Burka et al., (2024b), agricultural crops account for 60.2% of the land use and land cover in the watershed. The local people are dependent on agriculture for their livelihoods. However, it is common to see the failed crops at different kebeles in different seasons within BRW (Figure 1.4A and 1.4B).

According to Kuma et al., (2021). the most common soil types in this watershed are Luvisc Phaeozems, Eutric Fluvisols, Eutric Nitisols, Dystric Nitisols, Eutric Regosols, Vitric Andosols, Pellic Vertisols, Chromic Vertisols, Solonchaks, Chromic Luvisols, and Eutric Fluvisols.

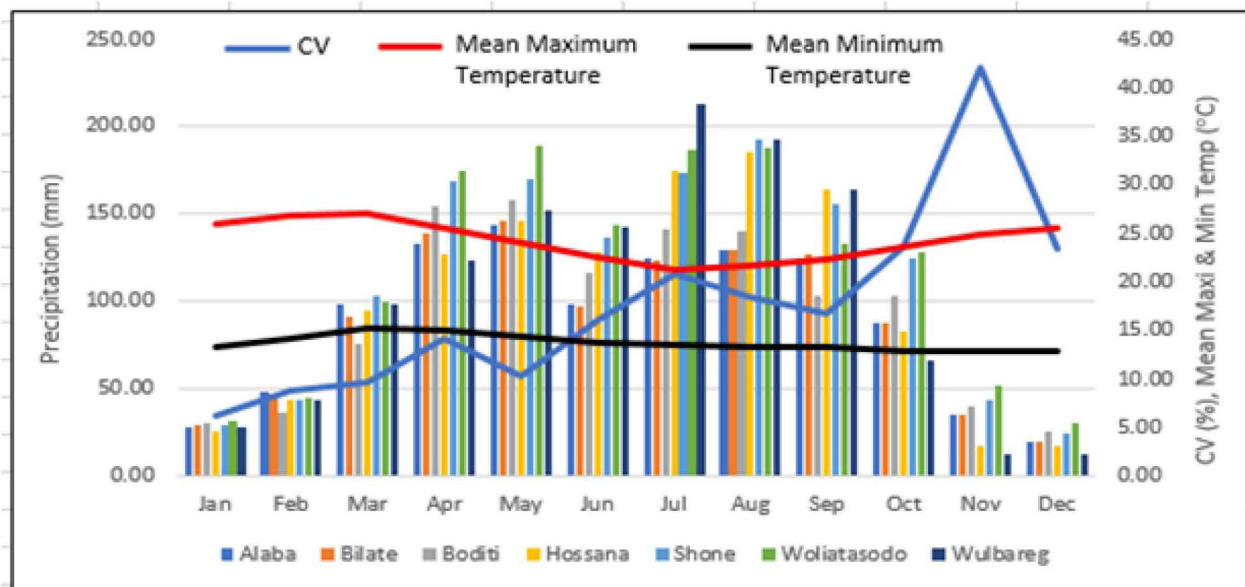


Figure 1.3: Average Monthly precipitation, minimum and maximum temperature, and CV in stations of BRW

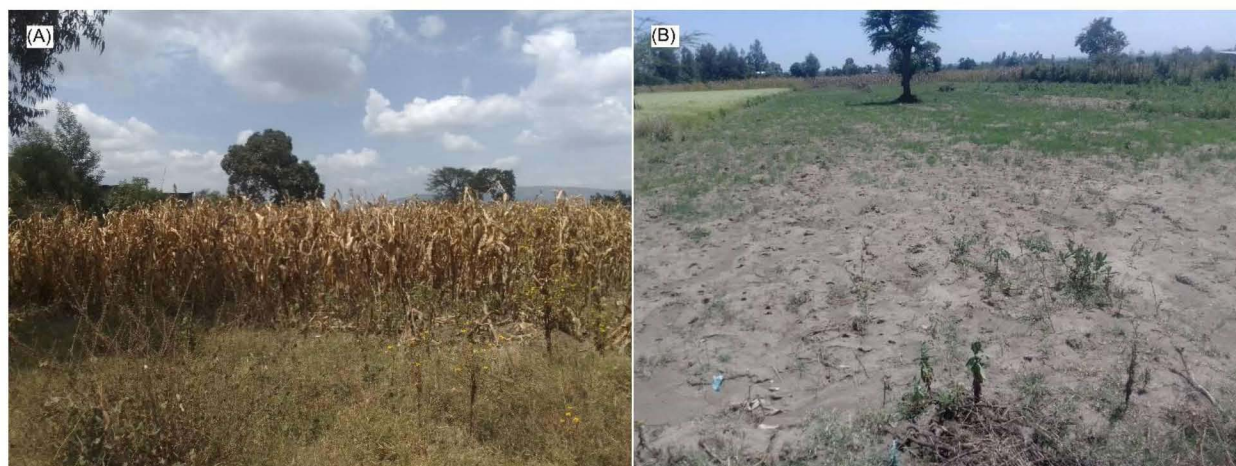


Figure 1.4: (A) Failed Maize crop in Lay Arsho Kebele, and (B) Failed Pepper in Shakete kebele of Alaba zone within Bilate river watershed (Photo by the author, June 15 and 17, 2023).



Figure 1.5: (A) Bilate river which is perennial, and (B) one of the tributaries of Bilate river which is intermittent nearby Alaba town within Bilate river watershed (Photo by the author, June 14, 2023)1.9.

1.9. Organization of the Dissertation

This PhD dissertation is structured under six chapters, each addressing a specific issue of the research. Chapter one provides an exhaustive introduction, with background information, describing the study area, declaring gaps in research, and giving reason to the study. Moreover, it formulates objectives and research questions that will lead the following chapters. Chapter 2 focuses on the comparative analysis of in-situ drought indices for historical spatio-temporal drought characterization. It applies run theory to determine drought severity, duration, and intensity, alongside conducting trend analysis to assess historical drought patterns. Chapter 3 discusses how the spatial mapping of drought events and associated patterns is undertaken with the help of the Google Earth Engine (GEE) cloud-based computation platform. For improving the mapping of drought, remote-sensing-based indices like the Vegetation Condition Index (VCI), Temperature Condition Index (TCI), and Vegetation Health Index (VHI) are used. Additionally, spatial statistics for the driest year are developed and presented in this chapter. Chapter 4 centers on drought modeling, employing geospatial techniques and the Analytic Hierarchy Process (AHP) model. By the integration of several biophysical and socioeconomic aspects, the chapter identifies the most drought-vulnerable areas of the basin. Future drought projection in Chapter 5 is under the latest climate model (CMIP6) at two emission scenarios: SSP2-4.5 (intermediate emissions) and SSP5-8.5 (high emissions). Analysis provides an approximation of the possible character of droughts in the future under several climatic circumstances. Lastly, Chapter 6 brings together

outstanding findings from earlier chapters in offering a general conclusion. It addresses the shortcomings of the research, makes suggestions, and identifies areas for further investigation.

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CHAPTER TWO

DROUGHT CHARACTERIZATION USING DIFFERENT INDICES, THEORY OF RUN AND TREND ANALYSIS IN BILATE RIVER WATERSHED, RIFT VALLEY OF ETHIOPIA¹

ABSTRACT

Droughts have become more powerful and frequent, affecting more people for longer periods than any other natural disaster, particularly in eastern Africa. The unprecedented climate change has increased the severity, duration, and frequency of droughts. The objectives of this study were to evaluate performances of different drought indices for spatiotemporal drought characterization in the Bilate river watershed that represents part of the rift valley drylands in Ethiopia. Historical data for 39 years (1981–2019) from seven stations were used for drought analyses using the following indices: Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Reconnaissance Drought Index (RDI), enhanced Reconnaissance Drought Index (eRDI) with different time scale and Self-Calibrated Palmer Drought Severity Index (scPDSI). Among them, SPI, SPEI, RDI and eRDI with 6-month and 9-month time scales were found to be the best correlated drought indices to characterize the historical drought events. Then, using the selected drought indices, temporal drought analysis showed occurrence of major drought events in the years: 1984/85, 1999/2000, 2002/3, and 2009. Some of these years are well known as famine years in some parts of Ethiopia including the study area. The results revealed spatial variation the severity of drought with extreme droughts occurred in the southern part of the Bilate watershed. Application of the theory of run confirmed that the maximum severity and duration of drought were observed at the Bilate Tena station that is located in the southern part of the watershed; the most severe being observed on a 9-month scale during 1984/85. Hossana and Wulbareg stations showed the highest frequency of drought over the study period. The Mann-Kendal trend test statistics showed an increasing trend of drought conditions at Hossana and Wulbareg stations in the study watershed.

Keywords: *Drought Indices, Drought Characterization, Theory of Run, Drought Frequency, Bilate River Watershed, Rift Valley, Ethiopia*

2.1. Introduction

Drought is a natural, periodic aspect of climate that occurs in almost all climates (Zarei et al., 2019; Ogunrinde et al., 2020). It is one of the most complicated natural hazards (Vangelis et al., 2013) affecting a wide range of industries and occurring frequently, making it difficult to find a single

¹Ashenafi Burka, Birhanu Biazin and Woldeamlak Bewket (2023), Drought characterization using different indices, theory of run and trend analysis in Bilate river watershed, rift valley of Ethiopia. *Front. Environ. Sci.* 11:1098113. DOI: 10.3389/fenvs.2023.1098113.

general description (Vangelis et al., 2013; Tigkas et al., 2017; Zarei et al., 2019). Droughts start slowly and spread over a large area, affecting an area for weeks, months, or even years (Jenkins Warren, 2015). It starts with a lack of precipitation in terms of timing, distribution, and intensity, leading to water scarcity that affects the ability of natural ecosystem to function properly (Asadi Zarch et al., 2015). This natural process leads to crop failures in agricultural areas, destabilizing food systems and thereby threatening local and global food security (Lesk et al., 2016). Moreover, the consequences of this climate phenomenon on the economy, society, and environment are high, and the harms associated with it are increasing at an unexpected rate (Mahmoudi et al., 2019). Hence, at any given time, droughts significantly harm a wide range of economic sectors and populations (Mohammed and Yimam, 2021).

Droughts have been increased dramatically in quantity and intensity in recent decades (Tigkas et al., 2012). Drought is becoming more severe and frequent, affecting more people for longer periods than any other natural disaster (Tigkas et al., 2012). Moreover, as a result of global warming, the severity, duration, and frequency of these unavoidable events are predicted to increase (Guenang & Kamga, 2014). This is also supported by Qi et al., (2022), who reported that as the world warms, potential evapotranspiration rises practically everywhere on earth. As a result, droughts would increase in severity worldwide (Wang et al., 2021). Moreover, according to RCP8.5, drought frequency in currently arid areas will probably increase by the end of the 21st century (IPCC, 2014).

Drought indices are commonly used to characterize droughts (Tigkas et al., 2015; Tigkas et al., 2019) and to quantify the severity of droughts (Yihdego et al., 2019). Various indicators based on different hydroclimatic elements such as precipitation, temperature, river flow, and others are used to calculate drought indices. Accordingly, numerous drought indices have been developed for characterization of meteorological, agricultural, and hydrological droughts (Jenkins & Warren, 2015) and used for monitoring in different locations (Asadi Zarch et al., 2015), such as the Standardized Precipitation Index (McKee et al., 1993; Ionita et al., 2016), Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al., 2010; Byakatonda, 2018), Reconnaissance Drought Index (Rahmat et al., 2015; Zarei et al., 2019), and Palmer Drought Severity Index (Bai et al., 2020 ; Ogunrinde et al., 2020).

Although none of the primary drought indices are necessarily better than others in all situations, some indices are better suited than others for specific purposes (Karavitis et al., 2011). Individual drought indices are not able to comprehensively assess drought conditions of a single terrestrial ecosystem (Yihdego et al., 2019); some are used for a wide range of applications, while others are designed to address drought-related challenges in specific systems, depending on their structure, characteristics, and ability to meet specific criteria (Tigkas et al., 2019). Hence, each drought index has unique shortcomings and advantages when calculating drought conditions (Yisehak and Zenebe, 2021). In most cases, it is required to consider more than one index because no single one is acceptable in all circumstances (Morid et al., 2006). Consequently, determining an acceptable drought index for a given region is critical for preventing and mitigating drought-related crises (Bayissa, 2018).

Comparative evaluation has been a subject of many drought studies. For instance, Barua et al., (2011) evaluated performance of four drought indices against five decision criteria in the Yarra River basin in Victoria, Australia, and the results showed that the Aggregated Drought Index (ADI) was superior to the other indices for drought management strategies. Jain et al., (2015) evaluated six drought indices for their suitability in drought-prone districts of the Ken River basin of India and found that the Effective Drought Index (EDI) was the most suitable drought index for the study basin. Bayissa et al., (2018) examined six drought indices to evaluate their effectiveness in identifying past drought episodes in the Upper Blue Nile (UBN) basin in Ethiopia and concluded that none of the six drought indices could individually identify the onset of all historical drought events. Dogan et al., (2012) examined six drought indices for detecting droughts in a semi-arid, closed catchment in Konya, Turkey, and concluded that the Effective Drought Index (EDI) was better for long-term drought monitoring. Morid et al., (2006) evaluated performance of seven drought indices in Tehran Province, Iran, and it was found that EDI was more responsive to the onset of drought and performed better. On the other hand, Payab & Türker, (2019) concluded that the performances of eight drought indices in monitoring the impact of drought on agriculture and groundwater were substantially and significantly connected.

There were few studies carried out to characterize drought in the rift valley of Ethiopia (for example, Edossa et al., 2010 ; Molero, 2018; Tesfamariam et al., 2019; Mohammed & Yimam,

2021; Nasir et al., 2021). However, none of them compared the performances of different drought indices in the area. This study compared five drought indices in conjunction with the application of the Theory of Run and trend analysis to evaluate the severity and frequency of drought over the last four decades in the Bilate River watershed in Rift Valley Lakes Basin (RVLB). It was hypothesized that there were differences in performances of the different indices and hence, the use of two or more indices may be recommended to more effectively characterize drought conditions in the Rift valley of Ethiopia. The objectives of the study were: (1) to compare different drought indices for further spatiotemporal drought characterization (2) to characterize droughts based on the Theory of Run, and (3) to evaluate the trends of drought in the study area.

2.2. Material and Methods

2.2.1. Study Area Description

The study was undertaken at the Bilate river watershed which is located in the south-western escarpment of the Main Ethiopian Rift Valley (Figure 2. 1). Geographically, it is located between $6^{\circ}32'40''$ - $8^{\circ}09'29''$ N and $37^{\circ}46'11''$ - $38^{\circ}18'43''$ E. The watershed covers about 5324 Km². The north and northeastern part of the watershed has steep slopes and the center and the south part has gentle slopes. Bilate river drains into lake Abaya with its tributaries. The altitude of the watershed ranges from 1116 to 3373 meters above sea level.

The watershed has a bimodal rainfall characteristic with a short and main rainy season. The short rainy season, (locally known as *Belg* Season) extends from March to April and the main rainy season (locally known as *Kiremt* season) extends from July to September. The average annual rainfall ranges between 1276.68 in the central and southwestern parts of the watershed to 1068.79 mm in the southeastern part of BRW. The *Kiremt* season receives 477, 457 and 349 mm at the high, medium, and low elevation areas of the watershed, respectively. Similarly, the *Belg* season receives 375.88mm, 426.04mm, and 375.33mm of rainfall at the high, mid, and low elevation areas of the watershed, respectively. Variability of rainfall is high in November and the Kiremt season (June to August) and low in January and Autumn season. Hossana and Wulbareg stations had high precipitation variability compared to other stations (Table 2. 1). In the summer season, the maximum and minimum average temperature is around 20°C and 12°C, respectively and it is

almost uniform in the summer season for all stations. The maximum average temperature is observed in the winter season for all stations.

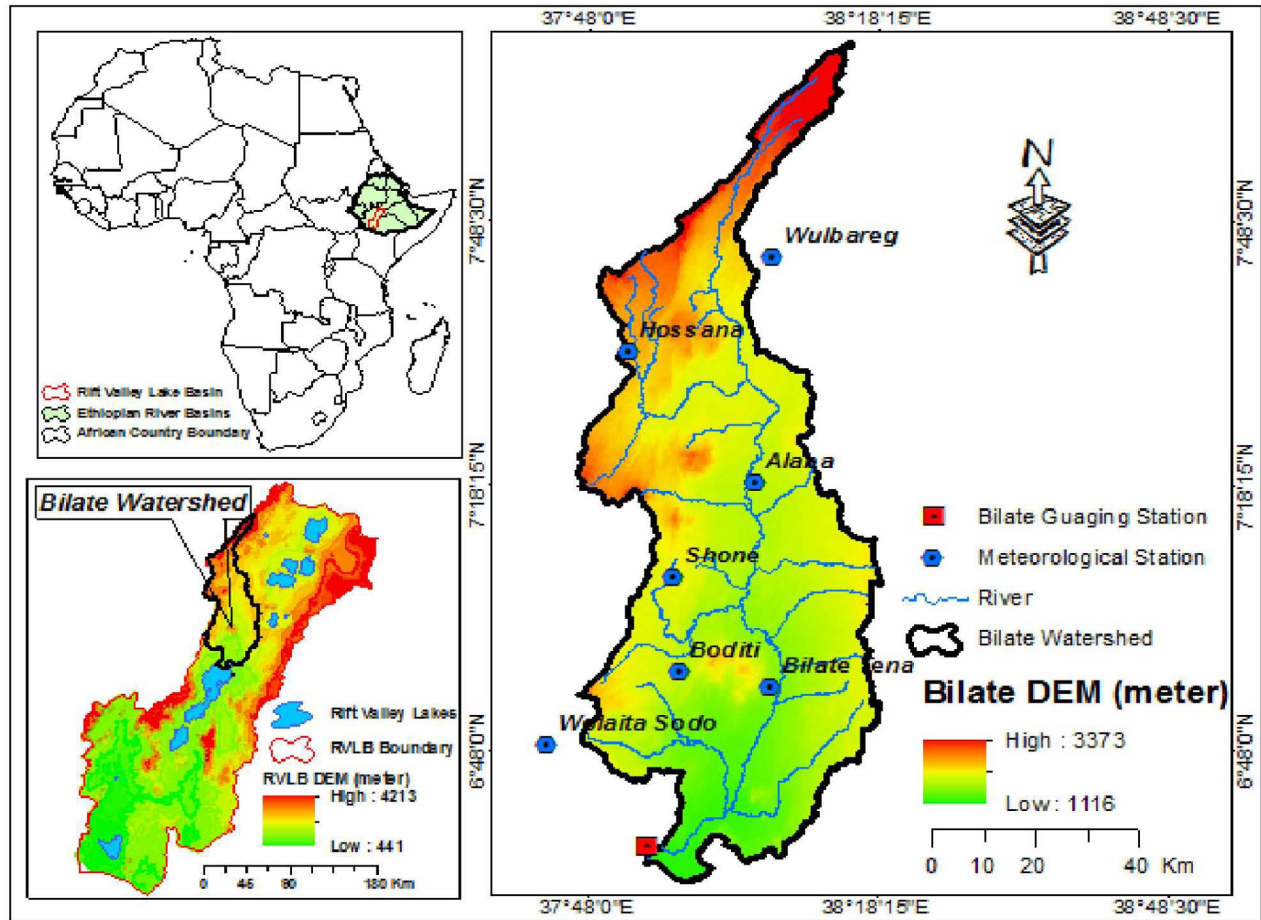


Figure 2.1: Location map of the Bilate River Watershed. (Data source: Ethio-GIS and USGS)

2.2.2. Data Source and Description

Historical climate data, including daily precipitation and daily minimum and maximum temperatures for the period from 1981 to 2019 were collected for seven stations from the National Meteorological Agency of Ethiopia. In the Bilate river watershed, seven stations were selected for this study whose data sets had less than 10% missing values. The list of meteorological stations and their coordinates, annual precipitation (AP), minimum mean annual temperature (MinAT), maximum mean annual temperature (MaxAT), and coefficient of variation (CV) of precipitation used in this study are shown in Table 2. 1.

Table 2.1: Meteorological Stations used in Bilate river watershed (Record period: 1981-2019)

Stations	Latitude	Longitude	Altitude(m)	AP (mm)	MinAT (°C)	MaxAT(°C)	CV (%)
Alaba Kulito	7.31	38.09	1780	1070.2	12.4	23.4	51.0
Bilate Tena	6.92	38.12	1418	1068.8	12.5	23.4	52.0
Hossana	7.50	37.87	2296	1202.6	11.3	22.4	63.0
Boditi	6.95	37.96	2044	1121.6	15.5	25.3	54.0
Shone	7.13	37.95	1972	1360.9	15.6	26.6	55.0
Wolayta Sodo	6.81	37.73	2030	1398.9	15.9	25.4	54.0
Wulbareg	7.74	38.12	2219	1245.0	12.4	23.2	68.0

Note: AP refers to annual precipitation, MinAT refers to minimum mean annual temperature, MaxAT refers to maximum mean annual temperature, and CV for coefficient of variation of precipitation.

2.3. Calculation of Drought indices

Although there are several drought indices, there are no clear criteria to identify the most appropriate for a given spatio-temporal condition (Byakatonda, 2018). However, the World Meteorological Organization (WMO) recommends selecting an index based on data availability and simplicity of the index (Svoboda et al., 2016). Accordingly, SPI, SPEI, RDI, eRDI, and scPDSI were selected for this study. The descriptions of selected indices are presented below.

2.3.1. Standardized Precipitation Index

The SPI depends solely on precipitation and assesses how far precipitation has deviated from historically established norms during a given period (Asadi Zarch et al., 2015). The number of standard deviations of a normally distributed random variable that deviates from its long-term average is measured by the SPI (Guenang & Kamga, 2014). A statistical distribution is fitted to the time series, which is then translated into a normal distribution (Tigkas et al., 2019). The index thus calculates rainfall deficit by combining cumulative rainfall data series for multiple reference time scales (Guenang & Kamga, 2014). It is perhaps the most widely used drought index in the world because it requires only precipitation data (Tigkas et al., 2019). It can be used to characterize drought conditions relevant for meteorological, agricultural, and hydrological purposes (Guenang & Kamga, 2014; Tigkas et al., 2019). The main criticism of the SPI is that it is calculated based solely on rainfall data (Vicente-Serrano et al., 2010; Lee et al., 2017). It does not take into account other factors that may affect droughts, such as temperature, evapotranspiration, wind speed, and

soil water storage capacity (Vicente-Serrano et al., 2010; Zhao et al., 2017). The SPI drought classification categories (McKee et al., 1993) are given in Table 2. 2.

As precipitation is typically not normally distributed, the SPI overcomes this disadvantage by fitting to suitable. distribution (gamma) then transforming into normal and further calculating in a way as presented from equation 1.1 to 1.9.

According to a probability density function, the Gamma distribution is (Thom, 1958):

$$f(x_i) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x_i^{\alpha-1} e^{-x_i/\beta}. \quad (1.1)$$

where α and β are the shape and scale parameters. The larger the shape parameter value is, the closer to normal distribution curve the density curve is. x_i (>0) is the precipitation within i consecutive months, namely, and i -time scales (Zhou and Liu, 2016):

$$x_i^{(j)} = \sum_{k=1}^i X_{j k} \quad j = 1, 2, \dots N. \quad (1.2)$$

where X_{jk} is the precipitation value of k -th month of j -th year. N is the number of years. For 1-month time scale, $i = 1$,

The Gamma function $\Gamma(\alpha)$ is given as:

$$\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt. \quad (1.3)$$

The alpha and beta parameters of the gamma probability density function are approximately estimated as:

$$\alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right). \quad (1.4)$$

$$\beta = \frac{\bar{x}_i}{\alpha}. \quad (1.5)$$

Where $A = \ln(\bar{x}_i) - \frac{1}{n} \sum_{j=1}^n \ln((x_i)_j)$.

Based on the probability density function (Equation 1.1), the cumulative probability $g(x_i)$ at the selected time scale is given as follows:

$$g(x_i) = \int_0^{x_i} f(x_i) dx_i = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^{x_i} x_i^{\alpha-1} e^{-x_i/\beta} dx_i. \quad (1.6)$$

The probability of no precipitation can be written as (Zhou and Liu, 2016) :

$$F(x = 0) = \frac{m}{n}. \quad (1.7)$$

where m denotes the number of zero precipitation in the calculated data sequence. In the case of zero precipitation, the cumulative probability can be expressed as:

$$H(x_i) = F(x_i = 0) + (1 - F(x_i = 0))g(x_i). \quad (1.8)$$

Finally, as cited by (Zhou and Liu, 2016), $H(x_i)$ can be transformed to SPI using the following equations by Milton et al., 1965.

$$SPI = \begin{cases} -\left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & t = \sqrt{\ln\left(\frac{1}{H(x_i)^2}\right)}, \text{ for } 0 < H(x_i) \leq 0.5 \\ \left(t - \frac{c_0 + c_1 + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & t = \sqrt{\ln\left(\frac{1}{H(x_i)^2}\right)}, \text{ for } 0.5 < H(x_i) < 1 \end{cases}. \quad (1.9)$$

where $c_0 = 2.515517$, $c_1 = 0.802853$, $c_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, and $d_3 = 0.001308$.

2.3.2. Standardized precipitation evapotranspiration index

The monthly difference between precipitation (X) and potential evapotranspiration (PET) is used by SPEI (Vicente-Serrano et al., 2010). Because it can be applied at different time scales, it can be used to analyze both short-term and long-term droughts (Bae et al., 2018; Hui-Average et al., 2018; Lee et al., 2017; Vicente-Serrano et al., 2010). By normalizing the difference between potential evapotranspiration and precipitation, SPEI describes the degree of deviation of dry and wet conditions from climatological average conditions (Zhao et al., 2017; Vicente-Serrano et al., 2010). The SPEI, which adds the evapotranspiration variables to the SPI and accounts for the Palmer Drought Severity Index (PDSI) property that evapotranspiration is temperature dependent (Vicente-Serrano et al., 2010). It can therefore be compared to the PDSI, which is self-calibrated (scPDSI) (Vicente-Serrano et al., 2010) and regularly used for drought assessments (Zhao et al., 2017).

According to Vicente-Serrano et al (2010) SPEI is simple to calculate, and is based on the original SPI calculation procedure which uses the monthly difference between precipitation and PET. With a value for PET, the difference between P and PET for the month i is calculated:

$D_i = X_i - PET_i$ which provides a simple measure of the water surplus or deficit for the analyzed month. Then, there are a series of calculations to standardize the variable, and finally, SPEI is calculated using the following formula;

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

where $W = \sqrt{-2 \ln(P)}$ for $P \leq 0.5$, P is the probability of exceeding a determined D_i value and is given as $P = 1 - F(x)$. If $P > 0.5$, P is replaced by $1 - P$ and the sign of the resultant SPEI is reversed. The constants are: $C_0 = 2.515517$, $C_1 = 0.802853$, $C_2 = 0.010328$, $d_1 = 1.432788$, $d_2 = 0.189269$, $d_3 = 0.001308$. The average value of the SPEI is 0, and the standard deviation is 1. The SPEI is a standardized variable, and it can therefore be compared with other SPEI values over time and space

SPI and SPEI could be calculated using the SPEI package of R statistical software (Vicente-Serrano et al., 2010) and the description is given in Table 2. 2.

2.3.3. Reconnaissance Drought Index

The Reconnaissance Drought Index (RDI) is one of the most important indexes for determining the severity of drought (Zarei, et al., 2019) and this measure takes into account both cumulative precipitation (P) and potential evapotranspiration (PET) (Abubakar et al., 2020; Rahmat et al., 2015). It is based on the precipitation-to-potential evapotranspiration ratio (Zarei et al., 2019; Vangelis et al., 2013). RDI is fitted to a gamma distribution that is comparable to that of SPI (Rahmat, Jayasuriya and Bhuiyan, 2015). The RDI standard is calculated using a technique similar to the one used to calculate the SPI (Rahmat et al., 2015). PET, in addition to precipitation, is a key variable in RDI's drought severity assessment as a result of rising greenhouse gas concentrations (Asadi Zarch, et al., 2015).

In RDI, drought characterization and monitoring can be done in three ways: the initial value RDI (k), the normalized RDI (nor), and the standardized RDI (std) (Abubakar et al., 2020; Vangelis et al., 2013) and it can be calculated using the following equations (Tigkas et al., 2017).

The initial form of the index (α) within a year for a reference period of k months is calculated as:

$$a_k = \frac{\sum_{j=1}^{j=k} P_j}{\sum_{j=1}^{j=k} PET_j} \quad (3)$$

The second form is a normalized expression of the index (RDI_n), calculated by the following equation: in which a_k is the long-term average of a k :

$$RDI_n(k) = \frac{a_k}{\bar{a}_k} - 1 \quad (4)$$

Assuming that the values of a_k follow the log-normal distribution, the standardized form of the index (RDI_{st}) is calculated using the following formula (Abubakar et al., 2020):

$$RDI_{st}(k) = \frac{y_k - \bar{y}_k}{\sigma_k^k} \quad (5)$$

In which y_k is equal to the $\ln a_k$, while $\bar{y}_k$ is its average and σ_k^k is its standard deviation, respectively.

2.3.4. Enhanced Reconnaissance Drought Index

The enhanced Reconnaissance Drought Index created by Tigkas et al. (2016) is one of the newest indices for determining the severity of droughts, with a focus on agricultural droughts (Zarei et al., 2019). For RDI adjustment, the use of effective precipitation rather than total precipitation is advocated, and this method is predicted to improve the index's applicability for assessing drought effects on agricultural systems, particularly for rainfed farming system (Tigkas, et al., 2016). Effective precipitation replaces precipitation in the upgraded RDI index (Tigkas et al. 2016; Zarei et al., 2019) It improves the index's performance in agricultural drought analysis (Zarei et al., 2019). When compared to total precipitation, effective precipitation more accurately indicates the amount of water that can be utilized productively by crops (Tigkas, et al., 2017). The eRDI was estimated using the ratio of effective precipitation to potential evapotranspiration (Zarei, et al., 2019). The main modification aspect in the proposed eRDI, is the substitution of the total precipitation by the P_e and the index (α_e) is calculated as (Tigkas et al., 2017):

$$a_e(k) = \frac{\sum_{j=1}^{j=k} P_{ej}}{\sum_{j=1}^{j=k} PET_j} \quad (6)$$

in which P_{ej} is the monthly effective precipitation of the j th month. The input parameter for RDI and eRDI is rainfall and temperature. RDI and eRDI could be calculated using DrinC software (Tigkas et al., 2015) and the description of the indices given in Table 2. 2. The effective

precipitation was calculated using U.S.B.R (Unites State Bureau of Reclamation) method since which is mainly proposed for arid and semi-arid region (Tigkas,et al., 2016).

2.3.5. Self-calibrating Palmer Drought Severity Index

The Palmer Drought Severity Index is based on a soil water balance and has been widely used in the past (Vangelis et al., 2013; Zhong et al., 2019). The original PDSI has significant flaws, including a large effect of the calibration period, usage limitations, and geographic comparability issues (Hui-Average et al., 2018; Sousa et al., 2011). This weakness is somewhat addressed by the Palmer self-calibrating system (Zhong et al., 2019). To calibrate the PDSI, the predefined coefficient is substituted with local conditions in scPDSI. Hence, at different sites, the updated scPDSI performed more consistently and allowed for more accurate drought determinations than the original PDSI (Wells, et al., 2004). As a result, the scPDSI which is spatially comparable and captures extreme dry and wet episodes under unusual conditions has improved this drought indicator (Wells, et al., 2004). The scPDSI suggests that temperature may play a key role in explaining drought conditions as a result of global warming (Vicente-Serrano et al., 2010). There is a series of computations in scPDSI which is indicated from equations 7.1 to 7.6.

According to Ogunrinde et al., (2020) four soil moisture-related variables and their potential covariates are computed for each month of the study period. Recharge (R), runoff (RO), potential recharge (PR), potential evapotranspiration (PET), loss (L), potential runoff (PR), and potential loss (PL) are the variables. The Thornthwaite PET method was used to compute PET. The only factor used to estimate these variables is the soil's AWC, or available water holding capacity. Four potential values are selected based on the local climate using the weighting factors using α , β , γ and δ and to represent the exiting climatic circumstances. The weighting factors, commonly known as the water-balance coefficients, can be calculated as follows:

$$\alpha = \frac{ET}{PET} \quad \beta = \frac{R}{PR} \quad \gamma = \frac{RO}{PR} \quad \delta = \frac{L}{PL}. \quad (7.1)$$

The existing climatic conditions potential values are combined to form the existing climatic conditions precipitation, X , which represents the amount of precipitation needed to maintain a normal soil moisture level for a period, e.g., a month.

$$X = \alpha PET + \beta PR + \gamma PR - \gamma PL. \quad (7.2)$$

where X stands for the amount of precipitation needed to maintain a normal soil moisture level for a particular month under consideration.

$$d = X - x = X - (\gamma PET + \beta PR + \gamma PR - \delta PL). \quad (7.3)$$

where X is the actual rainfall that was actually recorded for the month being considered, x is the amount of rainfall needed to stabilize the soil moisture in a normal condition for a month under the current climatic conditions, and d indicates moisture departure.

In order to allow for a strong link between the scPDSI values from a spatiotemporal perspective, Palmer (1965) equation was utilized to complement the d value in accordance with the local climate.

$$K = \frac{17.67}{\sum_{j=1}^{12} d_j K_j} K_j. \quad (7.4)$$

The result of multiplying the moisture departure, d , by K (empirical constant) is called the moisture anomaly index, or the Z index, and is denoted by Z , shown as

$$Z = dK. \quad (7.5)$$

Without taking current precipitation trends into account, the Z index is used to describe how dry or wet a month was and the equation is also used to predict the PDSI value for a given month (Ogunrinde et al., 2020):

$$Y_i = 0.897Y_{i-1} + \left(\frac{1}{3}\right)Z_i. \quad (7.6)$$

Where Y is the current value of the index. For example, to calculate the current value of Y_i , 0.897 times the previous PDSI value Y_{i-1} is added to one-third of the current moisture anomaly Z_i (Wells et al., 2004).

The sole difference between the PDSI and the scPDSI is that the empirical constants (K) and duration factors (0.897 and 1/3) are replaced with values derived automatically based on the research site's historical climate data (Ogunrinde et al., 2020).

scPDSI package of R statistical software (Palmer W., 1965; Wells et al., 2004) can be used for the calculation of scPDSI. The input variable for scPDSI is rainfall, temperature, and available water content of soils. Information on the water-holding capacity of soils can be used, however, defaults are also available and a serially complete record of temperature and precipitation data is required

(Svoboda et al., 2016). In this study, only precipitation and temperature were used for the analysis of scPDSI due to the unavailability of available water content of soils (available water content of soil was considered as 100% for all station). The description of scPDSI is given in Table 2. 2.

The potential evapotranspiration (PET) was calculated using Hargraves method in the case of SPI, SPEI, RDI and eRDI, using the minimum and maximum temperature of the stations, while PET was calculated using Thornthwaite method using average temperature of the station in the case of scPDSI.

Table 2.2: Drought class description of selected drought Indices

Normal (No Drought)	Moderate Drought	Severe Drought	Extreme Drought	Reference
$-0.99 < \text{SPI} < 0.99$	$-1.49 < \text{SPI} \leq -1$	$-1.99 < \text{SPI} \leq -1.5$	$\text{SPI} \leq -2$	Zhou &Liu, 2016
$-0.99 < \text{SPEI} < 0.99$	$-1.49 < \text{SPEI} \leq -1$	$-1.99 < \text{SPEI} \leq -1.5$	$\text{SPEI} \leq -2$	Bae et al., 2018
$-0.99 < \text{RDI} < 0.99$	$-1.49 < \text{RDI} \leq -1$	$-1.99 < \text{RDI} \leq -1.5$	$\text{RDI} \leq -2$	Tigkas et al., 2017
$-0.99 < \text{eRDI} < 0.99$	$-1.49 < \text{eRDI} \leq -1$	$-1.99 < \text{eRDI} \leq -1.5$	$\text{eRDI} \leq -2$	Tigkas et al., 2017
$0.49 < \text{scPDSI} < -0.49$	$-2 < \text{scPDSI} \leq -2.99$	$-3.0 < \text{scPDSI} \leq -3.99$	$\text{scPDSI} \leq -4$	Wells et al., 2004

2.4. Drought Indices Correlation Analysis

Each drought index was calculated first, then Pearson's correlation analysis was conducted for comparison of indices for the five drought indices of seven meteorological stations. The analysis was conducted using a *corrplot* package of R software and 3,6,9, and 12 months' time scales were selected. Furthermore, the drought indices that were analyzed by correlation analysis were tested with Kappa statistics. Inverse distance weighting (IDW) was used to visualize the spatial patterns of the drought occurrences in the watershed.

2.5. Cohen's (Fleiss') Kappa test

Most of the literature presented reports high correlations between drought indices does not always mean that the indices are similar (Vergni et al., 2021). Hence, the comparison of all potential pairs of indices in terms of the severity category assigned to each time series and subsequent quantification of their degree of agreement using the Cohen's Kappa test allowed for a more accurate and creative evaluation of the similarity between the indices. (Vergni et al., 2021).

Cohen (1960) introduced the proportion of agreement corrected for chance as a coefficient of agreement for nominal or ordinal scales, and this form of evaluation can be successfully attained by the Cohen's Kappa test (Vergni et al., 2021). The calculated outcomes range from -1 to 1, where 1 represents complete agreement while 0 denotes exactly what would be predicted by chance, and negative values denote agreement less than chance (Ezzine et al., 2014).

When there are either two assessment techniques with a single trial or one assessment method with two trials, Cohen's Kappa is used to measure the degree of agreement, while Fleiss's Kappa is an extension of Cohen's Kappa for three or more measurements. Hence, based on these assumptions Fleiss' kappa statistics was found suitable for this study and used to test the degree of agreement among SPI, SPEI, RDI and eRDI as drought assessment tools.

Because Kappa statistics works well with ordinal or nominal data, the continuous values of each drought assessment value (i.e., SPI, SPEI, RDI and eRDI) were transformed to ordinal data (drought classification in Table 2.2. i.e., class of extreme drought labeled as 1, severe drought as 2, moderate drought as 3, etc.). Then, the transformed data of each index were then used to calculate the degrees of agreement using Fleiss' kappa statistics. Then, the calculation of Fleiss' kappa statistics was carried out using *irr* package of R statistical software.

The formula for Cohen's Kappa statistics is given as (Cohen, 1960):

$$K = \frac{p_o - p_e}{1 - p_e} \quad (8)$$

where p_o is the total observed frequency of agreement and p_e is the proportion of agreement expected by chance.

2.6. Theory of Run (ToR) Application

Yevjevich's (1967) statistical theory of runs (ToR) is a useful tool for addressing drought features (Samantaray et al., 2019; Jasim & Awchi, 2020). This approach was developed to identify drought duration and severity based on values below a predetermined threshold level, as well as a method to calculate drought variables including duration, severity, and intensity (Maeng et al., 2017; Lee et al., 2017). Although ToR is not a drought indicator, it can be used in combination with others to identify drought parameters, and a drought event is defined as a time series that is less than the

crucial threshold level for some time (Rahmat, et al., 2015). The theory of run is simple to use and can be used to analyze hydrometeorological time series (Kwak et al., 2016) to differentiate drought as a feature (Huang et al., 2014). The ToR is applied to a predetermined threshold, which is the point where moisture and dryness meet (Jasim and Awchi, 2020). A run, according to ToR, is a segment of a drought variable's time series in which each value is either above or below the prescribed truncation level (Huang et al., 2014; Jasim & Awchi, 2020). Drought characteristics include a feature like duration, severity, and intensity of the drought (Bae et al., 2018). A cumulative shortfall of a drought metric below the threshold level indicates drought severity (Lee et al., 2017). The beginning and termination times of a drought, which define the duration of the drought, are critical parameters to quantify (Panu and Sharma, 2002). Hence, Drought severity is the sum of all negative values below the threshold value, drought duration is the time between the onset and termination of the drought events and intensity is the ratio of severity and duration. Therefore, drought severity, duration, intensity, and station-based frequency can be calculated with the following formulas:

$$D = (t_2 - t_1) \quad (9)$$

$$S = \sum_{i=1}^D -(SPL_i) \quad (10)$$

$$I = \frac{S}{D} \quad (11)$$

$$F = \frac{N}{T} * 100\% \quad (12)$$

Where D is drought duration, t_1 and t_2 are the onset and termination time of drought, S is the severity of drought, I represent the intensity of drought, F is the station-based frequency of drought, N is the number of drought events and T is the total number of years of the study period.

2.7. Drought Trend Analysis

The Mann-Kendall (MK) approach is frequently used to determine the monotonic trends of various hydro-meteorological data (Gumus et al., 2021). The MK test is a non-parametric (distribution-free) test used to determine whether a variable of interest has a monotonic upward or downward trend over time (Khosravi et al., 2018). Mann (1945) and Kendall (1948) suggested this approach for determining statistically significant trends in hydro-meteorological data (Gumus et al., 2021).

The Z value is used to determine a statistically significant trend and an upward or downward trend is indicated by a positive or negative value (Gumus et al., 2021).

In the MK test statistic, the S test statistic, the sign function, the variance of S, and the Z statistics are calculated using the formulas indicated in equations 13,14, 15, and 16 (Gumus et al., 2021) :

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(x_j - x_i) \quad (13)$$

$$\text{sign}(x_j - x_i) = \begin{cases} +1 & x_j > x_i \\ 0 & x_j = x_i \\ -1 & x_j < x_i \end{cases} \quad (14)$$

where n is the number of d

$$\text{Var}(S) = \left[n(n-1)(2n+5) - \sum_{i=1}^m t_i i(i-1)(2i+5) \right] / 18 \quad (15)$$

where t_i is the number of ties of extent i and m is the number of tied groups. For n larger than 10, the standard test statistic Z is computed as the MK test statistic as follows

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \quad (16)$$

The presence of a statistically significant trend is evaluated using the Z value. Positive values of Z indicate increasing trends, while negative values show decreasing trends. In the test for either an increase or decrease monotonic trend (a two-tailed test) at the α level of significance, H_0 should be rejected if the $|Z| > Z_{1-\alpha/2}$, where $Z_{1-\alpha/2}$ is obtained from the standard normal cumulative distribution Table 2.s. For instance, at the 5% significance level, the null hypothesis was rejected if $|Z| > 1.96$. A higher severity of the Z value indicates that the trend is more statistically significant. MK trend test was used at a significance level of 0.05 for this study.

2.8. Results

2.8.1. Correlation of Drought Indices

The correlations of the drought indices were made separately for all stations. The stations with the lowest elevation at Bilate Tena and the highest elevation at Hossana are presented in Figure 2. 2. The drought indices were highly correlated to each other for a similar time scale. For instance, SPI3, SPI6, and SPI9 were well correlated with most of the other drought indices. Similarly, SPEI3, SPEI6, and SPEI9 showed a very high correlation with a similar time scale of other drought indices (SPI, RDI, and eRDI). The correlation becomes higher on the short-time scale, particularly on the 3-month and 6-month time scales. On the other hand, scPDSI showed a strong correlation ($r=0.80$) with SPI3, SPI6, SPEI3, and SPEI6. Similarly, scPDSI showed a strong correlation with RDI3 ($r=0.79$) and RDI6 ($r=0.78$), but showed a medium correlation ($r=0.73$) with eRDI3 and eRDI6 compared to other drought indices. This indicates that scPDSI correlated better with SPI, SPEI, and RDI at the time scale of 3-month and 6-month time scale. The correlation of scPDSI decreases with the increasing time scale of drought indices. In this analysis SPI3 with SPEI3, SPI6 with SPEI6, and SPEI12 with RDI12 had a very strong correlation ($r=0.99$) at Bilate Tena station. The index eRDI also showed a high correlation with a similar time scale to other drought indices. Hence, the SPI, SPEI, and RDI were highly correlated for a similar time scale indicating that they can be used interchangeably.

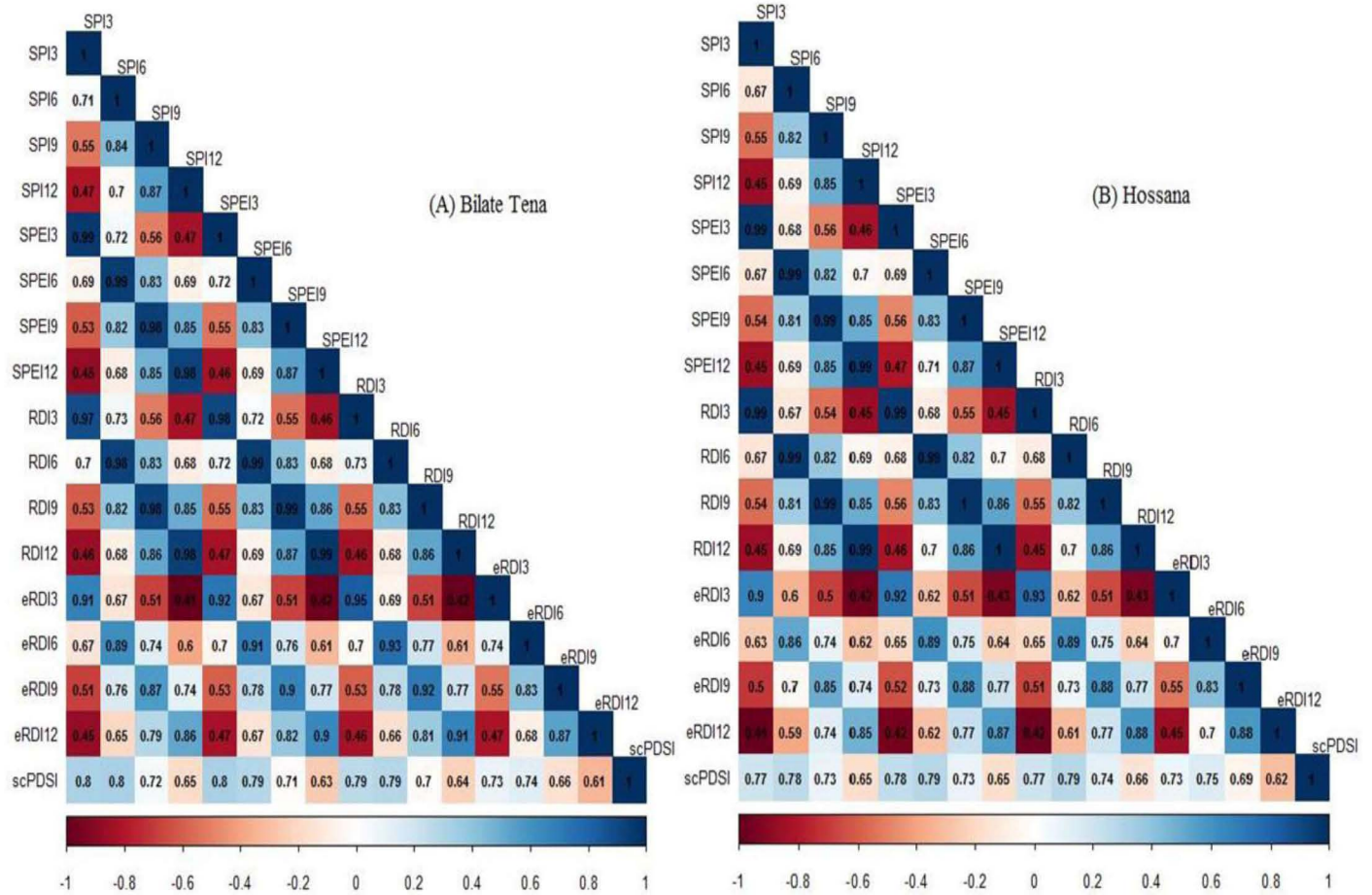


Figure 2.2: Pearson correlation matrix: (A) Bilate Tena Station (B) Hossana station (The number next to the drought index indicates the time scale. i.e., SPI3 indicates the SPI at a 3-month scale and so on). At $p < 0.05$, all correlation is statistically significant.

At the Hossana station, a similar time scale of the different drought indices showed a very high correlation (Figure 2. 2B). SPI3 with SPEI3, SPI6 with SPEI6, SPI9 with SPEI9, SPI12 with SPEI12, SPEI3 with RDI3, and SPEI6 with RDI6 showed a very strong correlation ($r=0.99$). The scPDSI showed a strong correlation with SPI3($r=0.77$), SPI6($r=0.78$), SPEI3 ($r=0.78$), SPEI6 ($r=0.79$), RDI3 ($r=0.77$), and RDI6 ($r=0.79$). The study revealed that scPDSI showed a better correlation with SPEI6 and RDI6 compared to other drought indices. Similar to what was shown at Bilate Tena station, the correlation of the scPDSI at Hossana station declined as the time scale of the drought indices increased.

The average correlation values of the drought indices were calculated using the results of the correlation analysis for all stations. The average correlation of all-time scales showed that the

average correlation value of 0.63 for SPI3 is the paired correlation of SPI3 with SPI6, SPI9, SPI12, SPEI3, SPEI6, SPEI9, SPEI12, RDI3, RDI6, RDI9, RDI12, eRDI3, eRDI6, eRDI9, eRDI12, and scPDSI (Figure 2. available as supplementary material). A similar analysis of all-time scales of the other drought indices for all stations showed that the maximum average correlation was observed at the 6-month and 9-month scales. This indicates that the best time scales for identifying historical drought events were the 6-month and 9-month time scales in BRW. Hence, all drought indices with 6-month and 9-month scales better explained the historical drought characterization in BRW. The average correlation of the scPDSI with other drought indices. The average correlation of the scPDSI was higher at the 3-month and 6-month time scales, indicating that the scPDSI better characterizes short-term and medium-term droughts.

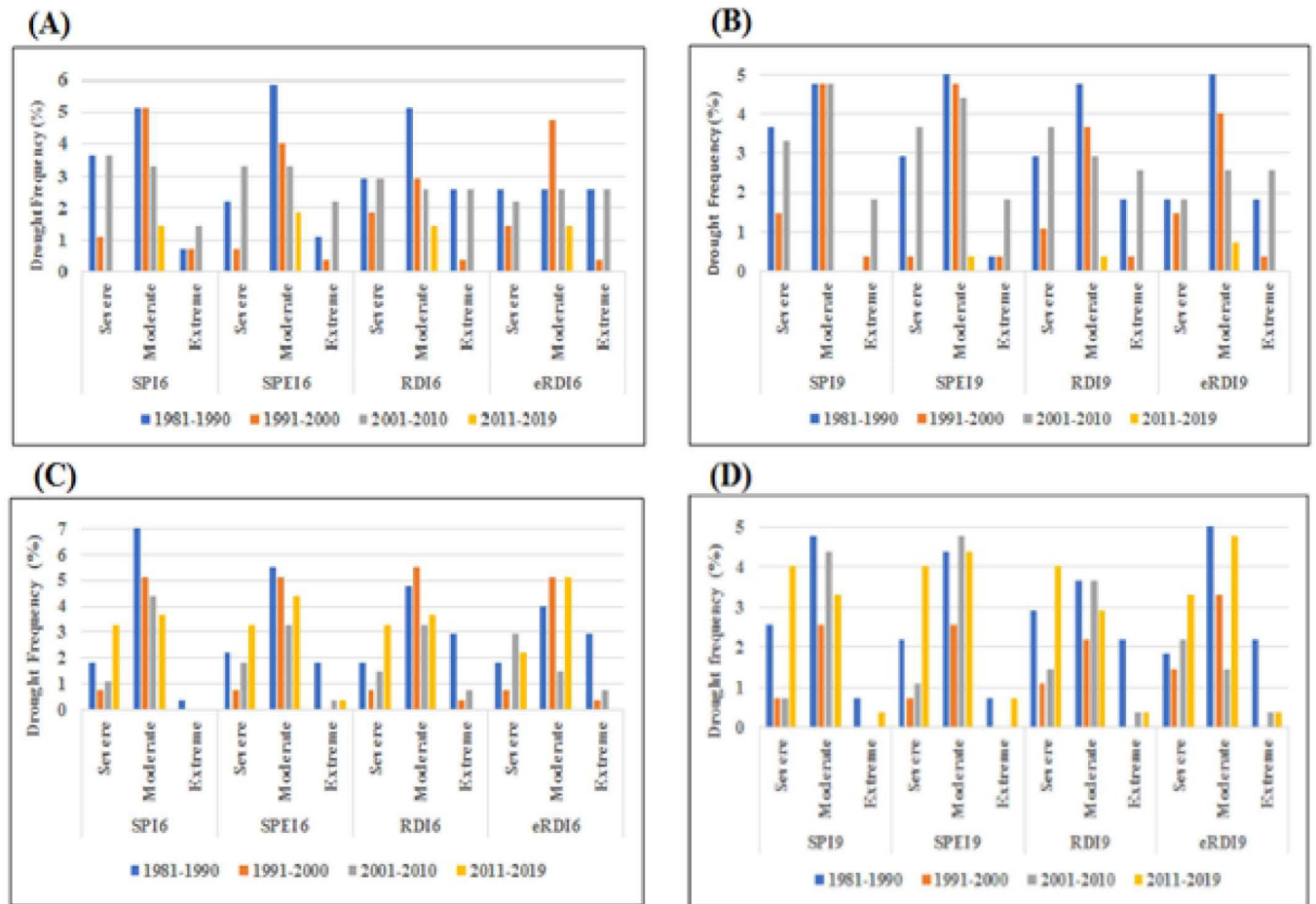


Figure 2.3: Frequencies of drought (number of stations multiplied by years in %) during 1981–2019 at Bilate and Hossana stations: (A) Bilate station in 6-month scale (B) Bilate station in 9-month scale (C) Hossana station in 6-month scale and (D) Hossana station in 9-month scale.

2.8.2. Fleiss' kappa test statistics

The Fleiss' Kappa Statistics result showed substantial degrees of agreement (0.61-0.80) among SPI, SPEI, RDI, and eRDI in 3-month, 6-month, and 9-month time scales, as well as in 12-month scale a moderate degree of agreement (0.61-0.80) which statistically significant at $p < 0.05$ at the Bilate station (Table 2. 3). Hossana station also showed comparable outcomes (Table 2. 3). The degree of agreement at the 6-month and 9-month time scales, however, was the closest to each as were observed in correlation analysis, therefore it was chosen for further characterization of historical drought at Bilate river watershed.

Table 2.3 Fleiss' kappa test statistics for the degree of agreement among SPI, SPEI, RDI and eRDI at BRW

(A) Bilate Station			
Time Scale	Kappa statistics	P-value	Degree of Agreement
3-month (SPI3, SPEI3, RDI3 & eRDI3)	0.713*	0.000	Substantial
6-month (SPI6, SPEI6, RDI6 & eRDI6)	0.663*	0.000	Substantial
9-month (SPI9, SPEI9, RDI3 & eRDI9)	0.643*	0.000	Substantial
12-month (SPI12, SPEI12, RDI12 & eRDI12)	0.565*	0.000	Moderate
(B) Hosanna Station			
Time Scale	Kappa statistics	P-value	Degree of Agreement
3-month (SPI3, SPEI3, RDI3 & eRDI3)	0.643*	0.000	Substantial
6-month (SPI6, SPEI6, RDI6 & eRDI6)	0.598*	0.000	Moderate
9-month (SPI9, SPEI9, RDI3 & eRDI9)	0.593*	0.000	Moderate
12-month (SPI12, SPEI12, RDI12 & eRDI12)	0.563*	0.000	Moderate

*Statistically significant at 95% confidence level.

2.8.3. Temporal distribution of drought events

The time series (1981–2019) of the drought indices were analyzed for all the stations. However, only the results for Bilate Tena and Hossana stations were selected and shown here in Figure 2.4 and 2.5. These two stations were considered as representatives of the lowland and highland parts of the watershed. The temporal analysis of drought indicated that almost all of the drought indices were capable of identifying the major historic drought years such as 1984/85, 2000, 2002, and 2009 (Figure 2. 4 & 2.5 and Table 2. 3 & 2.4). Based on the selected drought indices with time scale of 6-month and 9-months, the major drought events identified occurred in 1984/85, 2000, 2002, and 2009 at Bilate Tena and Hossana stations (Figure 2. 4 & 2.5 and Table 2.3 & 2.4). The historical drought years detailed drought severity, duration, intensity, onset, and termination of the

events were indicated in Table 2.3 and 2.4. A similar pattern of historical major drought events was detected on the other stations as well (Figure 2. available as supplementary material).

At Bilate station, the SPI6 values of extreme drought ranges from -2.46 in 1985 to -2.14 in 2009. The value of maximum severe drought occurred with the values of -1.93 in 1984 and minimum value was -1.52 in 2009. The value of moderate drought ranges from -1.17 in 1984 to -1.05 in 2012. Similarly, the SPEI6 values of extreme drought ranges from -2.36 in 1985 and to -2.25 in 2009. The value of maximum Severe drought was -1.78 in 1984 and the minimum value was -1.50 in 2009. The moderate drought maximum value was -1.48 in 1984 and minimum value of -1.07 in 1984. The RDI6 extreme drought ranges from -2.46 in 1984 to -2.88 in 2009, the maximum severe drought was -1.66 in 1984 and minimum was -1.90 in 2009. The moderate drought showed the maximum value of -1.46 in 2012 and the minimum was -1.00 in 1981. The eRDI extreme drought ranges from -2.38 in 1984 to -3.25 in 2009. eRDI6 showed the highest peak value compared to others drought index (Figure 2. 4A). These drought range records confirmed that the year 1984 and 2009 were the most intense drought affected years in the watershed. Similar observation was detected in the 9-month time scale of all drought indices.

At Hossana station, the SPI6 showed the extreme drought with a peak value of -2.27 in 1985, a severe drought with peak value of -1.87 in 2015, a moderate drought with a peak value of -1.34 in 1984. Similarly, SPEI6 showed extreme drought with a peak value of -2.15 in 1985, a severe drought with a peak value of -1.81 in 2009, and moderate drought with the peak value of -1.36 in 1984. RDI6 also showed the extreme drought with the peak value of -2.81 in 1984, severe drought with a peak value of -1.93 in 2009, and a moderate drought with a peak value of -1.34 in 2000. eRDI6 showed extreme drought with a peak value of -2.77 in 1984, severe drought with a peak value of -1.98 in 1984, and moderate drought with a peak value of -1.14 in 2015. Similar pattern of drought identified with the 9-month time scale of all drought indices. Hence, the year 1984, 2009 and 2015 were the most drought affected year at Hossana station (Figure 2. 5A). Similar observation was detected in the 9-month time scale of all drought indices.

The percentage of drought frequency that consider all stations was assessed using a total of 273 events (39 years of study period $\times$ 7 stations). At Bilate station, in the case of SPI6, the results indicate that high extreme drought occurred in 1980s and 2000s (0.73%). In the case of SPEI6,

high percentage of extreme drought occurred in the 2000s (1.47%). Whereas in the case of RDI6 and eRDI6 high percentage of drought frequency occurred in 2000s with the value of 2.20% and 2.56%, respectively indicating that the 2000s were the extreme drought decade throughout the study period (Figure 2. 3A). Severe drought showed high percentage of drought frequency in 1980s with values of 3.66% of SPI6, 2.93% of RDI6, and 2.56% of eRDI6, but 3.30% of SPEI6 in 1990s. The severe drought occurrence outweighs in 1980s than in 1990s indicating that the 1980s were the more severe drought affected decade. Moderate drought showed high percentage of drought frequency in 1980s with values of 5.13% of SPI6, 5.86% of SPEI6, 5.13% of RDI6, but 4.76% of eRDI6 in 1990s. The moderate drought occurrence outweighs in 1980 than in 1990s indicating that the 1980s were the more drought affected years. Regarding the pattern of the four decades of study period, it can be noted that severe drought pronounced in the 1980s and 2000s whereas moderate drought pronounced in the 1980s and 1990s. All the drought indices, accounts a total severe drought frequency percentage 11.36% and 18.68 % in 1980s. Thus, 1980s, 1990s and 2000s were drought prone decades specifically in terms of severe and moderate droughts whereas the last decade was less drought affected (Figure 2. 3A). Similar pattern was observed in the 9-month time scale of all drought indices (Figure 2. 3B).

At Hossana Station, in the case of SPI6, the results indicate that high extreme drought occurred in 1980s (0.73%). In the case of SPEI6, high percentage of extreme drought occurred in the 1980s (0.37%). Whereas in the case of RDI6 and eRDI6 high percentage of drought frequency occurred in 1980s with the value of 1.83% and 2.93%, respectively indicating that the 1980s were the extreme drought years throughout the study period (Figure 2. 3C). Severe drought showed high percentage of drought frequency in 2010s with values of 3.30% of SPI6, SPEI6 and RDI6, and 2.20% of eRDI6. Moderate drought showed high percentage of drought frequency in 1980s with values of 7.69% of SPI6 in 1980s, and 5.49 of SPEI6, & 5.13% of RDI6 in 1990s. The moderate drought occurrence outweighs in 1980s and 1990s indicating that the 1980s were the more drought affected years (Figure 2. 3C). Regarding the pattern of the four decades of study period, it can be noted that extreme drought pronounced in the 1980s whereas moderate drought pronounced in the 1980s and 1990s. All the drought indices, accounts a total extreme, severe and moderate drought frequency percentage 34.81% in 1980s indicating the most drought affected decade of the study period. Similar pattern was observed in the 9-month time scale of all drought indices (Figure 2.

3D). Generally, 1980s, 1990s and 2000s were drought prone decades specifically in terms of sever and moderate droughts whereas the last decade was less drought affected. Similar pattern was observed in the 9-month time scale of all drought indices.

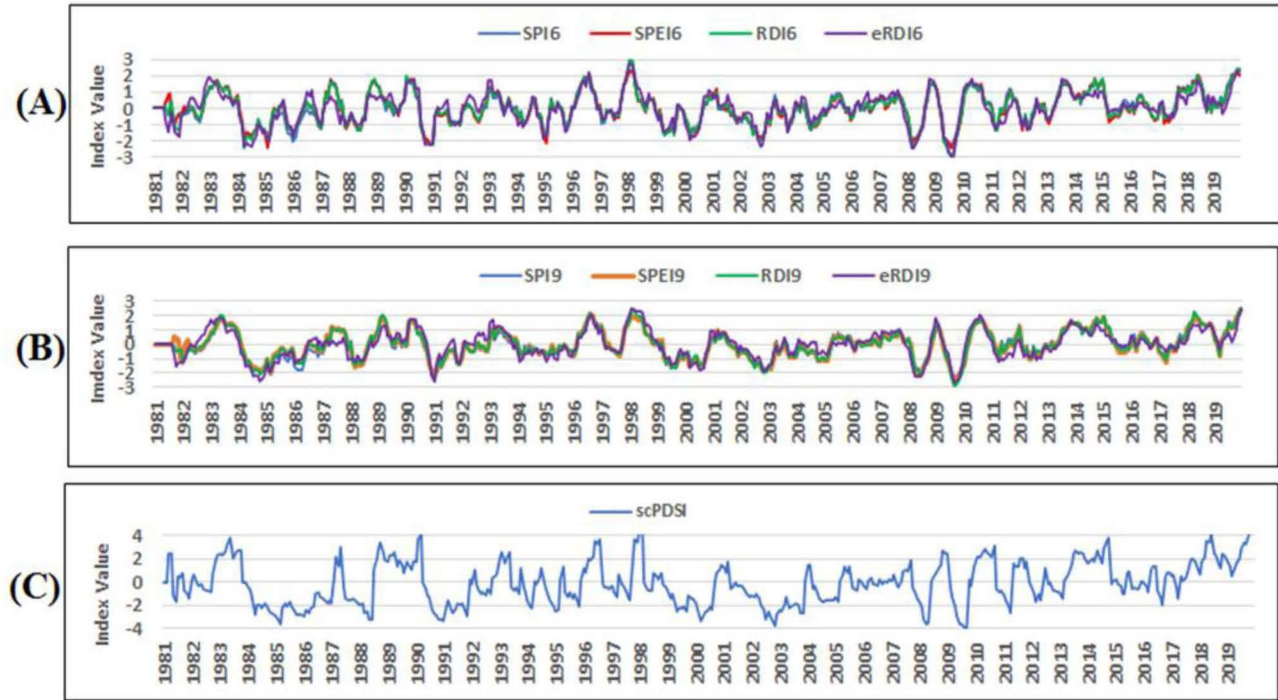


Figure 2.4: Time series drought events at Bilate Tena station: (A) 6 months, (B) 9 months, and (C) scPDSI

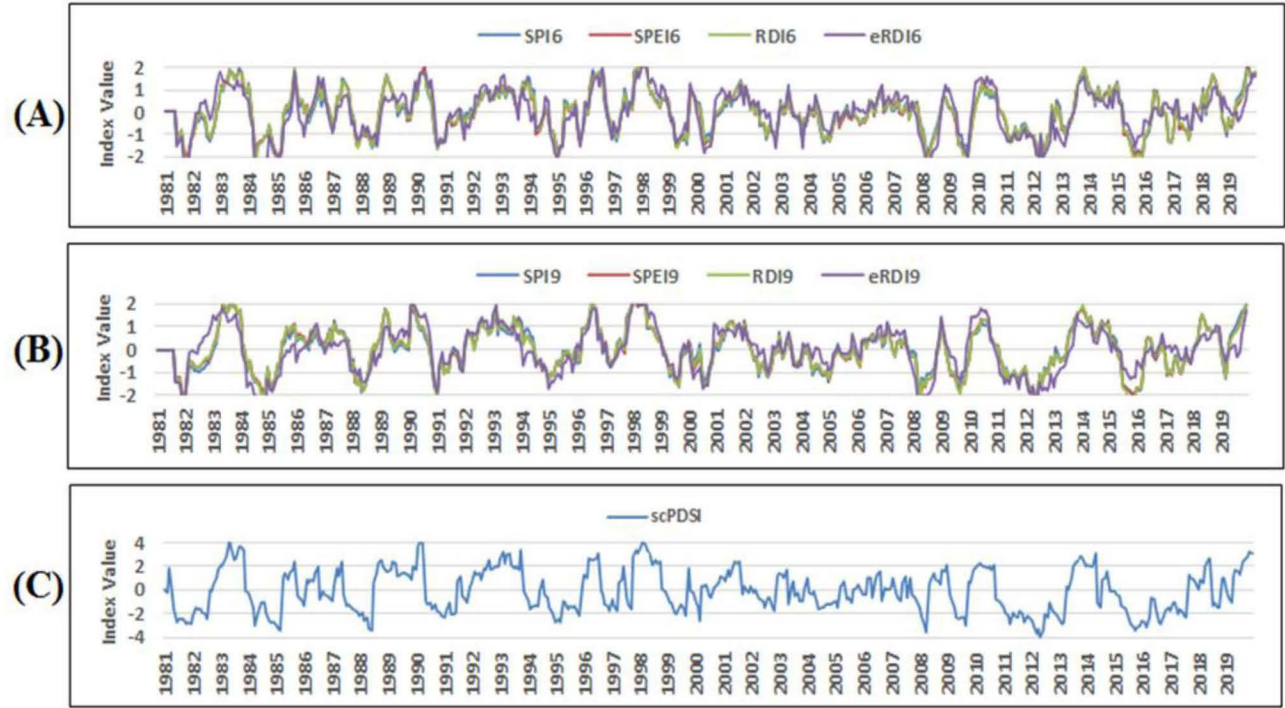


Figure 2.5: Time series drought events at Hossana station: (A) 6 months, (B) 9 months, and (C) scPDSI

2.8.4. Spatial distribution of drought events

The interpolated values of the highest drought severity at each station were used to produce the spatial map of drought events. In 1984, extreme drought was observed in the central and southern parts of BRW using SPI, SPEI, and scPDSI with small variations (Figure 2.6). However, the SPI indicates that the northern part of the watershed also experiences extreme drought exceptionally due to the higher drought severity recorded at Hossana station in 1984 (Figure 2.6). In 2009, extreme drought was observed in the central and southern parts of the watershed in all drought indices (Figure 2.6). Likewise, severe drought is also distributed at the central and southern parts of the watershed using SPEI and scPDSI (Figure 2.6). In 2009, SPEI and scPDSI showed similar patterns in indicating the distribution of historical drought events. Generally, the interpolated value of the drought maximum severity record at the seven stations indicated that the central and southern parts of the watershed experienced extreme and severe drought.

The interpolated values of the highest drought severity at each station were used to produce the spatial map of drought events. In 1984, extreme drought was observed in the central and southern parts of BRW using SPI, SPEI, and scPDSI with small variations. Particularly at the central (Alaba

station) and the south eastern (Bilate station) part of the watershed showed high extreme value that ranges from -2.46 to -2.22 (Figure 2.6A). However, the SPI indicates that the northern part of the watershed experiences extreme with the value of -2.21 to -1.97 exceptionally due to the higher drought severity value displayed at Hossana station in 1984. Severe drought also highly distributed in the central part of the watershed with the value of -1.96 to -1.92, southern and small part of the western (Wolayta Sodo station) parts of the watershed in 1984. Similarly, the moderated drought showed the highest distribution in the central part of the watershed with the value of -1.48 to -1.45 in 1984 (Figure 2.6A). In 2009, extreme drought was observed in the central and southern parts of the watershed in all drought indices in general. Particularly, intense extreme drought was distributed with the values that ranges from -2.6.2 to -2.33 at the western edge of central part of the watershed in 2009 (Figure 2.6B). The value of SPI6 extreme drought was higher in 2009 than the value of SPI6 in 1984. Severe drought also distributed in the south western part of the watershed with the value that ranges from -1.98 to -1.93 which was higher value compared to the SPI6 value of 1984 (Figure 2. 6B). The distribution of moderate drought showed at the north western and south western part of the watershed with the highest value that ranges from – 1.45 to -1.43 in 2009. Hence, the spatial drought distribution showed a shift from the central and southern parts in 1984 to the western edge of the watershed in 2009 with the drought index of SPI6.

SPEI6 in 1984 showed the highest extreme drought distribution at the central, north western and southern part of the watershed with value that ranges from -2.37 to -2.11 in 1984 (Figure 2.6C). Severe drought showed its distribution at the western part of the watershed with value that ranges from -1.89 to -1.86 in 1984. The moderate drought also distributed at the central and southern part of the watershed with the value that ranges from -1.48 to -1.46 in 1984 (Figure 2.6C). In 2009, SPEI6 showed the highest extreme drought distribution in the central part of the watershed with the value that ranges -2.76 to -2.45 which was highest to the value of 1984. Severe drought also distributed with high value that ranges from -1.98 to -1.93 at the central and southern part of the watershed. Moderate drought in 2009 was also highly distributed at the northern, north western, central southern part of the watershed with the value that ranges from -1.48 to -1.43 in 2009 (Figure 2.6D). The distribution of extreme drought shifts from central and southern part of the watershed in 1984 to the western part in 2009 with the drought index of SPEI6. The severe drought also shifts from western part in 1984 to eastern part in 2009.

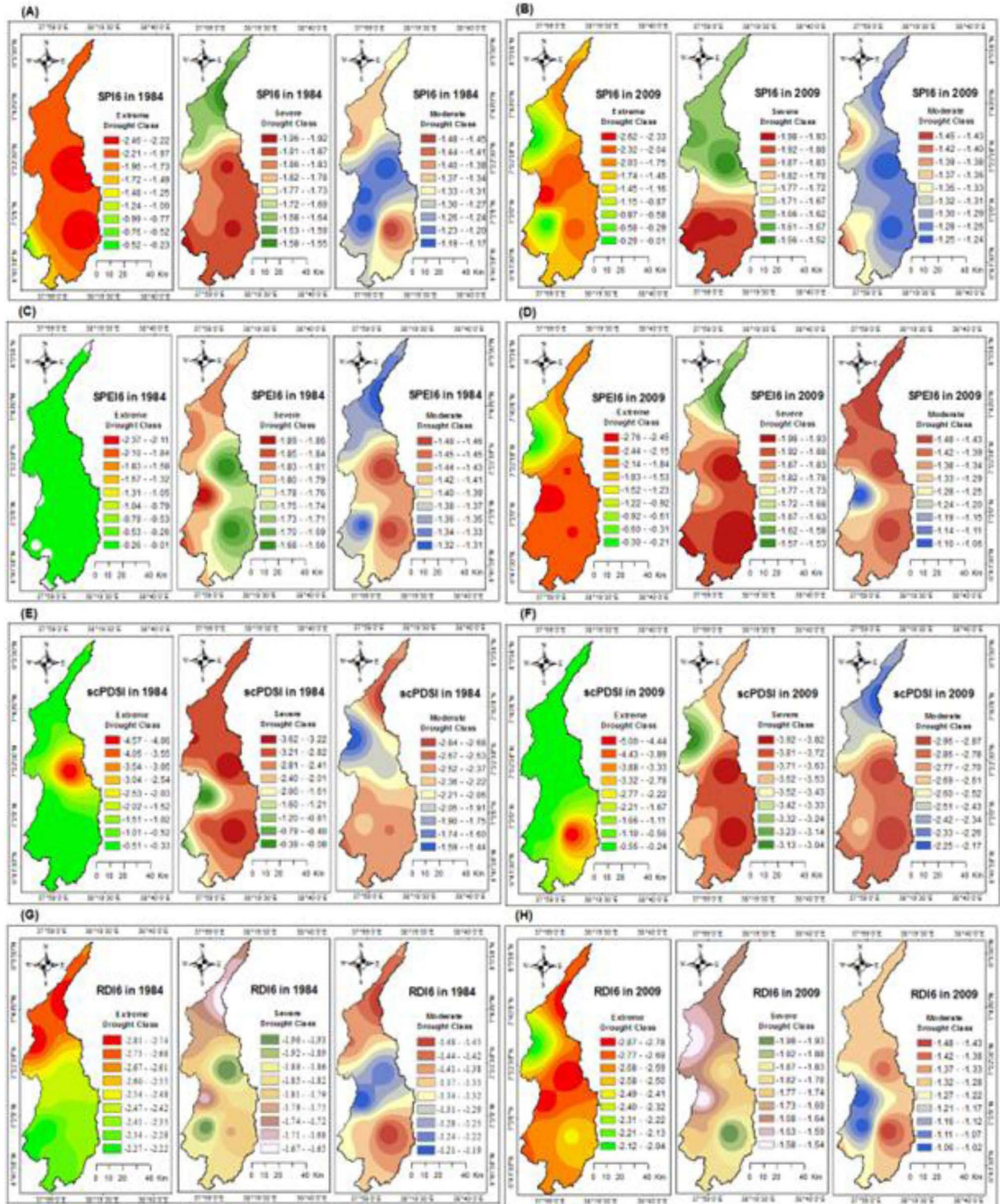


Figure 2.6: Spatial distribution of Extreme, Severe and Moderate droughts (A) SPI6 in 1984 (B) SPI6 in 2009 (C)SPEI6 in 1984 (D)SPEI6 in 2009 (E) scPDSI in 1984 (F) scPDSI in 2009 (G) RDI6 in 1984 and (H)RDI6 in 2009

However, the moderate drought did not show a spatial shift from 1984 to 2009. Similar pattern of drought class distribution was observed with the time scale 9-month. Even though the interpolation was only based on a small number of data (seven stations), it nevertheless depicts the overall pattern of drought in the watershed. Drought spatial distribution for various classes (extreme, severe and moderate drought) and year (1984 and 2009) showed a spatial pattern variation. However, the central and southern portions of the watershed experienced intense (extreme and severe) droughts during the study period, according to the spatial drought distribution map for all drought classes (extreme, severe, and moderate) and timescales (6-month and 9-month).

2.8.5. Drought characterization using the Theory of Run

At the Bilate Tena station, the highest drought was observed from the SPI9, SPEI9, RDI6, and scPDSI indices (Table 2.4 and 2.6). SPI9 showed a value of -11.87 from June 1984 to December 1984 with a duration of 7 months. Similarly, SPEI9 showed a value of -10.08 from July 1984 to December 1984 with a duration of 6 months, RDI6 showed a severity of -12.87 from May 2009 to September 2009 with a duration of 5 months and eRDI9 showed a severity of -13.43 from July 1984 to December 1984 with a duration of 6 months, the scPDSI index showed a value of -26.29 from 12, 2002 to 11, 2003 with a duration of 12 months. Therefore, SPI detected the drought early compared to SPEI. The longest duration of drought ranged from 3 to 5 months and 3 to 7 months for the 6-month and 9-month time scales, respectively. The average duration was 4 and 5 months for the 6-month and 9-month time scales, respectively. The maximum drought intensity was -2.29 with SPEI9, -2.57 with RDI6, and -3.71 with scPDSI.

At Hossana station (Table 2.5 and 2.6), the maximum drought severity with SPI9 was -15.70 from July 2015 to March 2016, with a duration of 9 months. SPEI9 was -15.50 from July 2015 to March 2016 with a duration of 9 months, and scPDSI was -29.64 from December 2010 to January 2012, with a duration of 14 months. eRDI6 showed a maximum severity of -11.81 from April 1984 to August 1984 with a duration of 5 months and eRDI9 showed a severity of -14.20 from July 1984 to December 1984 with a duration of 6 months. The longest duration of drought ranged from 4 to 6 months and 3 to 6 months for the 6-month and 9-month time scales, respectively. The average duration was 4 and 3 months for the 6-month and 9-month time scales, respectively. The maximum drought intensity was -2.08 with RDI9, -2.36 with RDI6, and -2.37 with eRDI9.

Table 2.4: Major Drought events analyzed using the ToR application at Bilate Tena Station during 1981-2019.

Index	O	T	D	Severity	Intensity	Drought	Index	O	T	D	Severity	Intensity	Drought
SPI6	Jul 2009	Sep, 2009	3	-6.45	-2.15	Extreme	RDI6	May, 2009	Sep, 2009	5	-12.87	-2.57	Extreme
	Apr 1984	Aug, 1984	5	-8.46	-1.69	Severe		May, 1984	Aug, 1984	4	-6.87	-1.72	Severe
	Nov,1984	Jan, 1985	3	-4.01	-1.34	Moderate		Sep, 2002	Nov, 2009	3	-5.71	-1.91	Severe
	Sep, 2002	Nov, 2002	3	-5.06	-1.69	Severe		Jul, 2002	Sep, 2002	3	-5.25	-1.75	Severe
	May, 2000	Jul, 2000	3	-3.48	-1.16	Moderate		Feb, 2000	Jun 2000	5	-5.99	-1.20	Moderate
SPI9	Aug, 2009	Oct, 2009	3	-6.54	-2.18	Extreme	RDI9	Aug, 2009	Nov, 2009	4	-10.83	-2.71	Extreme
	Jun, 1984	Dec, 1984	7	-11.87	-1.71	Severe		Jul, 1984	Sep, 1984	3	-5.51	-1.84	Severe
	Oct,2002	Jan, 2003	4	-6.57	-1.64	Severe		Oct,2002	Jan, 2003	4	-7.34	-1.84	Severe
	Oct, 2002	Jan, 2003	4	-6.57	-1.64	Severe		May, 2002	Aug, 2002	4	-6.63	-1.66	Severe
	Jul, 2000	Sep, 2000	3	-3.80	-1.27	Moderate		Feb, 2000	May, 2000	4	-4.94	-1.24	Moderate
SPEI6	Jul, 2009	Sep, 2009	3	-6.74	-2.25	Extreme	eRDI6	Apr, 1984	Aug, 1984	5	-11.13	-2.22	Extreme
	May, 2000	Aug, 2000	4	-5.02	-1.25	Moderate		Oct,1990	Jan, 1991	4	-8.74	-2.19	Extreme
	Apr, 2008	Jun, 2008	3	-5.39	-1.80	Severe		Apr, 2009	Aug, 2009	5	13.51	-2.70	Extreme
	May, 2000	Aug, 2000	4	-5.02	-1.25	Moderate		Jul, 1984	Dec, 1984	6	-13.43	-2.23	Extreme
SPEI9	Aug, 2009	Nov, 2009	4	-9.06	-2.27	Extreme	eRDI9	Apr, 2008	Jun, 2008	3	-6.61	-2.21	Extreme
	Jul, 1984	Dec, 1984	6	-10.08	-1.68	Severe		Aug, 2009	Nov, 2009	4	-9.89	-2.47	Extreme
	Oct, 2002	Feb, 2003	5	-8.44	-1.69	Severe		Apr, 2009	Jul, 2009	4	-10.83	-2.71	Extreme
	Oct, 2002	Feb, 2003	5	-8.44	-1.69	Severe		Nov, 1984	Jan, 1985	3	-3.54	-1.18	Moderate
	Jul, 2000	Sep, 2000	3	-4.23	-1.41	Moderate		Apr, 1999	Feb, 2000	11	-21.65	-1.97	Moderate
scPDSI	Jun, 2009	Aug, 2009	3	-11.11	-3.71	Severe	scPDSI	Dec,2002	Nov, 2003	12	-26.29	-2.19	Moderate
	Mar, 1984	Apr, 1985	11	-25.37	-2.31	Moderate		Mar, 1984	Jan, 1985	11	-25.37	-2.31	Moderate
	Mar, 2009	May, 2009	3	-6.33	-2.11	Moderate		May, 2000	Aug, 2000	4	-9.53	-2.38	Moderate

Note: *D = Drought Duration in months, O = Onset of the drought and T = Termination of the drought, and O & T represented by the first three letters of months. Only the drought events of three and more than three months of duration were considered.*

Table 2.5: Major Drought events analyzed using Theory of run application at Hossana Station from 1981 to 2019.

Index	O	T	D	Severity	Intensity	Category	Index	O	T	D	Severity	Intensity	Drought
SPI6	Jun, 1984	Sep, 1984	4	-4.84	-1.21	Moderate	RDI6	Jun, 1984	Sep, 1984	4	-3.81	-0.95	Moderate
	Jun, 1999	Sep, 1999	4	-5.17	-1.29	Moderate		Jun, 1999	Sep, 1999	4	-4.67	-1.17	Moderate
	Jul, 2015	Dec, 2015	6	-10.46	-1.74	Severe		Apr, 2000	Aug, 2000	5	-6.22	-1.24	Moderate
	Jun, 1999	Sep, 1999	4	-5.17	-1.29	Moderate		May, 2009	Aug, 2009	4	-6.86	-1.72	Severe
SPI9	Jun, 1981	Aug, 1981	3	-3.63	-1.29	Severe	RDI9	Nov, 2011	Jan, 2011	3	-3.17	-1.06	Moderate
	Sep, 1984	Nov, 1984	3	-5.31	-1.77	Severe		Nov, 2016	Jan, 2017	3	-3.62	-1.21	Moderate
	Jun, 1984	Aug, 1984	3	-3.96	-1.32	Moderate		Jun, 1984	Aug, 1984	3	-3.75	-1.25	Moderate
	Jul, 2000	Sep, 2000	3	-3.84	-1.28	Moderate		May, 2009	Jul, 2009	3	-3.21	-1.07	Moderate
SPEI6	Jul, 2015	Mar, 2016	9	-15.70	-1.74	Severe	eRDI6	Aug, 2009	Oct, 2009	3	-5.08	-1.69	Severe
	May, 1984	Sep, 1984	5	-6.11	-1.22	Moderate		Sep, 2015	Nov, 2015	3	-6.25	-2.08	Extreme
	Apr, 1999	Sep, 1999	6	-6.33	-1.22	Moderate		Apr, 1984	Aug, 1984	5	-11.81	-2.36	Extreme
	Apr, 2000	Aug, 2000	5	-6.57	-1.31	Moderate		Nov, 1984	Jan, 1985	3	-5.32	-1.77	Severe
SPEI9	Jun, 2009	Sep, 2009	4	-6.87	-1.72	Moderate	eRDI9	Apr, 2000	Jun, 2000	3	-4.93	-1.64	Severe
	Sep, 1984	Nov, 1984	3	-5.04	-1.68	Severe		Apr, 1999	Jul, 1999	4	-4.81	-1.20	Moderate
	Jun, 1984	Aug, 1984	3	-3.56	-1.19	Moderate		Jul, 1984	Dec, 1984	6	-14.20	-2.37	Extreme
	Jul, 1999	Sep, 1999	3	-4.05	-1.35	Moderate		Jul, 2000	Sep, 2000	3	-4.89	-1.63	Severe
scPDSI	May, 2009	Jul, 2009	3	-3.52	-1.17	Moderate	scPDSI	Jul, 1999	Sep, 1999	3	-3.53	-1.18	Moderate
	Jul, 2015	Mar, 2016	9	-15.50	-1.72	Severe		May, 2009	Jul, 2009	3	-3.52	-1.17	Moderate
	Mar, 1984	Jan, 1985	11	-22.85	-2.08	Moderate		Sep, 2015	Dec, 2015	4	-4.76	-1.19	Moderate
	Apr, 2009	Aug, 2009	5	-10.76	-2.15	Moderate		Feb, 1999	Sep, 1999	8	-12.64	-1.58	Moderate
	Dec, 2010	Jan, 2012	14	-29.64	-2.12	Moderate		Apr, 2009	Aug, 2009	5	-10.76	-2.15	Moderate

Note: *D = Drought Duration in months, O = Onset of the drought and T = Termination of the drought, and O & T represented by the first three letters of months. Only the drought events of three and more than three months of duration were considered.*

At Bilate Tena stations, the maximum severity and duration of drought were observed on the time scale of 9 months, especially in 1984/5 (Table 2.4 and 2.6). The maximum drought severity with SPI6 was shown at Boditi station with a duration of 6 months while the maximum intensity was shown at Shone station (Table 2. 6). SPI9 showed the highest drought severity at Wulbareg station for 9 months. SPEI6 and SPEI9 showed the highest drought severity at Hossana station with values of -10.74 and -15.50, respectively. scPDSI showed the highest drought severity at Wolayta Sodo station with a duration of 23 months. For all drought indices, the highest drought severity was observed at Hossana and Wulbareg stations, while the highest intensity was recorded at Shone station. The longest drought duration was observed from SPI9 and SPEI9 indices with duration ranging from 3 to 9 months at Bilate Tena station. Maximum drought severity was observed at all stations with a duration of 9 months except at Shone and Wolayta Sodo stations. The most intense drought was observed for all drought indices in all stations mostly at a time scale of 9 months. Among all stations, Hossana and Wulbareg showed highest drought severity, particularly on a 9-month scale which was also characterized by a high CV of precipitation (Table 2.1). The maximum value of drought characteristics identified for all stations with the Theory of run application is shown in Table 2. 6.

Table 2.6: Maximum drought Severity, Duration, and Intensity at each station in the BRW (1981- 2019).

Station	Drought	SPI6	SPI9	SPEI6	SPEI9	RDI6	RDI9	eRDI6	eRDI9	scPDSI
Alaba	Severity	-8.46	-11.87	-6.81	-10.08	-12.73	-10.84	-11.32	-11.42	-26.29
	Duration	5	7	3	6	5	4	5	5	12
	Intensity	-1.69	-1.70	-2.27	-1.68	-2.55	-2.71	-2.26	-2.28	-2.19
Bilate Tena	Severity	-8.46	-11.87	-6.84	-10.08	-12.87	-10.83	-11.13	-13.43	-25.37
	Duration	5	7	3	6	5	4	5	6	11
	Intensity	-1.69	-1.70	-2.28	-1.68	-2.65	-2.70	-2.22	-2.23	-2.31
Boditi	Severity	-10.71	-13.43	-6.40	-11.61	-9.80	-10.05	-9.81	-13.77	-25.46
	Duration	6	8	3	7	4	4	4	6	13
	Intensity	-1.78	-1.68	-2.13	-1.66	-2.45	-2.51	-2.45	-2.29	-1.96
Hossana	Severity	-10.46	-15.70	-10.74	-15.50	-6.86	-6.25	-11.81	-14.20	-33.88
	Duration	6	9	6	9	4	3	5	6	15
	Intensity	-1.74	-1.74	-1.79	-1.72	-1.72	-2.08	-2.36	-2.37	-2.26
Shone	Severity	-9.42	-6.68	-9.66	-9.03	-12.64	-9.75	-11.52	-14.23	-44.68
	Duration	4	3	4	4	5	4	5	6	23
	Intensity	-2.36	-2.23	-2.42	-2.26	-2.53	-2.44	-2.30	-2.37	-1.94
Wolayta Sodo	Severity	-8.87	-7.24	-6.81	-8.81	-12.32	-10.01	-7.98	-11.54	-48.78
	Duration	5	4	3	4	5	4	3	5	23
	Intensity	-1.77	-1.81	-2.27	-2.20	-2.46	-2.50	-2.66	-2.31	-2.12
Wulbareg	Severity	-7.34	-16.53	-7.47	-4.91	-12.05	-16.79	-9.58	-14.15	-31.97
	Duration	4	9	4	3	5	7	4	6	14
	Intensity	-1.84	-1.84	-1.87	-1.64	-2.41	-2.40	-2.40	-2.36	-2.28

Note: Only drought events with a duration of three or more than three months were considered

Table 2.7: Frequency of Extreme, Severe, Moderate drought events at each station (1981 to 2019).

Station	Drought Types	SPI6		SPI9		SPEI6		SPEI9		RDI6		RDI9		eRDI6		eRDI9		scPDSI	
		N	F	N	F	N	F	N	F	N	F	N	F	N	F	N	F	N	F
Alaba	Extreme	8	0.21	5	0.13	8	0.21	4	0.10	13	0.33	7	0.18	20	0.51	14	0.36	1	0.03
	Severe	25	0.64	29	0.74	22	0.56	23	0.59	25	0.64	24	0.62	18	0.46	19	0.49	18	0.46
	Moderate	40	1.03	40	1.03	45	1.15	46	1.18	36	0.92	44	1.13	36	0.92	37	0.95	143	3.67
	Total/Ave.	73	0.63	74	0.63	75	0.64	73	0.62	74	0.63	75	0.64	74	0.63	70	0.60	162	1.39
Bilate	Extreme	8	0.21	5	0.13	8	0.21	7	0.18	13	0.33	8	0.21	18	0.46	15	0.38	1	0.03
	Severe	25	0.64	29	0.74	22	0.56	23	0.59	20	0.51	22	0.56	19	0.49	15	0.38	18	0.46
	Moderate	40	1.03	40	1.03	45	1.15	46	1.18	42	1.08	43	1.10	40	1.03	40	1.03	143	3.67
	Total/Ave	73	0.63	74	0.63	75	0.64	76	0.65	75	0.64	73	0.62	77	0.66	70	0.60	162	1.39
Boditi	Extreme	3	0.08	3	0.08	5	0.13	5	0.13	11	0.28	10	0.26	11	0.28	12	0.31	0	0.00
	Severe	32	0.82	27	0.69	26	0.67	27	0.69	26	0.67	23	0.59	27	0.69	16	0.41	17	0.44
	Moderate	45	1.15	58	1.49	5	0.13	51	1.31	36	0.92	44	1.13	35	0.90	49	1.26	180	4.62
	Total/Ave	80	0.68	88	0.75	36	0.31	83	0.71	73	0.62	77	0.66	73	0.62	77	0.66	197	1.69
Hossana	Extreme	5	0.13	3	0.08	2	0.05	5	0.13	12	0.31	9	0.23	14	0.36	11	0.28	0	0.00
	Severe	24	0.62	27	0.69	26	0.67	27	0.69	22	0.56	25	0.64	30	0.77	24	0.62	15	0.38
	Moderate	64	1.64	50	1.28	65	1.67	53	1.36	53	1.36	47	1.21	49	1.26	49	1.26	161	4.13
	Total/Ave	93	0.80	80	0.68	93	0.80	85	0.73	87	0.74	81	0.69	93	0.80	84	0.72	176	1.50
Shone	Extreme	7	0.18	8	0.21	8	0.21	8	0.21	11	0.28	8	0.21	14	0.36	14	0.36	1	0.03
	Severe	20	0.51	22	0.56	18	0.46	20	0.51	21	0.54	16	0.41	24	0.62	20	0.51	19	0.49
	Moderate	52	1.33	38	0.97	55	1.41	44	1.13	43	1.10	41	1.05	39	1.00	43	1.10	155	3.97
	Total/Ave	79	0.67	68	0.58	81	0.69	72	0.62	75	0.64	65	0.56	77	0.66	77	0.66	175	1.50
Welayta Sodo	Extreme	4	0.10	6	0.15	4	0.10	7	0.18	12	0.31	11	0.28	12	0.31	14	0.36	0	0.00
	Severe	25	0.64	21	0.54	26	0.67	24	0.62	21	0.54	20	0.51	32	0.82	17	0.44	16	0.41
	Moderate	51	1.31	45	1.15	46	1.18	40	1.03	40	1.03	34	0.87	39	1.00	44	1.13	172	4.41
	Total/Ave	80	0.68	72	0.61	76	0.65	71	0.61	73	0.63	65	0.55	83	0.71	75	0.64	188	1.61
Wulbareg	Extreme	4	0.10	3	0.08	4	0.10	4	0.10	13	0.33	10	0.26	14	0.36	17	0.44	6	0.15
	Severe	30	0.77	31	0.79	24	0.62	22	0.56	24	0.62	26	0.67	20	0.51	16	0.41	16	0.41
	Moderate	54	1.38	52	1.33	61	1.56	54	1.38	49	1.26	45	1.15	43	1.10	43	1.10	140	3.59
	Total	88	0.75	86	0.73	89	0.76	80	0.68	86	0.74	81	0.69	77	0.66	76	0.65	162	1.38

Note: N= Number of drought events and F= frequency of drought events. Only a drought duration of three or more months was considered. Total = the sum of Extreme, Severe, and Moderate number of drought events, and Ave.= average frequency

In SPI6 index, the maximum number of droughts were observed at Hossana and Wulbareg stations with a value of 93 and 88, respectively (Table 2.7). In the SPI9 index, showed a maximum number of droughts were at Boditi and Wulbareg stations with the value of 88 and 86 drought events, respectively. SPEI6 showed the highest number of drought events at Hossana and Wulbareg stations with a value of 93 and 89, respectively. SPEI9 showed the highest number of drought events at Hossana and Wulbareg stations with a value of 85 and 83, respectively. Similarly, RDI and eRDI showed the highest number of drought events at Hossana and Wulbareg stations on both time scales. Thus, most drought events were recorded at Wulbareg, Hossana, and Boditi stations compared to the other stations. scPDSI showed the highest number of drought events at Boditi station with a value of 197.

The minimum and a maximum number of drought events on a time scale of 6 months varied from 73-93 for SPI6 with an average value of 81, 36-93 for SPEI6 with an average value of 75, 73-87 for RDI6 with an average value of 78, and 73-93 for eRDI6 with an average value of 79 (Table 2.7). Thus, a higher number of historical drought events were identified at a 6-month time scale than at a 9-month time scale. At a 6-month time scale, SPI6, RDI6, and eRDI6 had a higher average number of drought events with a value of 81, 78, and 79, respectively.

Drought frequency was calculated using all drought indices with 6-month and 9-month time scales (Table 2.7). At Hassanal station, the maximum average frequency of drought on a 6-month time scale with drought indices SPI6, SPEI6, and eRDI6 was 80%. At Wulbareg station, the frequency of drought was 75% for SPI6, 73% for SPI9, 76% for SPEI6, 74% for RDI6, and 69% for RDI9. With SPEI6 and RDI6, Alaba and Bilate Tena stations had a comparable drought frequency of 64%. In Boditi and Wolayta Sodo stations, the drought frequency was 75% with SPI6 and 71% with eRDI6. Consequently, the maximum drought frequency calculated with a 6-month scale was higher than the 9-month scale of drought indices. However, Hossana and Wulbareg stations had the highest percentage of drought frequency on both time scales, indicating that these stations experienced the most frequent drought.

2.8.6. Drought Trend

The SPI, SPEI, RDI, eRDI, and scPDSI values derived over 6-month and 9-month time scales were subjected to MK trend analysis. The results (Table 2.8) revealed that utilizing all drought indices, on all stations except Hossana and Wulbareg showed a statistically significant positive trend from 1981 to 2019, indicating an increasing trend of drought conditions. Therefore, drought conditions at BRW showed mostly an increasing trend from 1981 to 2019.

Table 2.8: MK trend test statistics for all stations using drought indices (SPI6, SPI9, SPEI6, SPEI9 and RDI6).

Stations	SPI6		SPI9		SPEI6		SPEI9		RDI6	
	Z	Sen'slope	Z	Sen'slope	Z	Sen'slope	Z	Sen'slope	Z	Sen'slope
Alaba	5.2512*	1.82E-03	5.8343*	2.07E-03	3.3409*	1.17E-03	3.412*	1.19E-03	3.7184*	1.29E-03
Bilate	5.2512*	1.82E-03	5.834*	2.07E-03	3.338*	1.17E-03	3.4114*	1.20E-03	3.9622*	1.33E-03
Boditi	6.8999*	2.44E-03	8.066*	2.89E-03	5.2083*	1.87E-03	6.0953*	2.16E-03	4.7722*	1.65E-03
Hossana	-0.273	-1.00E-04	-0.721*	-3.00E-04	-1.091	-4.10E-04	-1.683	-6.40E-04	-1.126	-4.10E-04
Shone	5.8609*	2.01E-03	6.4538*	2.29E-03	4.3634*	1.52E-03	4.5912*	1.65E-03	4.2675*	1.47E-03
Wolayta	5.8609*	2.01E-03	6.4538*	2.29E-03	4.3634*	1.52E-03	4.5912*	1.65E-03	4.2675*	1.47E-03
Wulbareg	-0.045	-1.26E-05	-0.442	-1.54E-04	-1.292	-4.77E-04	-1.876	-6.94E-04	-0.977	-3.61E-04

*Statistically significant at 95% confidence level.

2.9. Discussion

The correlation analysis revealed that similar time scales showed a high correlation value of 0.99 in all stations. This result is exactly similar with the research output of Rascón et al., (2021) that showed a correlation coefficient of 0.98 and 0.99 between SPI and SPEI at the same temporal scale. This result also agrees with those obtained by Stojanovic et al., (2018) who determined a correlation value of 0.96 between the SPI and the SPEI at a 1-month scale when assessing droughts in central Europe. Furthermore, the findings of correlation analysis showed that similar time scales of SPI, SPEI, RDI, and eRDI showed the highest correlation indicating that these indices could be used alternatively, which is similar to the research finding of Jain et al. (2015) and Wable et al., (2019). The correlation of the scPDSI decreased as the time scale of the drought indices increased, indicating that the scPDSI was well suited to detect short-term and medium-term droughts. In addition, the average correlation analysis showed that the 6-month and 9-month time scales were highly correlated and therefore selected to be used for further characterization of drought events in BRW. In the temporal drought analysis, significant drought events were detected in 1984/5, 2000, 2002, and 2009 in BRW. Thus, most of the drought indices were able to identify the

historical drought years of 1984/5, 2000, 2002, and 2009, which is consistent with the major historical drought events documented in Ethiopia (Degefu & Bewket, 2015; Suryabhagavan, 2017; Mera, 2018; Mohammed & Yimam, 2021). Drought conditions were prevalent throughout all of Ethiopia in a few years, primarily 1984 and 2009 (Viste et al., 2013).

In Bilate Tena station, the highest drought severity observed with SPI6 and SPI9 were -8.46 and -11.87, respectively in 1984 with a drought class of severe. Likewise, the highest drought severity observed with SPEI6 and SPEI9 were -6.74 and -10.08, respectively in 1984 and 2009 with a drought class of severe. The highest drought severity observed with RDI6 and RDI9 were -12.87 and -10.83, respectively in 2009 with a drought class of extreme. Similarly, scPDSI showed a severity of -25.37 in 1984 with a drought class of moderate. This indicate that the strongest drought was observe in the years 1984 and 2009 (Table 2. 4). Similarly, in Hossana station the highest drought severity observed with SPI6 and SPI9 were -10.46 and -15.70 in 2015 and 2016, respectively with a drought class of severe. The highest drought severity observed with SPEI6 and SPEI9 were -6.87 and -15.50 in 2009 and 2016, respectively with a drought class of severe and moderate. The highest drought severity observed with RDI6 and RDI9 were -6.86 and -6.25 in 2009 and 2015, respectively with a drought class of severe and extreme. Similarly, scPDSI showed a severity of -29.64 in 2012 with a drought class of moderate. This indicate that the strongest drought was observe in the years 1984 and 2009 (Table 2.5). In general, on applying the theory of run, almost all drought indices, the highest drought was observed at Hossana and Wulbareg stations, which had the highest precipitation variability (Table 2.1). In addition, Hossana and Wulbareg stations had the highest percentage of drought frequency at both time scales, indicating that they were the stations with the most recurrent drought in the BRW.

Although the spatial distribution of drought events was analyzed using interpolation of only seven-point data that represent meteorological stations, the results were coarse and may not show the real spatial distribution of historical droughts in BRW. This is due to the fact that there was insufficient meteorological data and its accuracy cannot always be guaranteed (Arekhi, et al., 2020). Instead, the spatial distribution of historical drought could be more accurately depicted by the interpolation of gridded meteorological data or through the appropriate analysis of satellite images. The use of

satellite imagery is particularly advantageous since it provides timely, accessible, extensive coverage, and continuous data (Orhan et al., 2014; TranTran et al., 2017; Wang et al., 2018).

The MK trend analysis showed that almost all drought indices were significantly and positively increasing. However, Hossana and Wulbareg showed a decreasing trend of drought which is not statistically significant. Overall, the Bilate watershed showed an increasing trend of drought throughout the study period and this finding was similar to the findings of previous research in Bilate watershed and in the Rift valley lake basin (Mohammed & Yimam, 2021; Haile et al., 2022).

2.10. Conclusion

The correlation analysis revealed three distinct patterns on almost all stations. First, all drought indices were highly correlated with similar time scales. Second, all drought indices were strongly associated with scPDSI at 3-month and 6-month time scales. Third, as the time scale increases, the correlation of the scPDSI with other drought indices decreases. As a result, the scPDSI can only detect drought events in a short and medium period.

To analyze the performance of drought indices and select the best-correlated one, an average correlation analysis of all drought indices was calculated. The result was that the 6-month and 9-month time scales had the highest average correlation, indicating that they were the best indices compared to other time scales. Thus, to identify and describe droughts in terms of duration, severity, intensity, and frequency, the theory of run was applied using 6-month and 9-month time scales for all drought variables. The most significant drought events identified at the Bilate Tena and Hossana stations based on the selected 6-month and 9-month drought index time scales occurred in 1984/85, 2000, 2002, and 2009. At the other stations, a similar trend was mostly observed for major drought episodes. The greatest severity and longest duration of the drought were observed at Alaba and Bilate Tena stations for 9 months, especially in 1984/5. With a severity of -48.78 and a duration of 23 months, the scPDSI at Wolayta Sodo station indicated the greatest drought. The greatest drought severity was observed at Wulbareg station, while the maximum intensity for all drought indices was observed at Shone stations. At Hossana station, a maximum average frequency of 80% was observed on a 6-month time scale with drought indices of SPI6, SPEI6, and eRDI6. Moreover, Hossana and Wulbareg stations had the highest percentage of drought frequency in both periods, indicating that they suffered from recurrent drought during 1981 to 2019. The results of the MK trend test statistics also showed an increasing trend in drought

conditions at Hossana and Wulbareg. Most drought indices also showed an increasing trend at all stations except Hossana and Wulbareg. This study used sparse and interpolated point data from a few meteorological stations to depict the spatial distribution of drought. Therefore, additional research utilizing geospatial data was recommended in order to comprehend the actual spatial distribution of historical drought in the watershed.

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CHAPTER THREE

SPATIAL DROUGHT OCCURRENCES AND DISTRIBUTION USING VCI, TCI, VHI, AND GOOGLE EARTH ENGINE IN BILATE RIVER WATERSHED, RIFT VALLEY OF ETHIOPIA²

ABSTRACT

Drought is a major natural hazard in Ethiopia, posing significant challenges and severe consequences. This research aimed to assess the occurrence and distribution of drought in the Bilate River Watershed (BRW) using the Vegetation Health Index (VHI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI), along with the Google Earth Engine (GEE) platform. Vegetation products (MOD13Q1) and LST products (MOD11A2) were selected from May to October each year, covering the period from 2000 to 2022. The VCI, TCI, and VHI maps were generated, identifying extreme and severe drought events with extensive spatial coverage in 2002, 2009, 2015, and 2022, which were the major drought years. According to the VHI, the watershed experienced extreme, severe, and moderate drought classes in May and October, affecting 62% and 70% of the area, respectively. The years 2009 and 2015 were particularly devastating in terms of drought. The extreme drought class mainly affected the southern and southwestern parts of the watershed, which receive relatively low rainfall and have lower elevation characteristics. The spatial autocorrelation analysis demonstrated significant positive autocorrelation of drought, as indicated by the values of Moran's I and z scores, which ranged from 0.23 to 0.79 and 8.66 to 24.64, respectively. The correlation analysis findings showed strong positive relationships among the vegetation indices and rainfall, while showing negative associations with temperature and land surface temperature. The frequency analysis also revealed a significant occurrence of drought in the southern portion of the watershed. Therefore, these results hold practical significance for decision-makers and practitioners involved in drought management planning within the BRW.

Keywords: *Spatial Drought, Google Earth Engine, VHI, Drought Frequency, Bilate River Watershed, Ethiopia*

3.1. Introduction

Drought is one of the most challenging natural disasters mainly occurring when seasonal precipitation drops below normal or long-term average (Pasteris et al., 2005; Mera, 2018; Veneros and García, 2021). Water availability, grazing capacity, and agricultural outputs are all

²Ashenafi Burka, Birhanu Biazin & Woldeamlak Bewket (2024) Spatial drought occurrences and distribution using VCI, TCI, VHI, and Google Earth Engine in Bilate River Watershed, Rift Valley of Ethiopia, *Geomatics, Natural Hazards and Risk*, 15:1, 2377672, DOI: 10.1080/19475705.2024.2377672.

significantly impacted by this hydrological imbalance, which has important ramifications for rural health and household food security (Wyss et al., 2022)

The effects range from a lack of water, ecological damage, agricultural output losses, and health effects to starvation and a food crisis (Du et al., 2018). Millions of people in sub-Saharan Africa are impacted by this natural calamity, which increases rural-urban migration and leads to starvation, water scarcity, and unplanned urbanization (Wyss et al., 2022).

Over the past 50 years, the frequency of droughts over the Greater Horn of Africa (GHA) has displayed discernible geographical patterns, with high rates seen in the Sudan, Tanzania, and portions of Ethiopia (Mpelasoka, et al., 2018). Humanitarian crises caused by drought are occurring more frequently in the Horn of Africa, where millions of people suffer from chronic water shortages and food insecurity (Thomas et al., 2020). In the GHA, it is recognized that precipitation patterns are changing (Marthews et al., 2019). This indicates that when compared to other land surface climatic variables, the variability of the precipitation pattern is well known. The most severe droughts in the GHA's history were in the years 1973-1974, 1984-1985, and 2010-2011, causing significant harm to societies and the environment (Gebremeskel Haile et al., 2020). Even if attempts to detect and predict drought have recently made headway, humanitarian disasters related to drought are growing in the GHA (Mpelasoka, et al., 2018). This indicates that despite progress in drought detection and prediction, the frequency of drought and its related effects have been rising in the GHA.

East Africa frequently experiences drought, which has serious humanitarian impacts (Anderson et al., 2012). For instance, in 2011, the international media reported that a string of weather disasters, including both floods and drought, had severely damaged eastern Africa (Nicholson, 2014). Over the past 50 years, Ethiopia has experienced varying degrees of drought in different geographic and temporal regions; and the eastern, south eastern, and rift valley regions of the country have experienced drought more frequently than other regions (Mera, 2018). Ethiopia experiences frequent, severe droughts and floods, which increase economic damage (Teshome and Zhang, 2019). For instance, in 2015 and 2016, the country suffered two consecutive droughts (Mera, 2018).

Drought monitoring requires high-quality and long-term data because it is a complex phenomenon (Aksoy and Sertel, 2021). The commonly used drought monitoring method is based on observation data from meteorological stations and calculating drought indices such as Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Reconnaissance Drought Index (RDI), etc. For drought monitoring, ground weather stations are a somewhat reliable source of data. However, due to the gauging stations' uneven distribution and coverage, they are often insufficient (Du et al., 2018). One of the most significant shortcomings of utilizing drought indicators based on station data for assessing the consequences of drought is the lack of spatial details (Moussa Kourouma et al., 2021). In developing countries, stations for rainfall and temperature measurement are not equally distributed and are instead scattered. As a result, the analysis of drought indices using these station data limits the reliability of drought indices. The spatial analysis of station data is done mostly using interpolation methods which has no detail information. Besides, drought monitoring is an even more difficult endeavor in poor countries where there are fewer functional stations (Du et al., 2018). However, the limitation of station data can be rectified by using remote sensing data.

Drought monitoring is made easier by the speedy advancement of remote sensing and its capacity to collect multi-source, multi-scale, and multi-time data rapidly and precisely (Zhao et al., 2021). The use of remote sensing for drought mapping and monitoring has become very popular and currently, there are more than 100 drought indicators (Wyss et al., 2022). The use of RS and GIS-based geospatial approaches is expanding because of the reliability and availability of the data as well as their ability to process and map enormous volumes of data at various scales (Okal et al., 2020). The use of remote sensing is generally an efficient method for gathering large and accurate spatial information (Moussa Kourouma et al., 2021).

Several drought indices have been employed in numerous studies to examine the spatiotemporal pattern of drought under conditions of global warming (Zhao et al., 2022). The use of drought indices and indicators is necessary to track droughts (Laachrate, et al., 2020). Besides, in comparison to drought indices based on meteorological stations, such as the Standard Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), Reconnaissance Drought Index (RDI), Palmer Drought Severity Index (PDSI), etc., those based on remote sensing are more accessible and continuous in time. The most widely used drought indicators derived from

remote sensing data are the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). However, vegetation drought is more accurately assessed if VCI is combined with TCI to form the VHI (Moussa Kourouma et al., 2021).

The modeling drought can assist in quantifying the possible effects on agriculture, water resources, ecosystems, and other sectors by simulating the spatial extent and severity of drought. Furthermore, regions exhibiting drought-induced vegetative stress, such as decreased growth, wilting, and productivity, can be precisely identified and mapped using spatial drought models. For instance, because grasslands and shrublands differ from forests in terms of plant physiology and environmental tolerance, they are more vulnerable to the cumulative impacts of drought (Qiao et al., 2024). Additionally, geographical drought models can identify regions with significant water stress, where demand by identifying susceptible areas, spatial drought modeling can assist in focusing drought mitigation and adaptation strategies. For instance, different time scales of meteorological droughts significantly impacted 17.3%-25.6% of China's area, with the 12-month drought having the largest impact (Qiao and Xia, 2024). The agricultural sector is one real-world use of the modeling approach. For example, the U.S. Geological Survey (USGS) and the National Drought Mitigation Center developed the Vegetation Drought Response Index (VegDRI), a geographic tool for monitoring drought developed by the U.S. Geological Survey (USGS) and the National Drought Mitigation Center (Brown et al., 2008). For the purpose of monitoring droughts, comparable models called VegDRI-SKorea (Nam et al., 2018) for South Korea and VegDRI-Canada (Tadesse et al., 2017) for Canada were developed.

The Google Earth Engine (GEE), a cloud computing platform, is a more popular and practical means for making geographical data available and analyzing it. GEE is a platform that runs in the cloud and facilitates access to high-performance computing resources for handling very large data (Gorelick et al., 2017; Mutanga and Kumar, 2019). In recent years, cloud-based systems have made significant strides, bringing new techniques for geospatial research (Zeng et al., 2019). Platforms for cloud computing enable users to efficiently store, access, and analyze datasets on extremely powerful servers by virtualizing supercomputers for users (Amani et al., 2020). GEE is one of the most popular cloud-based platforms that store enormous amounts of geographical data and enables users to handle massive data without downloading anything thanks to its robust hardware infrastructure and built-in algorithms (Aksoy and Sertel, 2021). In comparison to desktop

computing, the GEE platform offers high-performance computing infrastructure, which greatly accelerates the processing of large volumes of geospatial and time series data (Sazib et al., 2020).

The GEE platform's features are crucial for conducting drought monitoring analysis since it offers a wide range of geospatial tools and data, allowing for thorough handling of the entire process (Aksoy and Sertel, 2021). The user-friendly front end makes it simple to access interactive data and construct algorithms (Mutanga and Kumar, 2019). The GEE approach is time-saving as it enables quick access and processing of spatial and climatic data (Thilagaraj et al., 2021). The ability to access and analyze geospatial data online in GEE helps to overcome computational and storage bottlenecks and can significantly improve the effectiveness of spatio-temporal analyses (Zeng et al., 2019). In other words, adopting the GEE as a data processing platform lowers the technological obstacles to processing data, thus significantly accelerating the processing of large volumes of geospatial and time series data as compared to desktop computing (Sazib et al., 2020).

Given the magnitude and severity of drought-induced challenges in Ethiopia, there are many research outcomes on drought assessment and monitoring. For instance, in the Rift Valley of Ethiopia, Tesfamariam and Melgani, (2019) used the SPI to assess the spatiotemporal distribution and severity of meteorological droughts and found that the spatiotemporal distribution of drought events was variable within agro-ecological zones in the rift valley lake basin. Mohammed and Yimam, (2021a) used RDI to generate the intensity of drought at 3- and 12-time scales and used inverse distance weighting (IDW) to generate the spatial map and found different results across the seasons. Nasir et al., (2021) used SPEI at a 3-month time scale and found that severe drought occurred in all zones of the research area from years 1983 to 1991. Haile et al., (2022) used SPEI at SPEI-03 and SPEI-12 timescales and Aridity Index and the result revealed that 1988–2016 were years of continuous drought events in both timescales and spatially, the drought occurrences were observed in all areas of the watershed with varying magnitude. Burka et al., (2023) used the SPI, SPEI, RDI, enhanced Reconnaissance Drought Index (eRDI) with different time scales, and Self-Calibrated Palmer Drought Severity Index (scPDSI) to characterize temporal drought severity and IDW to map the spatial drought distribution and found that 1984/85, 2000, 2002, and 2009 were the most drought-prone years with severe drought manifestation at the southern part of Bilate river watershed, central rift valley of Ethiopia. Apart from the general spatio-temporal analysis of drought, neither online data processing nor open-source data were used concurrently in any of

these studies in the central Rift Valley of Ethiopia. Therefore, this research aims to analyze the drought occurrence and distribution using multiple satellite-based vegetation indices called VCI, TCI, and VHI, using the GEE cloud-computing platform. The specific objectives of the research were: (1) to use vegetation indices on a monthly basis to map and analyze spatial drought patterns, (2) to assess the autocorrelation of the drought indices throughout the watershed, and (3) to examine the frequency of drought and its distribution.

3.2. Material and Methods

3.2.1. Study Area Description

The research was undertaken at the Bilate river watershed (BRW) which is located in the southwestern escarpment of the Main Ethiopian Rift Valley (Figure 3. 1). One of the main catchments in the Lakes Basin of the Ethiopian Rift Valley is the Bilate watershed (Orke and Li, 2021). Geographically, it is located between 6°32'40'' to 8°09'29'' N and 37°46'11'' to 38°18'43'' E. The watershed covers about 5,324 km². The north and north-eastern parts of the watershed have steep slopes and the center and the south part have gentle slopes. Bilate river is the main river of the watershed that drains into lake Abaya with its tributaries. The altitude of the watershed ranges from 1,116 to 3,373m a.s.l. It is distinguished by a climate that is semi-arid on the rift floor and humid in the western highlands (Haji et al., 2018). June to September (locally called Kiremt) and February to May (locally called Belg) are the major and minor wet seasons, receptively, and October to January (locally called Bega) is the dry season in the area. The watershed's climate is characterized by arid and semi-arid conditions (Orke and Li, 2022). The BRW covers parts of the densely populated and drought-vulnerable areas in the country such as Hadiya, Kembata, Wolayta, Alaba, Silte, and Gurage administration areas. The local people are dependent on agriculture for their livelihoods. The area is known for its mixed farming and provides irrigation for crops like maize, tobacco, and vegetables (Orke and Li, 2021).

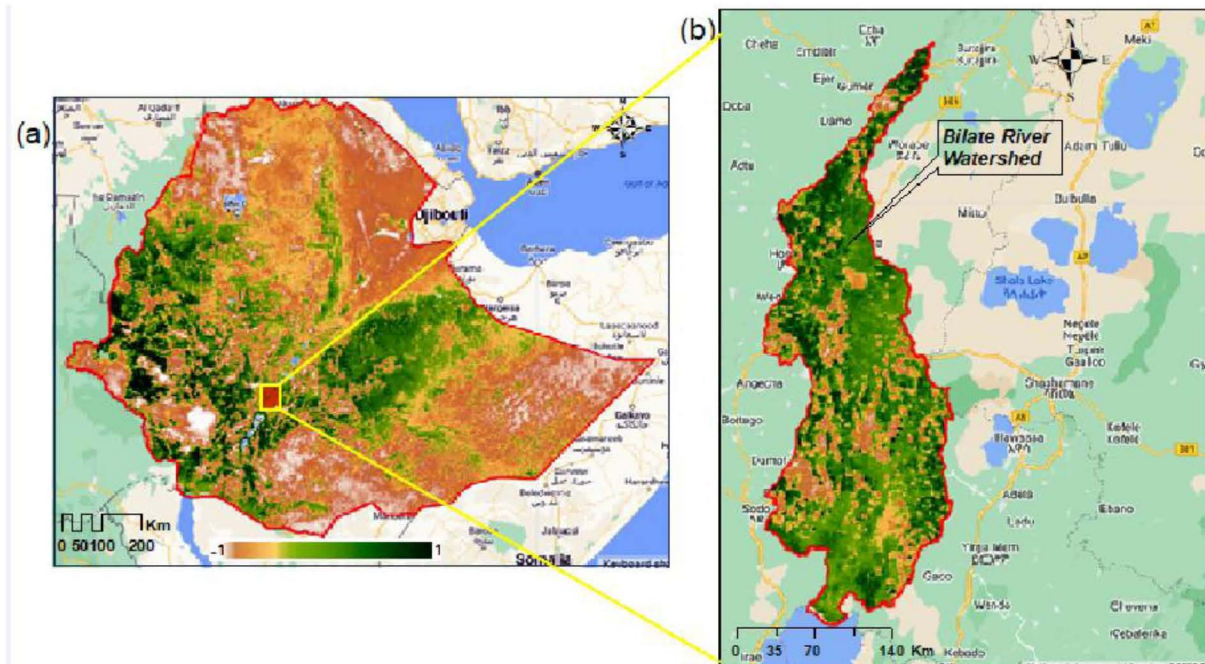


Figure 3.1: Location of study area (Source: GEE, 2023): (a) MODIS Terra NDVI of Ethiopia in 2018, (b) MODIS Terra NDVI of Bilate River Watershed in 2018.

3.2.2. Data types and sources

The data were accessed using the codes of GEE provided by the UN-Spider knowledge portal (www.un-spider.org), which allows for the analysis of drought from 2000 to 2022. In this research, Moderate Resolution Imaging Spectroradiometer (MODIS), which has 36 spectral bands in 0.4 μm to 14.4 μm and launched in 1999, images were used. MOD13Q1 (MODIS/Terra Vegetation Indices 16-Day L3 Global 250 m SIN Grid) NDVI data and MOD11A2 (MODIS/Terra Land Surface Temperature/Emissivity 8-Day L3 Global 1 km SIN Grid) daily LST data were used for the drought analysis. The MODIS data is ideal for research on monitoring drought Zhao et al., (2021). One benefit of adopting GEE is having access to all raw images as well as processed, cloud-cleared, and mosaicked images. Moreover, the Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) rainfall dataset and Digital Elevation Model (DEM) were used for correlation analysis with the drought indices. The CHIRPS dataset is useful for drought monitoring in regions with complicated topography like Ethiopia (Funk et al., 2015). For the analysis of drought indices, six consecutive months (May - October) were selected including the months of the main crop-growing season of the watershed. Furthermore, to extract raster values of each drought index, 217 stratified sample points based on the LULC were generated within the boundary of the BRW and uploaded to GEE. Samples that fall on the small open water removed

were removed and not included in the analysis. Hence, raster values of VCI, TCI, VHI, CHIRPS precipitation, CHIRTS temperature, NDVI, LST, and DEM elevation were extracted for autocorrelation (Moran Index) and correlation analysis. A summary of data sources and their descriptions is presented in Table 3.1.

Table 3.1: Description of data types and sources used in this research.

No	Dataset	Product Used	Resolution		Dataset Provider	Description
			Temporal	Spatial		
1	MOD13Q1.006 Terra Vegetation Indices 16-Day Global 250m	NDVI	16 days	250m	NASA LP DAAC at the USGS EROS Center https://www.earthdata.nasa.gov/centers/lp-daac	Terra Vegetation Indices 16-Day Global 1Km is a global product
2	MOD11A2.006: Terra Land Surface Temperature and Emissivity.	LST	8 days	1000m	NASA LP DAAC at the USGS EROS Center https://www.earthdata.nasa.gov/centers/lp-daac	Terra Land Surface Temperature and Emissivity Daily 1km
3	CHIRPS (Version 2.0)	Precipitation	Pentad	0.05° x 0.05°	UCSB/CHG- (University of California Santa Barbara-Climate Hazard Group) https://ewx3.chc.ucsb.edu/ewx/index.html	CHIRPS use in-situ station data and satellite imagery.
4	LULC	Generated from Sentinel-2		10m	ESRI https://livingatlas.arcgis.com/landcover/	2022
5	CHIRTSmax	(Maximum Temperature)		0.05° x 0.05°	University of California, Santa Barbara (UCSB) & U.S. Geological Survey (USGS). https://ewx3.chc.ucsb.edu/ewx/index.html	2000-2016
6	NASA SRTM Digital Elevation Model	Processed to fill data voids	-	30m	NASA / USGS / JPL-Caltech https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm	2002

3.2.3. Methodological approaches

3.2.3.1. Calculation of drought indices

The data were extracted and processed using the JavaScript code editor in the GEE platform. with access to MODIS datasets from the Earth Engine library, spatial drought analysis was carried out for 22 consecutive years (2000-2022) of selected months. NDVI and LST were computed first and VCI and TCI were calculated with the time series maps of NDVI and LST. Furthermore, the VHI was computed as the combination of vegetative nature VCI and TCI. The actual vegetation condition is illustrated by VCI, but the vegetative health was determined by VHI (vegetation interaction with temperature). VHI was calculated for the whole Bilate River watershed using the long-term VCI and TCI which reveals the occurrence of drought-related vegetative stress.

During each month (May to October), the VCI, TCI, and VHI were calculated to determine the severity of the drought in the Bilate River watershed. The whole MODIS operation period served as the basis for the estimates (2000 - 2022). The final products of the indices (series of maps) used for spatial coverage, Moran Index, and spatial frequency, and correlation analysis using GIS and R software.

3.2.3.2. Normalized difference vegetation index

The spectral reflectance measurements obtained in the visible red (R) band and near-infrared (NIR) band are combined to generate the NDVI, which is used to evaluate the health and expression of vegetation. The computation is predicated on the idea that radiation in the red band is significantly absorbed by chlorophyll in plants and that radiation in the NIR band is strongly reflected by healthy vegetation. Red band reflection rises when vegetation vitality falls, whereas NIR band reflection falls. NDVI is calculated using the following equation (Bhuiyan et al., 2017; Moussa Kourouma et al., 2021):

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (1)$$

where NIR is a near-infrared band and RED is the red band in the satellite image bands.

In NDVI computation, cloud masking entails locating and eliminating cloudy pixels from the study. By using the masking techniques, it is possible to derive NDVI values more precisely, which leads to the provision of trustworthy data for assessing droughts.

3.2.3.3. Vegetation condition index

The VCI, which was proposed by Kogan, (1995b), uses observations of changes in the vegetation as well as comparisons with historical minimum and maximum NDVI values to assess the effects of drought on the vegetation as well as the severity of the drought. Low index values suggest stressed vegetation and high values imply above-normal conditions, which indicate healthy vegetation conditions. Table 3.2 indicates the threshold for the drought classification in VCI. VCI is calculated using the following equation (Kogan, 1995b):

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (2)$$

Where NDVI is the current NDVI value, $NDVI_{min}$ is the minimum NDVI value and $NDVI_{max}$ is the maximum NDVI value of the research period. In this research, $NDVI_{min}$ and $NDVI_{max}$ are the minimum and maximum values of NDVI from 2000 to 2022.

3.2.3.4. Temperature condition index

TCI recognizes vegetation stress caused by high temperatures as well as by an abundance of moisture. Low TCI values signify hot weather, and over a longer time frame, they signify droughts. Droughts are recognized using the same VCI threshold value (Table 3.2). TCI is calculated using the following formula (Kogan, 1995a; Zhao et al., 2021):

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \quad (3)$$

Where LST is the current Land Surface Temperature, LST_{min} is the minimum LST value and LST_{max} is the maximum LST value of the research period. In this research, LST_{min} and LST_{max} are the minimum and maximum values of LST from 2000 to 2022.

3.2.3.5. Vegetation health index

The Vegetation Health Index (VHI) was proposed by Kogan, (1995a) and considers the NDVI and LST and is weighted by the VCI and TCI (Zhao et al., 2022). The commonly used VHI agricultural drought index is calculated as the weighted average of the TCI and VCI. It is regarded as a reliable indicator, particularly for climates that are arid, semi-arid, and dry sub-humid (Gidey et al., 2018a). VCI and TCI should normally have equal weights of 0.5 because the ideal weights for both variables are typically unknown. Droughts are recognized using the same VCI and TCI threshold values (Table 3. 2). VHI is calculated using the formula (Bhuiyan et al., 2017; Zhao et al., 2021):

$$VHI = \alpha * VCI + (1 - \alpha) * TCI \quad (4)$$

Where VCI is the vegetation condition index, TCI is the temperature condition index and α is the weighing constant, usually given 0.5 (Kogan, 1995a). The methodological workflow of this research is indicated in Figure 3.2.

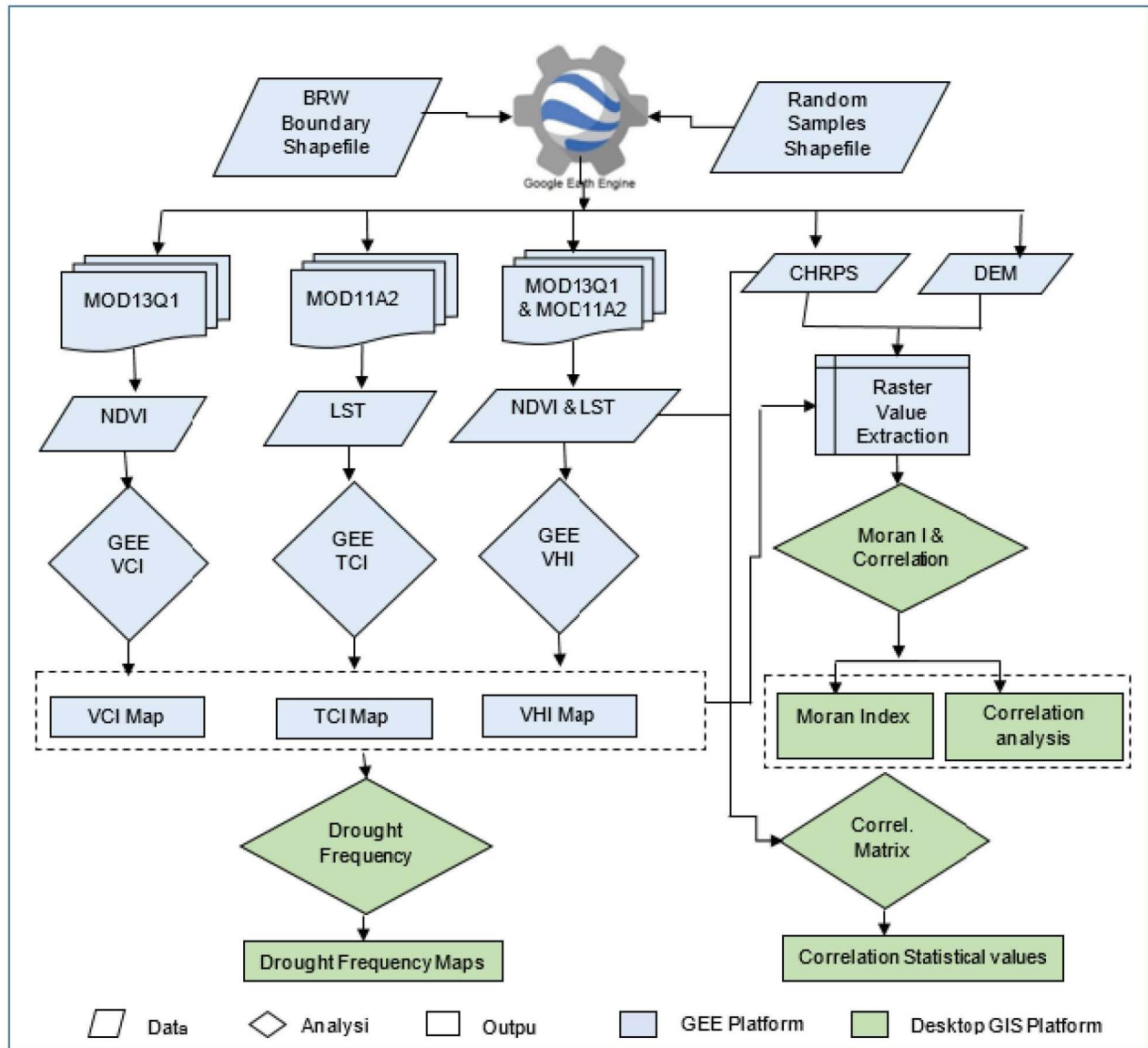


Figure 3.2: Methodological workflow followed in this research using GEE platform and GIS environment

Table 3.2: Drought classification using VCI, TCI, and VHI.

Drought Class	VCI (Kogan, 1995b)	TCI (Kogan, 1995a)	VHI (Bhuiyan et al., 2017)	Given Code*
Extreme Drought	< 10	< 10	< 10	(1) Extreme
Severe Drought	< 20	< 20	< 20	(2) Severe
Moderate Drought	< 30	< 30	< 30	(3) Moderate
Mild Drought	< 40	< 40	< 40	(4) Mild
No Drought	>40	>40	>40	(5) No Drought

* The code was given on the GEE platform during the Vegetation Index analysis.

3.2.4. Spatial autocorrelation using the Moran's I

Spatial autocorrelation is frequently measured using Moran's I (Fu et al., 2014; Nejadrekabi et al., 2021). Moran's I, using both unit locations and unit values at once, calculates the spatial accumulation (Zhang et al., 2022). Moran's I index will have a value between -1 and 1. If the Moran index has a positive value, then the desired features are a component of the cluster since the desired feature (in this case, drought) is surrounded by other features. If the Moran index value is negative, the desired feature is surrounded by features that are completely unrelated to it (Nejadrekabi et al., 2022). Hence, negative spatial autocorrelation has dispersion, positive spatial autocorrelation will have aggregated values, and random is extremely near to zero. The tool generates a Z-score and p-value to indicate the significance of Moran's index. Moran's spatial autocorrelation analysis can be used to determine the mean spatial difference between all spatial characteristics (pixels) and their surrounding features as well as to define the spatial qualities of a variable across a wide area (Nejadrekabi et al., 2022). To determine whether there is geographic clustering in a research region, the global Moran's index is a summary measure (Zhang et al., 2022). In the case of this tool, the null hypothesis (H_0) is that there is no spatial clustering between drought index values (Nejadrekabi et al., 2021). The Moran's I statistics for spatial autocorrelation is computed using equation 5 (Darand et al., 2017):

$$I = \frac{n}{S_o} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j} z_i z_j}{\sum_{i=1}^n z_i^2} \quad (5)$$

Where z_i is the deviation of an attribute for a feature I from its mean ($x_i - \bar{X}$), $w_{i,j}$ is the spatial weight between feature I and j, n is equal to the total number of features, and S_o is the aggregate of the spatial weights:

$$S_o = \sum_{i=1}^n \sum_{j=1}^n w_{i,j} \quad (6)$$

The Z_I score for the statistics is computed as:

$$Z_I = \frac{I - E[I]}{\sqrt{V[I]}}. \quad (7)$$

where $E[I]$ and $V[I]$ calculated as:

$$E[I] = -1/(n - 1) \quad (8)$$

$$V[I] = E[I^2] - E[I]^2 \quad (9)$$

To investigate the spatial characteristics of VHI, a spatial autocorrelation analysis was carried out using 217 stratified samples based on the land use and land cover of the study area used that were dispersed within BRW. The stratified samples were uploaded to GEE to extract raster values of all variables. The level of spatial autocorrelation at each specific site was determined using the Moran index. Besides, the extracted raster values also using Pearson correlation analysis.

3.2.5. Spatial drought frequency

Drought frequency maps in the BRW were determined by taking an at the VCI, TCI, and VHI maps that were obtained from the MODIS dataset analyzed using GEE. All VCI, TCI, and VHI maps were classified to detect the occurrence of drought (Table 3.2). The classified maps were then converted into binary maps (1 and 0), where 1 (VCI, TCI, and VHI values less than or equal to 3) indicates drought and 0 (VCI, TCI, and VHI values greater than 3) indicates a normal situation (Frischen et al., 2020). Finally, the total drought frequency was determined using Equation 10 (Kundu et al., 2016):

$$SDF = D_1 + D_2 + D_3 + D_n \quad (10)$$

Where SDF is the spatial drought frequency of each pixel and $D_{1...n}$ is drought events in different time

The average drought frequency was also determined by dividing the total drought frequency maps by total number of years of study to get the average drought frequency within the study period. The estimated frequency of drought was also classified into five categories (very high, high, medium, low, and very low based on the analysis of this research).

3.3. Results and Discussion

3.3.1. Spatial distribution of drought

The spatial distribution of drought throughout the BRW from 2000 to 2022 is shown in Figure 3.3, 3.4, and 3.5, respectively, as obtained by VCI, TCI, and VHI. The results revealed that the occurrence and severity of drought vary with years and months. In the case of VHI, the results showed that extreme droughts occurred highly in May, September, and October. In the case of TCI, a high distribution of thermal stress that exacerbate extreme drought condition observed in May, August, and September, whereas in the case of VCI, a high distribution moisture stress that aggravate extreme drought condition observed in May, September, and October. The variation among the months is attributed to the variation of LST in May and October and precipitation variation within June to September. In terms of years, all the indices showed high drought severity in the years 2002, 2009, 2015, and 2022.

VHI showed the watershed experienced drought conditions mainly during the crop-growing season (June - September). For instance, the southern, central, and south-western parts of the watershed, were affected by extreme and severe drought on May 2009 and 2015, June and July 2002, 2009 and 2022, August 2002 and 2009, September 2002, 2009, 2015 and 2019, and October 2002 and 2015 (Figure 3.4). Similarly, TCI showed nearly the whole watershed was affected by extreme and severe drought on May 2009, June 2009, July 2002, August 2015, September 2002, and October 2015 (Figure 3.4).

For May 2002, 2009, and 2015, as well as September and October 2002, 2009, and 2015, VCI also showed a high distribution of extreme and severe drought conditions, primarily in the southern and central portions of the watershed (Figure 3.5). Overall, despite differences in the spatial distribution extent, all vegetation indices detected drought during the watershed's main growing season (June-September). The VHI demonstrated a reliable distribution of drought compared to TCI and VCI since it is the blended outcome of the two indices.

The area calculation showed variation in each month and year of the study period. For instance, in May 2009, the percentage of extreme, severe, and moderate drought classes was 7.2%, 21.8%, and 33.1%, respectively. In May 2009, the sum of extreme, severe, and moderate drought accounts for the highest percentage (62.1%) which is the highest of all years (Figure 3.6a). That means in May

2009, 62.1% of the Bilate river watershed was affected by drought condition. In 2015, the sum of extreme, severe, and moderate drought classes was 40.2%, and in 2022 it was 39.2% (Figure 3.6b). Thus, in May 2009, 2015, and 2022, a large percentage of the area in the Bilate river watershed was exposed to drought. Similarly, in June 2009 the percentage of extreme, severe, and moderate drought was 1.6%, 5.7%, and 21.4%, respectively. The total area coverage of these drought classes was 28.7% in June 2009 which was the highest of the study period (Figure 3.6b). The other highest total area coverage in June was in 2017 (12.4%) and 2022 (15.5%). In July 2002, the percentage of extreme, severe, and moderate droughts was 0.7%, 5.0%, and 20.3%, respectively. The total area coverage of these drought classes was 26.0% in July 2002 which was the highest of the study period (Figure 3.6c). The other highest total area coverage in July was in 2009 (14.1%) and in 2022 (18.9%). In August 2015, the percentages of extreme, severe, and moderate droughts were 1.6%, 7.0%, and 15.8%, respectively. The total area coverage of these drought classes was 24.4% in August 2015 which was the highest of the study period (Figure 3.6d). The other highest total area coverage in August was in 2002 (22.6%) and 2009 (19.14%). In September 2002, the percentage of extreme, severe, and moderate drought was 5.9%, 9.7%, and 14.5%, respectively. The total area coverage of these drought classes was 30.1% in September 2002 which was the highest of the study period (Figure 3.6e). The other highest total area coverage in September was in 2009 (30.1%) and 2015 (26.7%). In October 2002, the percentage of extreme, severe, and moderate drought was 19.5%, 27.0%, and 24.0%, respectively. The total area coverage of these drought classes was 70.4% in October 2002 which was the highest of the study period (Figure 3.7f). The other highest total area coverage in October was in 2012 (52.4%) and 2015 (58.6%).

In comparison to other years throughout the study period, a wide area was exposed to extreme, severe, and moderate droughts in 2002, 2009, 2015, and 2022. The extreme, severe, and moderate drought in 2002 was 0.5%, 2.1%, and 4.8%, respectively. The spatial extent of extreme, severe, and moderate drought coverage in 2009 were 7.2%, 21.8%, and 33.1%, respectively. Whereas in 2015 and 2022 the extreme, severe, and moderate drought coverage were 4.5%, 13.3%, and 22.4% in 2015, and 3.2%, 12.2%, and 23.8% in 2022, respectively. However, 2009 was the year with the highest risk of drought, and BRW was exposed to drought during all of the study months, with May (62.1%) and October (70.4%) exhibiting the highest coverage of drought. These months fall outside of the main growing season of crops (June to September) in the watershed.

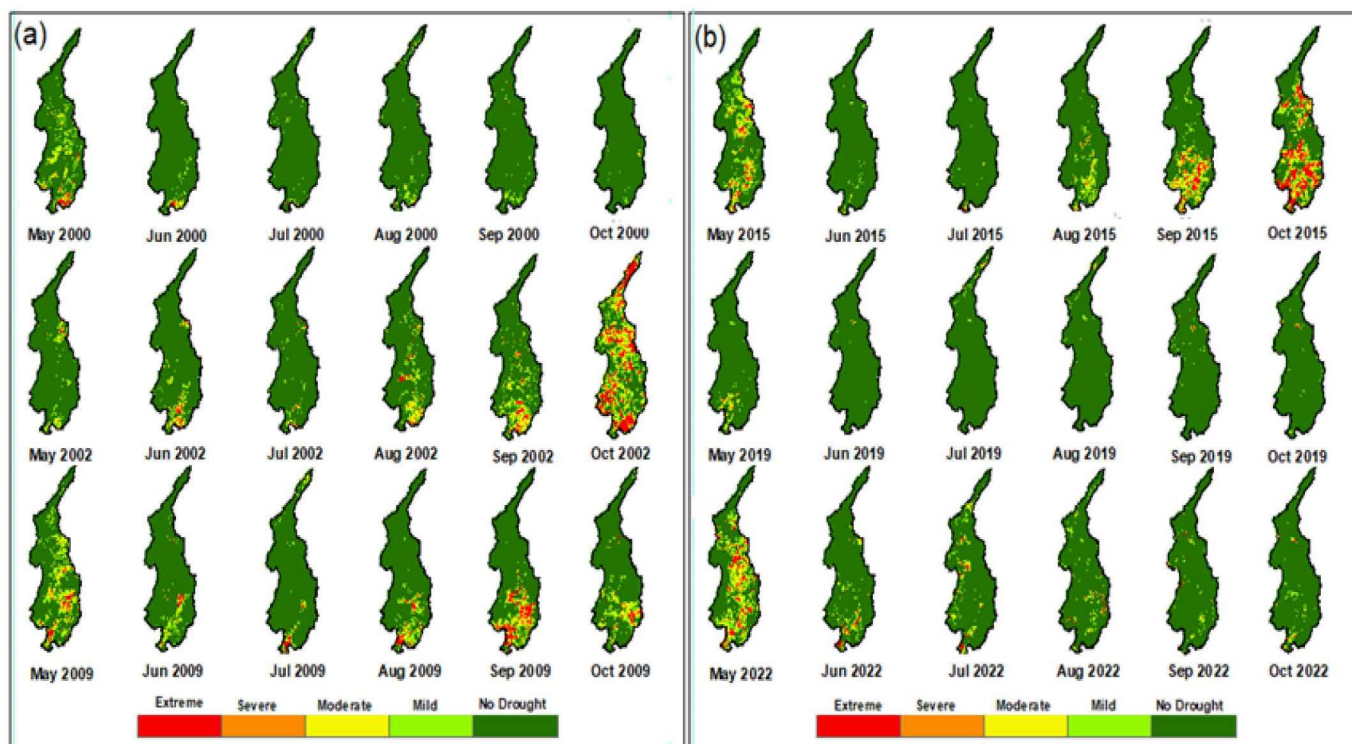


Figure 3.3: Spatial distribution of drought through VCI (a) 2000-2009, and (b) 2015-2022

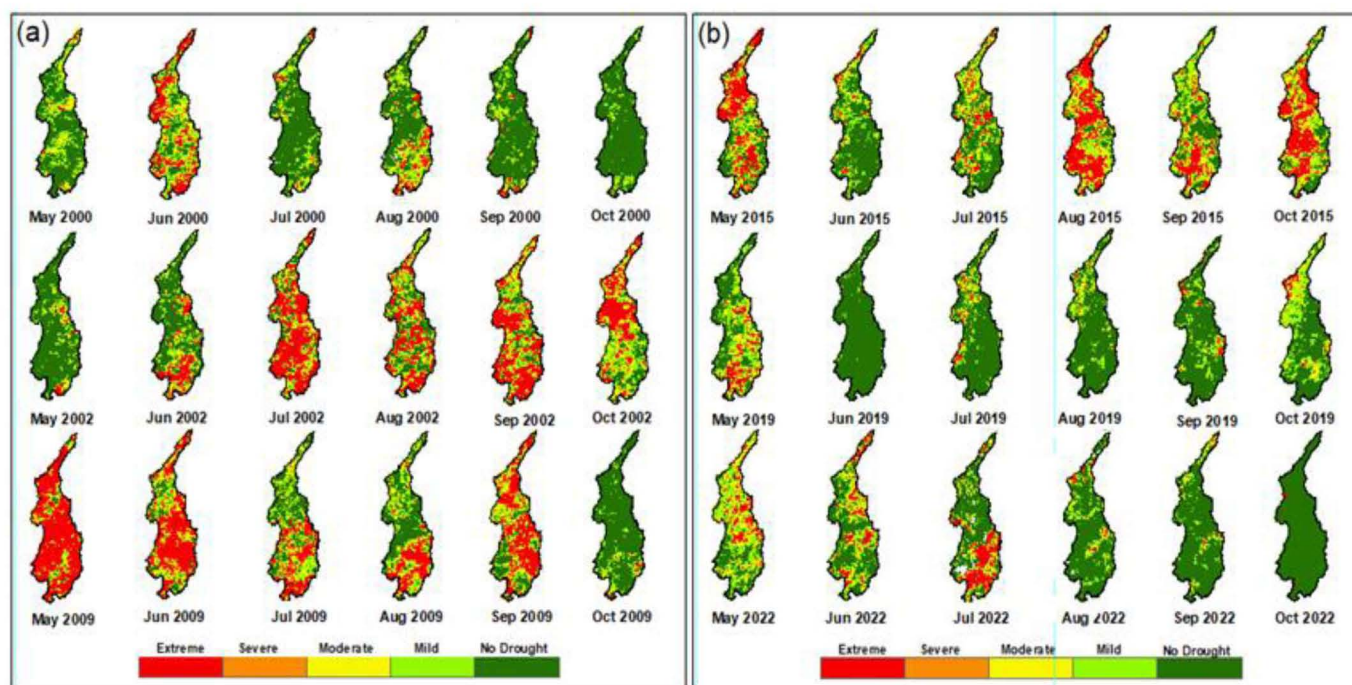


Figure 3.4: Spatial distribution of drought through TCI (a) 2000-2009, and (b) 2015-2022

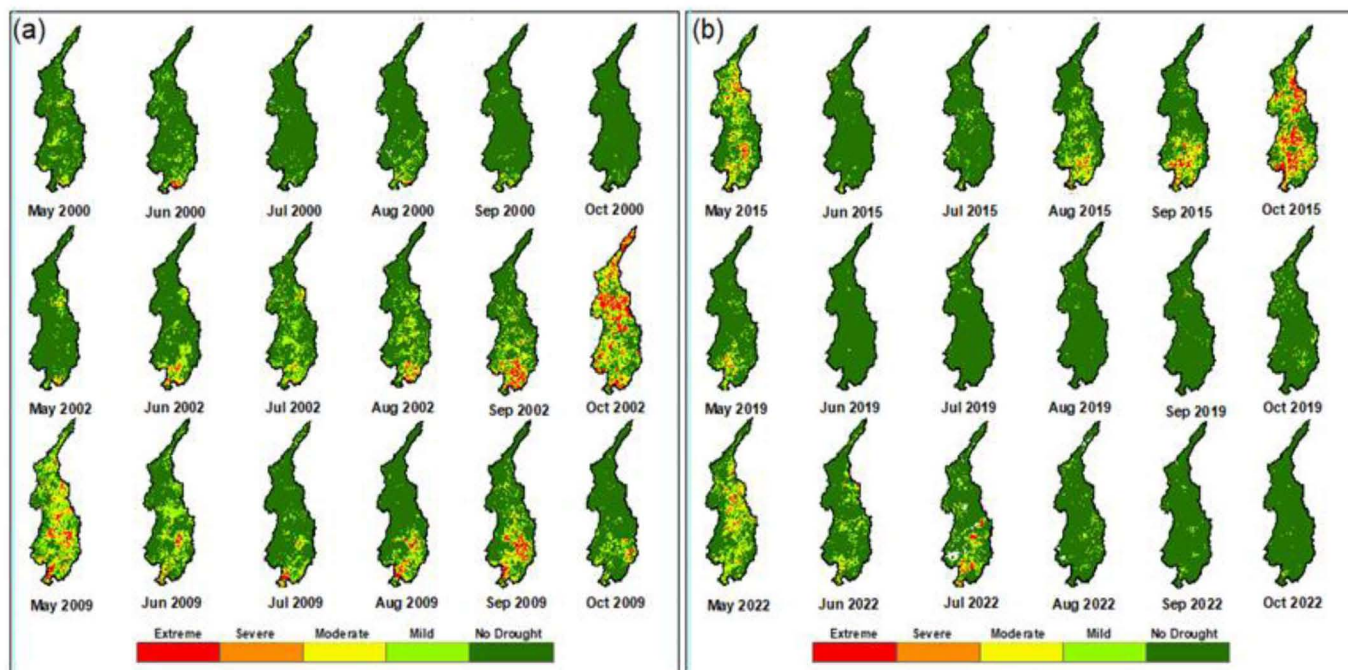


Figure 3.5. Spatial distribution of drought through VHI: (a) 2000-2009, and (b) 2015-2022

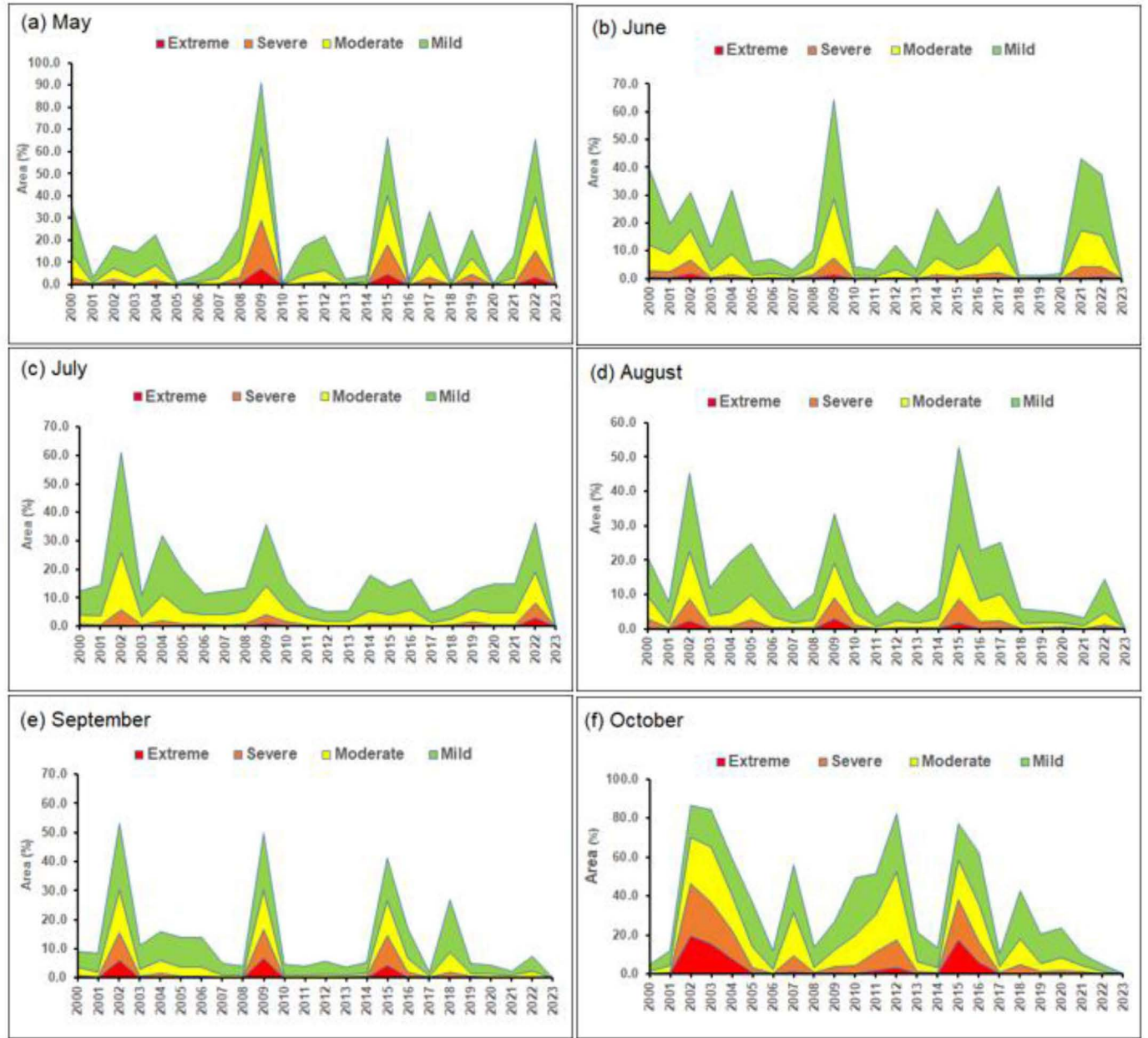


Figure 3.6: Drought Area coverage (%): (a) May, (b) June, (c) July, (d) August, (e) September and (f) October

The drought analysis using the GEE platform revealed the temporal pattern and spatial distribution through the VCI, TCI, and VHI. The findings showed that the Bilate River watershed was mostly affected by extreme and severe droughts in the central, southern, and southwestern parts. In the case of VHI, the distribution of extreme drought was concentrated in the central, southern, and southwestern parts of the watershed in 2002, 2009, 2015, and 2022. When compared to other months, May (62.1%) and October (70.4%) had the highest area coverage of extreme, severe, and

moderate droughts. Similarly, almost the entire watershed was affected by an extreme and severe drought in May 2009, June 2009, July 2002, August 2015, September 2002, and October 2015, according to TCI. For May 2002, 2009, and 2015, as well as September and October 2002, 2009, and 2015, VCI also showed a high distribution of extreme and severe drought conditions, mostly in the southern, southwestern, and central parts of the watershed. Overall, the years 2002, 2009, 2015, and 2022 were the years that showed high spatial drought coverage compared to other years of the research. This result is consistent with Ethiopia's major historical drought events (Kogan, 2002; Mohammed and Yimam, 2021; Wolteji et al., 2022). In comparing the different months and years, the VHI's result is more useful than TCI and VCI. This is confirmed by Jiang et al. (2021) and Gidey et al. (2018) that the VHIs have been successfully used for drought detection.

Extreme droughts showed increasing trends in 2002 from May to October. In 2009 and 2015 extreme drought showed a decreasing trend from May to July and an increasing trend from July to October (Figure 3.7a). In contrast to 2002, extreme drought showed a decreasing trend from May to October in 2022. Similarly, severe drought patterns were observed from May to October (Figure 3.7b). Moderate droughts showed a decreasing trend in 2009 and 2022 (Figure 3.8c). In terms of area coverage, 2009 is the most severe and moderate drought-affected year whereas extreme drought was more widespread in 2015 (Figure 3.7d). Hence, 2009 and 2015 were the worst drought years that had high spatial coverage of extreme, severe, and moderate droughts.

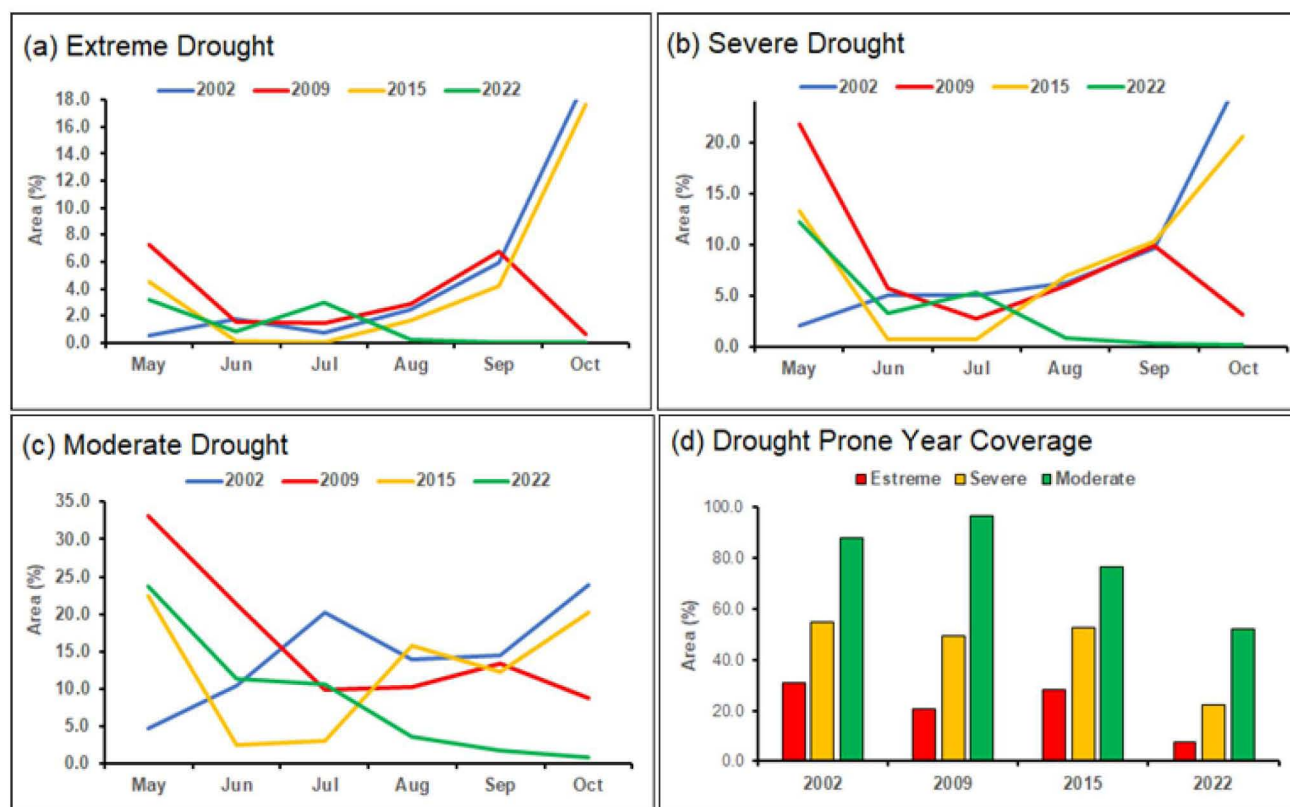


Figure 3.7: Drought class trends and distribution (a) Extreme Drought (b) Severe Drought (c) Moderate Drought and (d) Drought class area coverage in the most intense drought years.

3.3.2 Spatial autocorrelation analysis

Table 3.3 presents the summary of autocorrelation results throughout the study period. The graphical representation of Moran's index analysis is presented only for the year 2009 and 2015 which were the strongest drought years as observed in Figure 3.3, 3.4, and 3.5. The highest Moran index values were also recorded in the year 2009 and 2015 compared to other years (Table 3.3).

Table 3.3 Summary statistics of autocorrelation analysis using Moran Index.

May	2000	2002	2009	2015	2019	2022
Moran's Index	0.52*	0.52*	0.56*	0.50*	0.63*	0.43
Z-score	16.15	16.15	17.35	15.58	19.38	13.15
P-value	0.00	0.00	0.00	0.00	0.00	0.00
June						
Moran's Index	0.39	0.66*	0.51*	0.50*	0.51*	0.44
Z-score	12.12	20.23	15.67	15.55	15.67	13.45
P-value	0.00	0.00	0.00	0.00	0.00	0.00
July						
Moran's Index	0.39	0.44	0.60*	0.25	0.59*	0.54*
Z-score	12.06	13.45	18.59	7.76	18.50	16.69
P-value	0.00	0.00	0.00	0.00	0.00	0.00
August						
Moran's Index	0.52*	0.59*	0.79*	0.60*	0.46	0.23
Z-score	16.16	18.16	24.64	18.54	14.21	8.66
P-value	0.00	0.00	0.00	0.00	0.00	0.00
September						
Moran's Index	0.56*	0.53*	0.72*	0.63*	0.34	0.57*
Z-score	17.24	16.49	22.26	19.54	10.49	17.68
P-value	0.00	0.00	0.00	0.00	0.00	0.00
October						
Moran's Index	0.52*	0.43	0.58*	0.63*	0.42	0.39
Z-score	15.93	13.31	17.94	19.53	12.98	12.16
P-value	0.00	0.00	0.00	0.00	0.00	0.00

**Statistically significant at 95% confidence level.*

The results of the spatial autocorrelation in August 2009 indicate that the pattern of drought (VHI) at each feature location was clustered. The Moran's Index was 0.79, the z-score was 24.64, and the p-value was 0.00 (Figure 3.8a). Similarly, the results of Moran index values in September and October exhibit similar results as in August 2009 (Figure 3.8b and 3.8c). The results of the spatial autocorrelation in August 2015 indicate that the pattern of drought (VHI) at each feature location was clustered. The Moran's Index was 0.60, the z-score was 18.54, and the p-value was 0.00 (Figure 3.8d). Likewise, in September and October 2015, the Moran index and were 0.63 and 0.63, and the s-score were 19.54 and 19.53, respectively (Figure 3.8e and 3.8f). The Moran index, Z-score, and p values of the all months and major drought years summarized in Table 3.3. Overall, the drought characteristics extracted by stratified samples with raster values of VHI statistically proved that the watershed has similar spatial characteristics (drought in this case) in the major drought years (2002, 2009, 2015 and 2022).

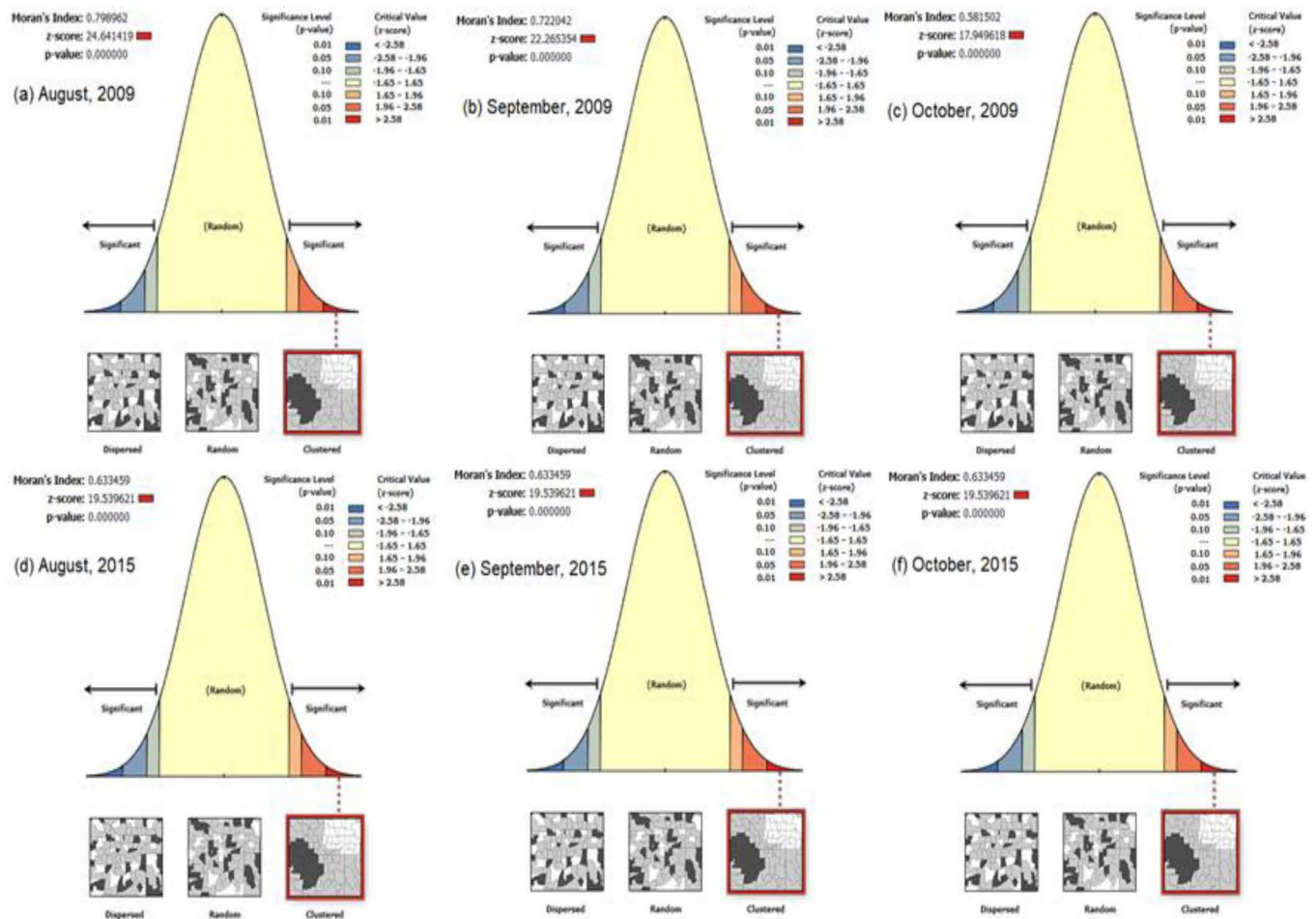


Figure 3.8: Spatial autocorrelation between the Vegetation Health Index (VHI) and the Moran's Index on: (a) Aug. in 2009, (b) Sep. in 2009, (c) Oct. in 2009, (d) Aug. in 2015, (e) Sep. and 2015, and (f) Oct. in 2015.

According to Figure 3.8 and Table 3.3 the degree of spatial patterning of drought index VHI was found using Moran's I spatial autocorrelation analysis on the major drought intense years. For instance, the VHI index showed a considerable spatial clustering of comparable VHI values in August 2009, with a very high Moran's I of 0.79, which is likely indicative of the watershed was under drought stress. With a Moran's I of 0.63 in October 2009, the VHI index indicated a moderate degree of spatial autocorrelation, indicating a more fragmented spatial pattern of vegetation condition. Likewise, the other drought years have a significant value of Moran I values. Hence, more precise targeting of mitigation measures may result from taking these shifting spatial patterns into account while monitoring droughts. A very small P-value and higher Z-value indicate the

rejection of H_0 and the clustered pattern of VHI values in these months. This clustered pattern of VHI values shows that VHI has a spatial autocorrelation.

In general, the examination of spatial autocorrelation showed that the raster values of VHI used to extract the drought features from a stratified sample statistically showed that the watershed shared similar geographical characteristics (drought in this case). The Moran index and P-values in Table 3.3 demonstrated the rejection of H_0 in all months and years where the spatial characteristics of drought were autocorrelated. The geographical distribution of VHI in the BRW, as shown in Table 3.3, appeared to be significantly autocorrelated, as all of the Moran index values were above zero and passed the confidence test at level 95%. In other words, the drought characteristics in terms of VHI were described with a spatial similarity. As indicated by Li et al., (2022) a better spatial autocorrelation was suggested by greater Moran index values of VHI than by lower ones. Hence, specifically in 2009 and 2015, the values in all months were higher than in the other years, showing that this year's drought had higher spatial autocorrelation features compared to other years.

3.3.3. Spatial drought frequency

The VCI, TCI, and VHI estimates of the drought analysis results were used to create the drought frequency map. Understanding of the incidence of drought has enhanced with the integration of the two indicators in VHI, which is an improvement over TCI and VCI. Based on the VHI total, it is evident from the frequency map (Figure 3.9c) that the region had drought more than nine times in the twenty-two-year period from 2000 to 2022. The VHI total frequency map showed that a high-frequency class (23–31) was 13.3% and a very high-frequency class (32–62) was 3.67% of the region that had experienced drought frequently. The majority of the areas affected by this frequency of drought were primarily in the southern section of the watershed (Figure 3.9c). It is also important to note that the southern part of the watershed has seen drought in a very high-frequency class according to this research, meaning that it has affected these areas every two years. Furthermore, as shown in Figure 3.9f, the average VHI frequency maps showed that the watershed was impacted by very high and high-frequency drought classes, respectively, by 3.68% and 31.09%. The results for the average and total VHI frequency map are nearly identical.

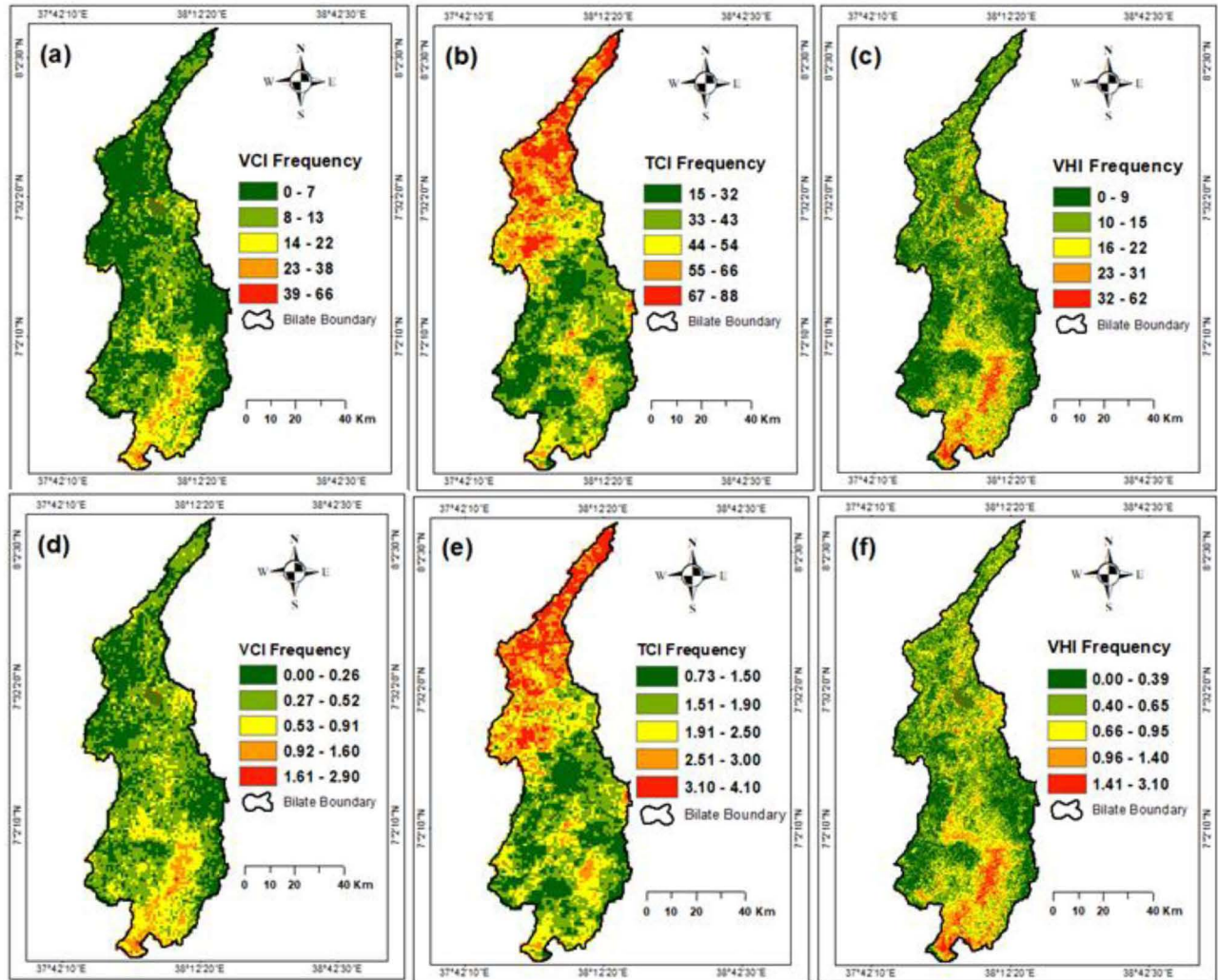


Figure 3.9: Drought frequency: (a),(b),& (c) total drought frequency & (d), (e), & (f) Mean drought frequency

3.4. Relationships of drought indices with other environmental variables

Raster values extracted using 500 using Neyman allocation formula based on stratified samples were used to create a correlation matrix of VCI, TCI, VHI, NDVI, LST, precipitation, temperature and altitude to examine their relationship. Figure 3.10 shows the relationship of all drought indices and other variable on September and October of 2009 and 2015.

The relationships found in this research offer insightful information for studying droughts. The significant positive correlation ($r=0.76$) seen in Figure 3.10a between VHI and VCI highlights the significance of vegetative health as a drought indicator. Furthermore, the negative correlations between LST and VCI ($r=-0.71$), NDVI ($r=-0.73$), and VHI ($r=-0.56$) demonstrate how negatively

higher temperatures affect the health of the vegetation, which in turn increases the sensitivity to drought. The fact that rainfall and altitude have a positive association (0.38) highlights how terrain affects moisture availability and possible drought hotspots.

Although there is no direct association between altitude and the other parameters in the correlation matrix, it may have an indirect effect on them. Rainfall patterns and the health of the plants are significantly influenced by altitude. Greater vegetation greenness and healthier vegetation are generally found at higher elevations, according to the positive relationships between NDVI and altitude ($r=0.77$) and VCI and altitude ($r=0.74$) (Figure 3. 10a). This may suggest that, in the event of a drought, higher altitude locations may be less vulnerable to drought conditions because of their comparatively healthier vegetation. Besides, there is a significant negative correlation ($r=-0.81$) between temperature and altitude, meaning that temperature drops with altitude. This is consistent with the known atmosphere's vertical temperature gradient.

With correlation coefficients of 0.75 and 0.64 for VCI and TCI, respectively, the VHI exhibits moderately positive correlations with both variables in October 2009 (Figure 3. 10b). Similarly, in September 2015, there was a 0.81 and 0.61 connection between VHI and TCI and VCI, respectively (Figure 3. 10c). As of October 2015, VHI and TCI had correlations of 0.78 and 0.62, respectively (Figure 3. 10d). These findings demonstrate the high degree of similarity in how the drought indicators represented the drought condition.

The correlation matrix revealed several significant relationships between the variables. VHI, VCI, and NDVI were all strongly positively correlated with each other ($r > 0.73$) (Figure 3.10a), indicating these vegetation indices are closely linked. VHI and VCI were also weak positively correlated with rainfall ($r > 0.006$), but negatively correlated with temperature and LST ($r < -0.5$, $p < 0.05$), suggesting drier, hotter conditions reduce vegetation health. TCI had a strong negative correlation with rainfall ($r = -0.54$) and a positive correlation with temperature and LST ($r > 0.8$) (Figure 3.10 a), as expected given TCI's sensitivity to temperature anomalies. Altitude showed a significant positive relationship with VHI, VCI and NDVI ($r > 0.54$), likely due to differences in vegetation types and climate at higher elevations. Overall, the vegetation indices (VHI, VCI, and NDVI) have substantial positive relationships with one another, suggesting that they can be used independently or in combination to monitor the health and condition of the vegetation as a drought indicator. These indices may adequately represent the vegetation's reaction to precipitation

shortfalls and high temperatures, which are major causes of drought, as seen by their positive association with rainfall and negative relationship with temperature/LST. The findings suggest that TCI may offer additional insights into the thermal aspect of drought stress on vegetation, given its inverse relationship with rainfall and its positive connection with temperature/LST. Drought state can be more thoroughly assessed by keeping an eye on temperature anomalies and vegetation condition using VHI/VCI and TCI, respectively.

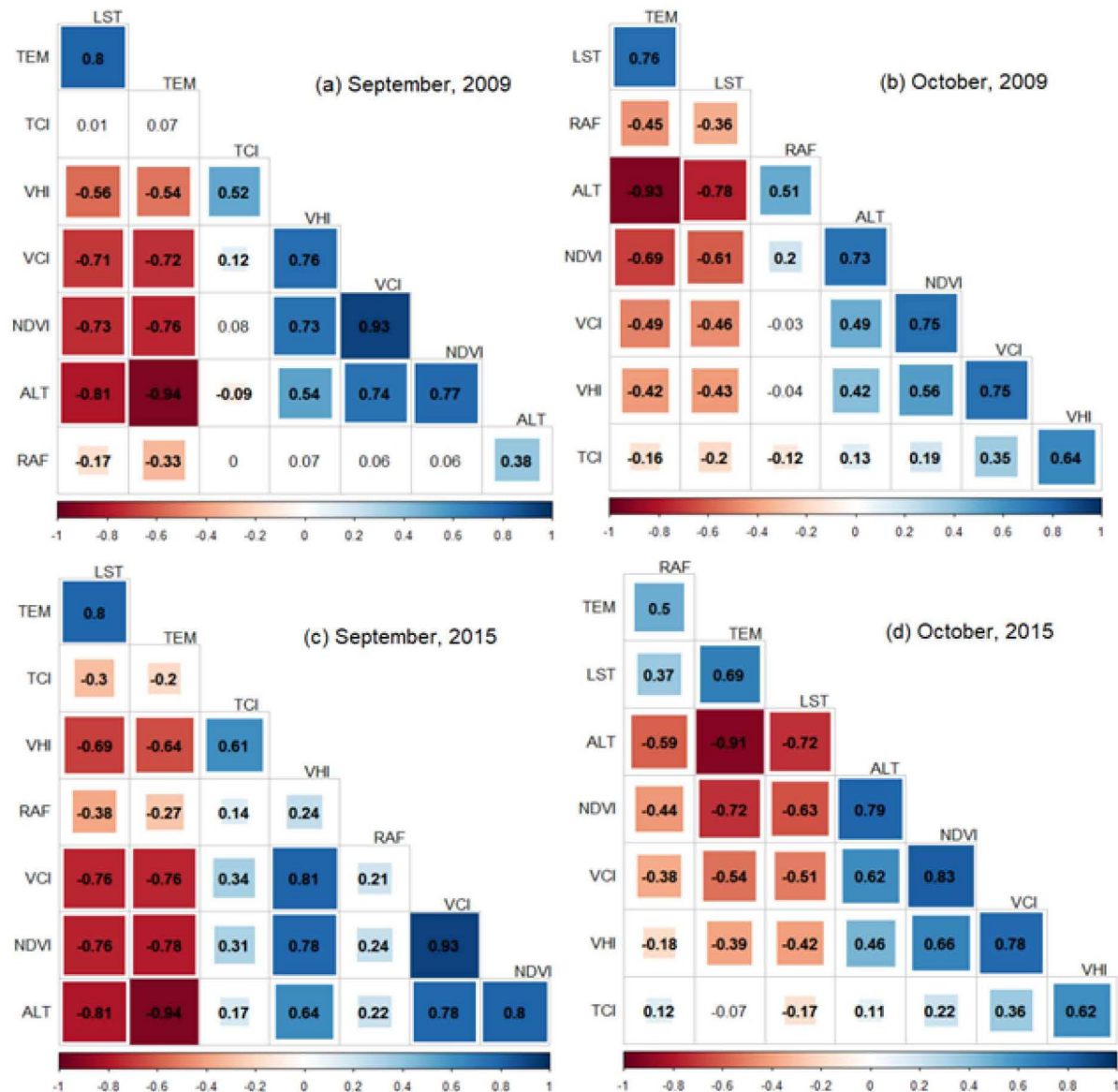


Figure 3.10: Correlation Matrix of all drought indices with other variables: (a) Sep, 2009, (b) Oct 2009, (c) Sep 2015, and (d) Oct 2015. Note: RAF = precipitation, TEM = temperature = NDVI, and ALT = altitude

According to Figure 3.10, NDVI has a positive correlation with VCI, TCI and VHI, but a negative correlation with LST mostly. The relationship VCI, TCI, VHI, NDVI and LST are in line with the finding of Gidey et al., (2018b), Arekhi et al., (2020), Wassie et al., (2022), Ghasempour et al., (2022), Ejaz et al., (2023), and Hakam et al., (2023). Moreover, a positive correlation among VCI, TCI, VHI, and NDVI is consistent with the findings of Tabassum and Khan, (2024), Sun et al., (2020), Ali et al., (2021), and Ali et al., (2022). Correlation between LST and NDVI also revealed a significantly negative relationship which is in line with the finding of Tran et al., (2017). The negative correlation of LST and NDVI is in agree with similar with the findings of Masitoh and Rusydi, (2019).

Altitude may have an indirect impact on the other factors in the correlation matrix even though it is not directly related to them for a variety of reasons. Hence, on Figure 3.10a, 3.10b, 3.11 c and 3.10d, the relationship of drought and altitude showed a positive relationship indicating that as altitude increases, the values of VHI increase indicating that the drought condition decreases which is consistent with the research findings of Hosseini et al. (2020). Besides, on Figure 3. 10 a, b and c, altitude was positively related to precipitation, indicating that precipitation increases with elevation, which is quite similar to the previous research by Tanteliniaina et al., (2020). As a result, the correlation analysis provides informative data by analyzing the connections between the drought indices and other environmental variables. In the end, this research output advances our knowledge of the intricate interactions between environmental factors and helps practitioners implement plans for resource management and drought mitigation in the studied area.

Even though VHI, which combines the VCI and TCI drought indices, allows for improved drought monitoring, several factors other than climatic variables can exacerbate drought conditions. For instance, fundamental population, economic, and land-use characteristics appear to be associated with drought susceptibility (Simelton et al., 2009). As a result, it is recommended that future studies consider other biophysical and socioeconomic factors affecting the watershed to identify more vulnerable areas and give those areas priority in creating a better drought preparedness plan.

3.5. Conclusion

A cloud-based GEE platform was employed to examine and map the geographic distribution and severity of drought using vegetation indicators VCI, TCI, and VHI. The vegetation indices from 2000 to 2022 were used to calculate drought from May to October in the Bilate River Watershed.

It was found that the Bilate river watershed experienced extreme and severe drought, primarily in its southern, southwestern, and central parts, according to the results of VHI. In terms of area coverage, a higher extreme, severe, and moderate drought was noted in the watershed in 2009 and 2015. The characteristics of the drought were also geographically autocorrelated. To develop a strategy for drought mitigation measures, this research provides empirical evidence about the occurrence and spatial distribution of drought during May to October of the watershed. The southern portion of the watershed was also frequently impacted, according to the examination of drought frequency. Besides, the correlation analysis indicated the relationships among the drought indices and other environmental variables, that yields useful information. Given that this is the first paper on the use of GEE for drought monitoring in Ethiopia's central Rift Valley, it provides insight for local experts to keep track of the drought in near real-time. The research has also demonstrated that GEE is a useful tool for drought monitoring at the watershed scale. Further research should be conducted in the watershed taking into consideration additional drought-causing and aggravating factors such as socioeconomic and other biophysical data to determine the area's vulnerability to drought effects.

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CHAPTER FOUR

DROUGHT SUSCEPTIBILITY MODELING WITH GEOSPATIAL TECHNIQUES AND AHP MODEL: A CASE OF BILATE RIVER WATERSHED, CENTRAL RIFT VALLEY OF ETHIOPIA³

ABSTRACT

Drought continues to be the worst natural hazard in the world affecting ecosystems, economies and overall human welfare with severe consequences in developing countries. While drought is an unavoidable climatic phenomenon, actions can be made to improve preparedness and mitigate the impacts upon proper forecast on susceptibility. Drought susceptibility modeling plays a key role in determining how best to mitigate and adapt to drought occurrences. This research explores the application of geospatial techniques and Analytic Hierarchy Process (AHP) in drought susceptibility modeling for the drought-prone Bilate River watershed, located in the central Rift Valley drylands of Ethiopia. A total of 15 parameters were used including rainfall, temperature, evapotranspiration, soil moisture, normalized difference vegetation index, land surface temperature, soil texture, land use-land cover, topographic wetness index, modified normalized difference water index, drainage density, slope, elevation, population density, and aspect to model drought susceptibility. Findings showed that nearly 70.2% of the area falls under the moderate drought category, followed by the severe (23.2%), mild drought (6.6%), and extreme (0.02%) drought categories in the watershed. Based on zonal administration, Wolayta Zone has a high spatial coverage of severe drought with 54.1% (659.3 km²) while Hadiya has a high spatial coverage of moderate drought with 24.6 % (908.9 km²). The drought susceptibility model (DSM) receiver operating characteristic (ROC) curve was then created, and the area under curve (AUC) was calculated. The results of the analysis showed that the AUC is 0.701 (70.1%) indicating that the model is reasonably good model. Hence, geospatial approaches in conjunction with the AHP model improved the drought susceptibility modeling's reliability, which has significant implications for drought adaptive management and preparedness planning.

Keywords: *Drought susceptibility, Geospatial techniques, AHP, Bilate river watershed, Rift Valley, Ethiopia*

4.1. Introduction

Drought is increasingly a recurring natural disaster, particularly in arid and semi-arid parts of the world, as a result of changes in worldwide patterns of climatic variables, notably temperature and precipitation (Khorrami and Gündüz, 2022). Drought continues to be the worst natural hazard in the world affecting ecosystems, economies and overall human welfare (Frischen et al., 2020). There are four main categories of drought: (i) meteorological, which is defined as a decrease in

³Ashenafi Burka, Birhanu Biazin & Woldeamlak Bewket (2024) Drought susceptibility modeling with geospatial techniques and AHP model: a case of Bilate River Watershed, Central Rift Valley of Ethiopia, Geocarto International, 39:1, 2395319, DOI:10.1080/10106049.2024.2395319.

precipitation; (ii) agricultural, which is defined as a deficiency of moisture in the soil; (iii) hydrological, which is determined by the reduction in stream flows and runoffs; and (iv) socioeconomic droughts (Yihdego et al., 2019). The frequency and intensity of droughts have grown recently on the global scale (Drisya and Sathish Kumar, 2023). According to Bharambe et al., (2023), more extreme weather conditions and a rise in the frequency of severe to intense droughts are expected as the world continues to warm. For instance, drought will significantly worsen in the tropical and subtropical areas during the twenty-first century if climate change is forced by the Representative Concentration Pathway 8.5 (RCP8.5) (Kim et al., 2020). The world is currently experiencing a critical phase with respect to the continuous rise in surface temperatures (Alharbi et al., 2022). Moreover, population growth, land degradation, and desertification have increased susceptibility to droughts (Kundu et al., 2021). Drought severely affects the food security and way of life for almost two billion people who live in arid regions, which make up 41% of the earth's terrestrial surface (Solh and Van Ginkel, 2014). In the dry and semi-arid parts of east Africa, droughts are very common and cause disastrous effects on the environment, agriculture, and livestock which in turn affects local economies and fuels civil unrest (Lindvall et al., 2020). Thus, the media rightly focuses a lot on droughts in Africa in general and east Africa in particular (Naumann et al., 2014). In the past, drought has affected nearly every sector in Ethiopia, including agriculture, water resources, industry, decreased electricity output, and so forth (Bogale and Erena, 2022). The majority of rural households in Ethiopia are subsistence farmers, who have historically had very high vulnerability to weather risks (Hill and Porter, 2017).

Drought is an unavoidable climatic phenomenon. But actions can be taken to improve preparedness and mitigate its impacts (Solh and Van Ginkel, 2014). Besides, drought recurrence in the world that has been altered by humans has been linked more to society's impact on the environment than to natural climate variability and anthropogenic climate change (Haile et al., 2020). As cited also by Khorrami and Gunduz, (2021), the destructive impacts of droughts are projected to be amplified with the current ascending trends of climate change and population growth (Gerdener et al., 2020). For instance, in the absence of natural drivers of drought, human activities (i.e. deforestation, agricultural activities, afforestation, etc.) can also be the cause of drought because they have an impact on water input, output, and storage (Van Loon et al., 2016). Hence, implementing appropriate adaptation and mitigation measures requires a thorough understanding of drought risk and susceptibility. Adaptation is the process of adjusting to an actual

or predicted climate and its impacts. Susceptibility includes a range of concepts and components, such as sensitivity and lack of capacity to cope (Field and Barros, 2014). Enhancing resilience and lessening the effects of drought episodes can be achieved by optimizing effectiveness and efficiency of adaptation and mitigation techniques by customizing them to the unique vulnerabilities and requirements of a given context.

The Rift Valley dryland area of Ethiopia is one of the most drought-prone areas in the country (Chimdesa, 2016; Tesfamariam and Melgani, 2019; Wolteji et al., 2022). The Central Rift Valley has significant land degradation, which is due to the region's steep slopes, rugged terrain, and heavy rainfall (Chimdesa, 2016). A number of factors, including declining vegetation cover, low soil moisture retention capacity, unreliable rainfall pattern, and improper land management techniques contribute to this region's susceptibility to drought. Different parts of the Rift Valley have varying degrees of susceptibility as a result of variations in these characteristics.

Planning for drought management requires detailed mapping of drought vulnerabilities. Mapping and assessing drought risk is crucial to mitigating drought impacts (Saini et al., 2022). Susceptibility to drought has steadily gained attention and become a study hotspot for academics worldwide in recent years (Guo et al., 2021). In recent times, scientists from diverse fields across the world have given drought susceptibility assessment a high priority (Saini et al., 2022). There are several approaches based on remote sensing that can be used to map, measure, track, and predict droughts in an area (Ahmed and Sheikh Suleimany, 2023). Numerous studies have been conducted on drought susceptibility mapping in different places (Karamouz et al., 2015; Ekrami et al., 2016; Palchaudhuri and Biswas, 2016; Hoque et al., 2020; Sivakumar et al., 2021; Saha et al., 2021; Saini et al., 2022; Koem et al., 2022; Mahato et al., 2023). These studies have focused on AHP/Fuzzy AHP and GIS tools for mapping of susceptibility to drought. For example, Hoque et al., (2020) used AHP and GIS techniques in the northwestern region of Bangladesh and identified 16 drought-prone districts. Sivakumar et al., (2021) employed similar methods in Namakkal District of Tamilnadu in India and found out 17% of the districts were under severe drought. Hoque et al., (2021) applied Fuzzy AHP with GIS in southern Queensland in Australia and their finding indicated severe to extreme susceptibility in specific areas, aiding in the development of proactive drought mitigation strategies.

Koem et al., (2022) applied AHP and GIS in Kampong Speu Province of Cambodia for integrating drought hazard mapping that combines all influence parameters to develop detailed information to support drought mitigation plans and their result showed that Basedth, Samraong Tong, Odongk, and Kong Pisei districts are more prone to drought hazards. Mahato et al., (2023) employed geospatial techniques and the fuzzy AHP to formulate such a map for northwestern Odisha, India and the outcomes indicated that roughly 33% of the area is classified as having high drought vulnerability. Remote sensing data provides an effective source of spatial information to map drought susceptibility accurately (Mokarram et al., 2021). Each parameter's contribution to drought susceptibility is obviously not equal. To deal with this, one popular multi-criteria weighing technique is the AHP that is used to give weight to the influence of each parameter (Mokarram et al., 2021). When a weighting system is established for every parameter, susceptibility evaluation is considered more trustworthy (Mun et al., 2020). The resulting drought susceptibility maps are useful tools for examining regional variability of the severity of droughts (Drisya and Sathish Kumar, 2023).

Geospatial techniques make it easy to handle many data layers required for multi-criteria evaluation in order to identify drought risk zones (Palchaudhuri and Biswas, 2016). The ranking and finalization of the parameters and decision making comes from the user's knowledge, expertise, and insight from available literature (Sivakumar et al., 2021). To prepare for future land development, avert droughts, and lessen their negative effects, it is essential to gather data and carry out risk assessments in areas susceptible to droughts (Wijitkosum and Sriburi, 2019). To provide comprehensive susceptibility information for developing drought mitigation strategies, a multi-criteria-based spatial mapping approach for drought susceptibility that incorporates all drought-causing and aggravating characteristics using an appropriate weighting scheme is important.

In Ethiopia, there are only a few studies on drought susceptibility, despite the fact that drought is the biggest natural disaster affecting the country. Specifically, there is no study covering the Bilate river watershed that considers multiple drought-causing and aggravating factors. Therefore, the objective of this study was to undertake integrated spatial drought susceptibility modeling in the Bilate river watershed using geospatial and AHP techniques. The study also assessed the spatial

coverage of different drought severity categories in the watershed as well as by administrative units.

4.2. Materials and Methods

4.2.1. Study Area Description

The study was undertaken for the Bilate river watershed which is located in the south-western escarpment of the Main Ethiopian Rift Valley (Figure 4. 1). The Bilate watershed is a part of the Ethiopian Rift Valley which is part of the Great East African Rift Valley (Sulamo et al., 2021). Geographically, it is located between 6° 32'40'' - 8°09'29'' N and 37°46'11'' - 38°18'43'' E. The watershed covers an area of about 5,260 km². The north and northeastern part of the watershed has steep slopes and the central and the southern parts have gentle slopes (Burka et al., 2023). Bilate river is the longest river, with a length of 257 km, in the Abaya-Chamo sub-basin and the only river that flows into Lake Abaya from the north (Yilma et al., 2023). Bilate river is one of the inland rivers of Ethiopia, whose source is located in the Gurage mountains in central Ethiopia (Sulamo et al., 2021). Altitude of the watershed ranges from 1,116m to 3,373 m above sea level (Figure 4.1a). The watershed includes parts of Hadiya, Kembata, Gurage, Silte, Wolayta, Alaba, Sidama, and small parts of the West Arsi zones (Gintamo, 2015). According to (Orke and Li, 2022), the watershed has arid and semi-arid climatic conditions, with mean annual rainfall ranging from 916 to 1407 mm/year and temperature variations of 10.9 °C to 30.4 °C. The watershed has a bimodal rainfall characteristic with a short and main rainy seasons. The short rainy season (locally known as Belg season) extends from March to April and the main rainy season (locally known as Kiremt season) extends from July to September (Burka et al., 2023). Figure 4.5b shows that the watershed's western and northern parts receive more rainfall compared to the southernmost part. The northern and small portions of the watershed have a lowest temperature, while the southern and central parts have higher temperatures (Figure 4.5c). Agriculture is the dominant economic activity, particularly, in the highlands which receive relatively higher amount of rainfall, rain-fed cereal crop production, mixed farming, and agroforestry-based perennial crop production are the main livelihoods of the inhabitants. (Tesfamariam et al., 2019). The Bilate watershed is characterized by mixed cultivation and supports irrigation to grow commercial plants such as tobacco, vegetables, and maize (Orke and Li, 2021). The watershed is dominated by agricultural crops (60.2 %) of the land use and land cover (Figure 4.3h).

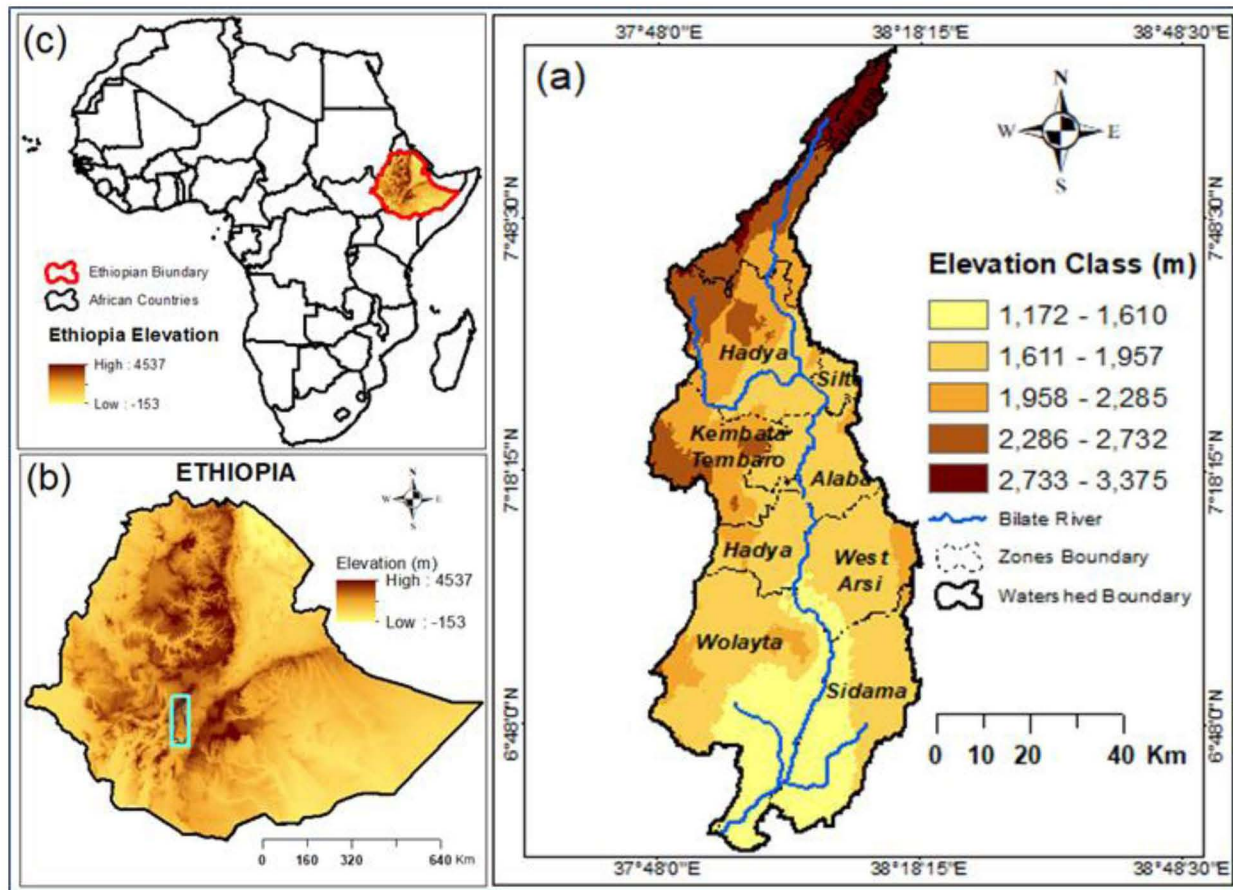


Figure 4.1: Location map of BRW: (a) elevation & zonal administration boundaries, (b) Study area location within Ethiopia in rectangular shape, and (c) location of Ethiopia within Africa. (Data source: Ethio-GIS and USGS).

4.2.2. Data types and sources

A combination of socio-economic characteristics, agro-climatic parameters, land use land cover, vegetation characteristics, and GIS/Remote sensing data was used to map the vulnerability to drought. For instance, meteorological data such as temperature and rainfall were used to to characterize drought patterns. Population density and other socioeconomic data are useful in assessing susceptibility from a societal perspective. Land use and cover data was collected to identify areas potentially impacted by drought. Slope and elevation were topographic parameters that were collected in this study to determine the effect on runoff and water availability. Soil texture and moisture retention capacity were collected.

Selecting the susceptibility parameters is an important part of the research methodology. Accordingly, 15 parameters were used to model drought in the Bilate River Watershed (BRW).

These include Rainfall (R), temperature (T), evapotranspiration (ET), elevation (E), slope (S), aspect (A), population density (PD), land use and land cover (LULC), normalized difference vegetation index (NDVI), land surface temperature (LST), modified normalized difference water index (MNDWI), topographic wetness index (TWI), drainage density (DD), soil moisture (SM), and soil texture (ST). Table 4.1 presents the lists of the key parameters, their descriptions, sources and temporal scope.

Table 4.1: Data types, sources and related attributes of data used in this research.

No.	Parameters	Data Type	Resolution	Data provider	Source (Data extraction website)	Period
1	RF	CHIRPS	0.05° x 0.05°	University of California, Santa Barbara (UCSB) & U.S. Geological Survey (USGS)	https://earlywarning.usgs.gov/fews/ewx	2000-2022
2	T	CHIRTSmax (max.Temperature)	0.05° x 0.05°	University of California, Santa Barbara (UCSB) & U.S. Geological Survey (USGS)	https://ewx3.chc.ucsb.edu/ewx	2000-2016
3	ET	Global ET data Version 6.0	1 x 1 Km	USGS FEWS NET	https://earlywarning.usgs.gov/fews/ewx	2021
4	SM	Soil Moisture expressed as volumetric water content % ((m ³ /m ³) * 100)	0.1°x0.1°	Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (https://LDAS.GSFC.NASA.GOV/FLDAS)	https://ewx3.chc.ucsb.edu/ewx	2019
5	NDVI	Satellite-derived index that measures the density of chlorophyll (greenness)	1Km x 1K m	U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center	https://www.chc.ucsb.edu	2012-2022
6	LST	MODIS LST	0.05° x 0.05°	U.S. Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center	https://earlywarning.usgs.gov/fews/ewx	2022
7	ST	Africa Soil Profiles Database (AfSP) v1.2	250m x 250m	ISRIC - World Soil Information	https://data.isric.org	2015
8	LULC	Generated from Sentinel-2	10m x 10m	ESRI	https://livingatlas.arcgis.com	2022
9	TWI	Generated from DEM	30m x 30m	NASA / USGS / JPL-Caltech	https://earthengine.google.com	2000
10	MNDWI	Generated from 'LANDSAT/LC08/C01/T1_TOA'	30m x 30m	U.S. Geological Survey (USGS)	www.googleearthengine.com	2020
11	DD	Generated from DEM	30m x 30m	NASA / USGS / JPL-Caltech	https://earthengine.google.com	2000
12	S	Generated from DEM	30m x 30m	NASA / USGS / JPL-Caltech	https://earthengine.google.com	2000
13	E	Generated from DEM	30m x 30m	NASA / USGS / JPL-Caltech	https://earthengine.google.com	2000
14	PD)	Global 2019 is a global Population (LandScan Global 2019)	1° x 1°	Oak Ridge National Laboratory for the United States Department of Defense	https://earlywarning.usgs.gov/fews/ewx	2019
15	A	Generated from DEM	30m x 30m	NASA / USGS / JPL-Caltech	https://earthengine.google.com	2000
16	VHI	Blended from VCI and TCI	1Kmx1Km	National Integrated Drought Information System	www.noasart.gov	1984

Note: RF (Rainfall), T (Temperature), ET (Evapotranspiration), SM (Soil Moisture), NDVI (Normalized Difference Vegetation Index), LST (Land Surface Temperature), ST (Soil Texture), LULC (Land Use and Land Cover), TWI (Topographic Wetness Index), MNDWI (Modified Normalized Difference Water Index), DD (Drainage Density), S (Slope), E (Elevation), PD (Population Density), and A (Aspect).

4.2.3. Drought Susceptibility Modeling

This research has undertaken a multi-criterion integrated spatial drought susceptibility modeling approach that uses geospatial techniques and AHP model incorporating pertinent drought causing and aggravating parameters in the context of the study area. AHP geospatial approaches combined provide useful tools for evaluating overall drought susceptibility (Ekrami et al., 2016). To create a map of drought susceptibility, the parameters were assessed and combined using weighting and ranking. Figure 4. 2 provides details regarding the modeling procedure and the parameters created.

4.2.3.1. Multi-Criteria Decision Analysis (MCDA)

Assessment of regional drought with MCDA was initially formulated using the AHP technique by Saaty (Hammami et al., 2019). According to Babaei et al., (2013) and Pandey and Srivastava, (2019), the major factors of the MCDA method is the performance matrix whereby a decision matrix is applied to explain an MCDA problem. In an MCDA problem, where the rows correspond to alternatives A_i ($i=1, 2, \dots, n$) and columns correspond to criteria $C = (C_j = 1, 2, \dots, m)$, the matrix for the problem has N rows and M columns. Entries for a_{ij} ($i = 1, 2, \dots, n, j = 1, 2, \dots, m$) is a number value or a single grade for all alternatives across all criteria as indicated in equation 1.

$$A = \begin{matrix} & \begin{matrix} W_1 & W_2 & \dots & W_m \\ C_1 & C_2 & \dots & C_m \end{matrix} \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix} \end{matrix} \quad (1)$$

The following step involves a decision-making process to determine the weights ($W_1, W_2, \dots, W_m$) for the criteria, which indicate each parameter's relative weight in relation to a goal.

In line with this, Spatial Multi-criteria Decision Analysis (SMCDA) is a process where geographical data are combined and transformed into a decision (Palchaudhuri and Biswas, 2016). Using geospatial techniques and multi-criteria decision analysis results in more versatile solutions for modeling drought-prone areas. One of the most extensively utilized MCDA techniques is Analytical Hierarchy Process (AHP) which has been established by Thomas L. Saaty in the 1970s (Kim et al., 2020; Olii et al., 2021).

4.2.3.2. Analytical Hierarchy Process (AHP)

Since its initial development by Saaty in 1980, the AHP has been applied to a variety of multi-criteria decisions. It is feasible to incorporate assessments of both qualitative and quantitative components using this technique (Babaei et al., 2013). It was used to create pairwise comparison matrices and determine each parameter's weighting factors (Kim et al., 2020 ; Sivakumar, Radha et al., 2021; Alharbi et al., 2022). Saaty's importance scale is used to generate the pairwise comparison matrix of n parameters, which serves as the fundamental input for calculating the weightage factors (Palchaudhuri and Biswas, 2016). Therefore, a scale of 1 to 9 may be used to build the decision matrix for the criteria impacting the decision (Table 4.2).

Table 4.2: Scale for various Table 4.s (Saaty, 1977; Saaty, 2008).

Intensity	Definition	Explanation
1	Equal Importance	Two elements contribute equally to the objective
3	Moderate Importance	Experience and judgment slightly favor one element over another
5	Strong Importance	Experience and judgment strongly favor one element over another
7	Very strong Importance	One element is favored very strongly over another, its dominance is demonstrated in practice
9	Extreme Importance	The evidence favoring one element over another is of the highest possible order of affirmation
2,4,6,8	Express intermediate values the two adjacent judgments	Where compromise is needed

Personal judgment and a survey of the literature were utilized to weigh the various parameters considered in this research. According to Kim et al., (2020), four steps make up an AHP assessment: identifying the decision element hierarchy, comparing decision components pairwise, estimating relative weights, and aggregating relative weights. Hence, the following were the basic processes for figuring out the system's consistency ratio (CR) and normal weight:

Multiple pairwise comparisons in AHP are based on a nine-level standard comparison scale (Table 4.2). Let $p = \{P_j \mid j = 1, 2, \dots, n\}$ be the set of parameters. The result of the pairwise comparison on n parameters can be summarized in a p ($n \times n$) evaluation matrix M in which every element p_{ij} ($i = 1, 2, \dots, N, j = 1, 2, \dots, N$) is the quotient of weights of the criteria, as shown in equation 2 (Babaei et al., 2013) :

$$M = \begin{bmatrix} p_{11} & p & \dots & p_{1n} \\ p_{21} & p_{22} & \dots & p_{2n} \\ \dots & \dots & \dots & \dots \\ p_{n1} & p_{n2} & \dots & p_{nn} \end{bmatrix}, p_{ij} = 1, p = \frac{1}{p_{ij}}, p_{ij} \neq 0 \quad (2)$$

Then, the biggest eigenvalue of the pairwise comparison matrix (λ_{max}) could be estimated using the following formula (Pandey and Srivastava, 2019):

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n \frac{x_i}{c_i} \quad (3)$$

Where n is the number of criteria; and c_i and x_i are the relative degree of importance (weight) and approximation to the eigenvector of the i^{th} objective.

The next step involves applying mathematics to normalize and determine the relative weights of each matrix. The right Eigenvector (w) that corresponds to the biggest Eigenvalue (λ_{max}) provides the relative weights as:

$$A_w = \lambda_{max} w \quad (4)$$

In the final analysis, it is imperative to verify the uniformity of the weights. The consistency is defined by the relation between the entries of $M=p_{ij} \times p_{jk} = p_{jk}$ as a consistency index (CI) and calculated as (Zagade and Umrikar, 2021):

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (5)$$

Where λ_{max} is the maximum eigenvector of the pairwise comparison matrix, if the pairwise comparisons are completely consistent, the matrix has rank 1 and $\lambda_{max} = n$. The weights can be found by normalizing any of the rows or columns. Finally, the consistency ratio (CR) is the comparison between the consistency index (CI) and the random consistency index (RI) and is calculated as (Zagade and Umrikar, 2021):

$$CR = \frac{CI}{RI} \quad (6)$$

The accuracy of the relation is assessed using the consistency ratio (CR), where a ratio of less than or equal to 0.1 suggests an adequate reciprocal matrix and a ratio of more than 0.1 suggests that the matrix needs to be changed (Koley and Jeganathan, 2023). RI can be obtained in Table 4.5a, whereas CI and CR indicated in Table 4.5b. The pairwise comparisons of the parameters were conducted using the built-in AHP module in TerrSet 2020 software.

4.2.3.3. AHP-Weighted Overlay Analysis

In this study, a 15 x 15-dimensional matrix (i.e., fifteen parameters) was taken as input in the AHP multi-criteria decision-making process for drought susceptibility modeling of the BRW. Weight of each parameter has been assigned according to the respective importance among the parameters. Rainfall is considered as the main controlling factor for drought susceptibility of the watershed. Because a lack of rainfall is the primary cause of drought (Palchaudhuri and Biswas, 2016). Temperature is the second most important parameter, followed by soil moisture, NDVI, LST, soil texture, LULC, TWI, modified NDWI, drainage density, slope, elevation, population density, and aspect.

Before the overlay analysis, all parameters were given ranks based on their contribution to drought susceptibility. Accordingly, due to their great susceptibility to drought, the low ranks (extreme drought) and high weights were given to areas with lower rainfall, while the highest ranks (no drought) and low weights were given to areas with the highest rainfall. In temperature parameter, areas having the highest temperatures were given low rank and high weight, and vice versa. In evapotranspiration parameter, areas with the highest evapotranspiration were assigned low ranks and high weights, and vice versa. In soil moisture, areas with the lowest soil moisture were given the lowest rankings and highest weights since there is a greater chance of drought, and vice versa. Because clay soil has a poor infiltration capacity and therefore a greatest risk of drought, locations with finer soil texture were given higher weights and lower ranks. Because there is a greater danger of drought in locations with the highest drainage density values due to increased rainfall water flow, those areas were given low rank and high weights, and vice versa. In NDVI parameter, areas with the lowest NDVI values have the highest risk of drought, so they were given high weights and low rank. In LST parameter, areas with the greatest LST values were assigned low ranks and high weights, indicating a maximum danger of drought, and vice versa. In TWI parameter, areas with the lowest TWI values had the most chance of drought, hence they were given the lowest rank and highest weights, and vice versa. In MNDWI parameter, areas with the lowest MNDWI values had the highest danger of drought, hence they were given high weights and low ranks, and vice versa. In slope

parameter, areas with the highest slope area were given the lowest rankings and highest weights since there is a greater likelihood of drought, and vice versa. In elevation parameter, places in the highest elevation class were assigned large weights and low ranks because of their higher susceptibility to drought. In LULC parameter, in comparison to other land uses and land covers, crops have a higher risk of drought vulnerability, so they are assigned lower ranks and heavier weights and built-up areas come in second. Finally, in population density parameter, the low ranks and high weights were allocated to areas with highest population density values as there is a maximum risk of drought and vice versa.

The final modeling can begin after all the parameters in thematic layers have been prepared, together with their matching weight. When combining and utilizing multiple layers to offer information, most geospatial analytic techniques involve the overlay process (Olii, et al., 2021). Hence, for assessing potential drought-prone area, the weighted overlay analysis provides a quick, straightforward, and adequate method. The parameters were given a numerical proportionate rating on a 1–5 scale based on their significance. Additionally, weights and ranks were assigned to the parameter classes; higher weights and lower ranks indicated a larger influence on the drought susceptibility in this research. After multiplying each parameter by its weights using equation 7 in the GIS environment, the drought susceptibility map (DSM) was generated. DSM was categorized into five classes: Extreme, Severe, Moderate, Mild and No drought.

$$DSM = \sum_{i=1}^n W_j * T_i \quad (7)$$

Where, W_j means the weights of each parameter multiplied by the drought parameter layers (T).

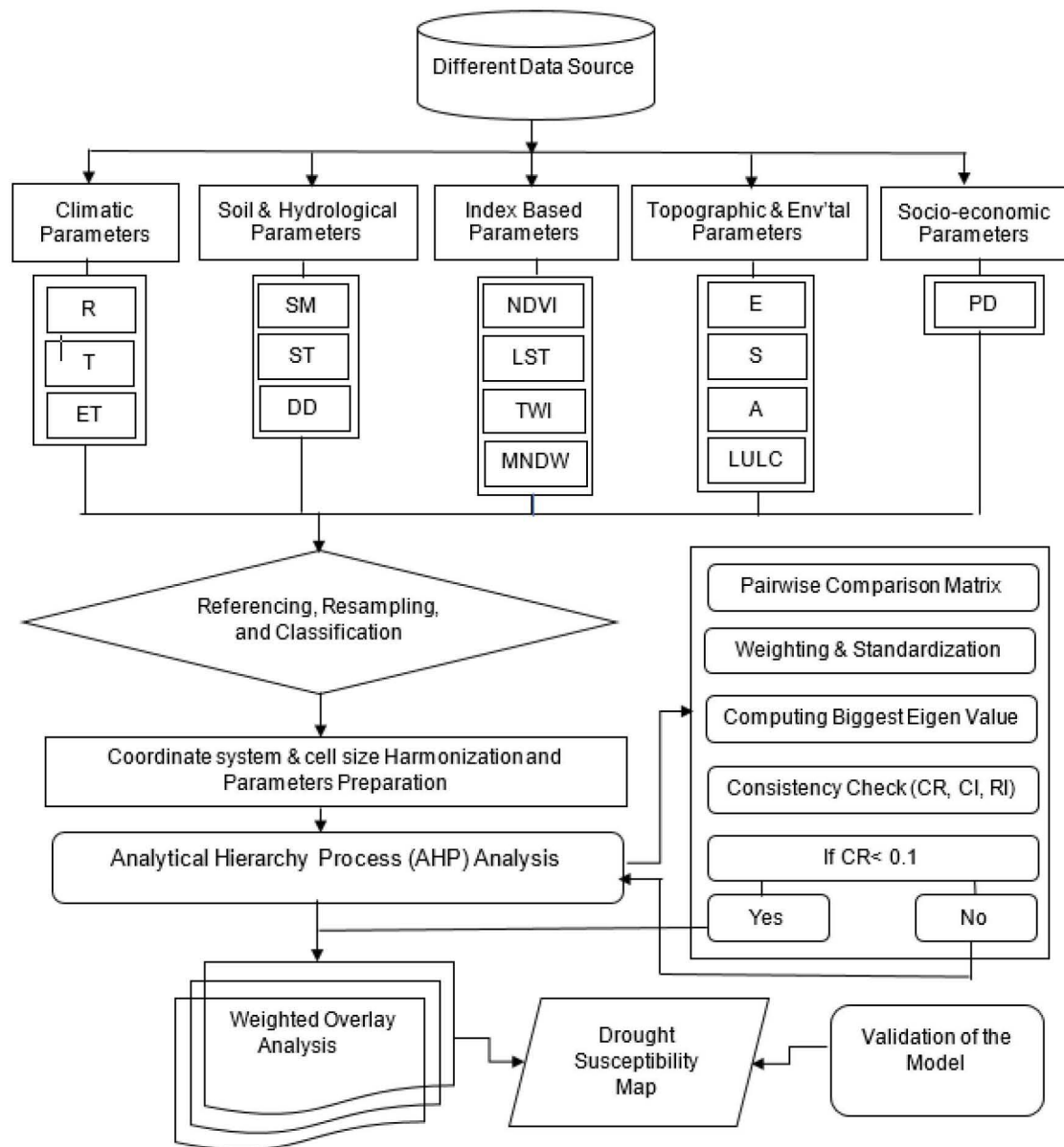


Figure 4.2: Methodological flowchart for drought susceptibility modeling applied in this research.

The spatial data preprocessing, modeling and mapping of the final results were conducted using ArcGIS software.

4.2.3.4. Validation of the Model

Validating the drought model and estimating the robustness of the employed approaches are crucial steps in determining the correctness of the results (Arabameri et al., 2022). To validate the susceptibility model's performance, the AUC-ROC approach was employed. The conventional technique can be used to evaluate how accurate the susceptibility model is (Hoque

et al., 2021) and it is among the most significant statistical metrics (Abedi et al., 2022). An evaluation metric that is widely used and unaffected by threshold selection is the AUC-ROC (Jiao et al., 2019). The AUC-ROC analysis was conducted using ArcSDM analysis tool of ArcGIS software.

The model's ability to distinguish between positive and negative categories is indicated by the AUC. Plotting the true positive rate (sensitivity) against the false positive rate (specificity) for different categorization thresholds, it displays the area under the ROC curve. The range of the AUC is 0.5 to 1 (Luu et al., 2021) and more effective model performance is indicated by higher values of AUC (Wang et al., 2023). Area under the curve (AUC) characterizes model competency (Saha et al., 2021; Wang et al., 2023).

On the other hand, the Receiver Operating Characteristic (ROC) provides a graphic representation of the relationship between the true positive rate and the false positive rate. The true-positive rate versus the false-positive rate at various thresholds is plotted to create the ROC curve (Jiao et al., 2019; Eini et al., 2020). The validation dataset was utilized to plot and compute the area under the ROC curve (Rahmati et al., 2020). Because of the absence of documented historical drought information at watershed scale, the global validated VHI (Vegetation Health Index) of 1984 data was downloaded (www.drought.gov) to be used for validation of the model. 1984 was one of the worst drought years in most parts of Ethiopia. From the VHI data, 500 stratified random samples were generated and extracted the raster values of VHI. The VHI values that have greater than 40 were eliminated, and 347 random points were selected as a validation dataset. The ROC-AUC, sensibility and specificity calculated on the following equations (Jiao et al., 2019):

$$AUC - ROC = \left(\frac{\sum TP + \sum TN}{(P+N)} \right) \quad (8)$$

$$PTP(Sensitivity) = \frac{TP}{(TP+FN)} \quad (9)$$

$$PTN(Specificity) = \frac{TN}{(FP+TN)} \quad (10)$$

where, TP is true positive, FN is false negative, PTP is proportion of false positive, and PTN is proportion of true negative.

The other statistical method used for determining the relationship between the DSM (Drought Susceptibility Model) and the VHI data that was downloaded for validation purpose is correlation coefficient. Correlation coefficient ('r') is a commonly used test statistic that quantifies the degree of convergence between two array and its value is number between -1 and 1 using equation 11 (Jain et al., 2015):

$$r = \frac{\sum_{i=1}^n (DSM_i - \overline{DSM})(VHI_i - \overline{VHI})}{\sqrt{\sum_{i=1}^n (DSM_i - \overline{DSM})^2} \sqrt{\sum_{i=1}^n (VHI_i - \overline{VHI})^2}} \quad (11)$$

Where, n is the number of observations, DSM is the value of Drought Susceptibility Model, VHI is the value of Vegetation Health Index, $\overline{DSM}$ is the mean of DSM and $\overline{VHI}$ is mean of VHI. The correlation analysis was conducted using R statistical software package.

4.3. Results and Discussion

4.3.1. Drought Susceptibility Raster layers

4.3.1.1. Climatic Parameters: Rainfall, Temperature, and Evapotranspiration

The mean annual rainfall shows a very high spatial variability in the watershed (Figure 4.3a). The highest average rainfall range recorded was 93.83 – 104 mm, with the lowest range being 44.88 - 62.97 mm, with an area coverage of 5% and 4.86%, respectively as shown in Table 4.6. The north and northwest have more rainfall than the south.

The intensity of temperature also determines the severity and duration of drought. Compared to low-temperature locations, high-temperature areas are more vulnerable to drought. Hence, temperature is the second most influential parameter in determining the occurrence of drought. The highest average temperature range was 28.20 – 30.26 °C, with the lowest range being 20.11 - 24.33 °C, with area coverages of 19.6% and 7.03% of the watershed, respectively as shown in Table 4.6. About 33% of the watershed is covered with average temperature range of 26.13- 27.23 °C. The southern part of the watershed showed the highest temperature class (Figure 4.3b).

Availability of moisture in soils and plants is determined by evapotranspiration. If there is more evapotranspiration, the loss of moisture is higher and consequently more drought condition is

expected. Hence, evapotranspiration is the other most influential parameter in determining the occurrence of drought. The highest average evapotranspiration range was 82.09 -155.7 mm, with the lowest range being 0.58-23.09 mm, with area coverages of 1.56% and 9.53% of the watershed, respectively, as shown in Table 4.6. About 33% (highest coverage) of the watershed is covered with the average temperature range of 40.12 - 54.10 mm.

4.3.1.2. Soil and Hydrological Parameters: Soil Moisture, Soil Texture and Drainage Density

The highest average soil moisture range was 0.32-0.33 mm, with the least range being 0.23-0.25 mm, with an area coverage of 6.03% and 18.40% of the watershed, respectively (Table 4.6 and Figure 4.3d). The highest coverage (27.27%) of the watershed covered with the average temperature range of 0.26-0.27mm. Storing moisture and supplying it to plants during dry spells is one of the soil's primary roles (Jain et al., 2015). The availability of moisture in soil is determined by its water holding capacity. If there is more moisture in the soil, the growth of plants becomes better and the probability of drought condition is low. Hence, soil moisture is the other influential parameter in determining the occurrence of drought.

Soil texture determines the water holding capacity of soils, because soil texture affects soil infiltration rate (Ekrami et al., 2016). Soil that has a coarser soil texture drain the water rapidly and consequently vulnerable to drought. Hence, clay soil is the least vulnerable to drought due to its capacity in water holding. Soil texture of the watershed varies from clay to sandy loam (Table 4.6). Majority of the watershed (52.53%) is covered with clay loam soils. This soil covers mostly the northern, western and southwestern parts of the watershed. The coarser texture soil like sandy clay loam that have 15.44 % coverage of the watershed is found at the southwestern part of the watershed. Sand and sandy loams are among the most permeable soils, allowing for rapid infiltration; clay and clay loam soils, on the other hand, are the least permeable soils, also having lower infiltration rates (Nyayapathi et al., 2023).

The drainage density, which is measured in km/km^2 , indicates the total length of streams per unit area, influences the rate of infiltration (Zagade and Umrikar, 2021). It links the processes that take place along the stream course with the landform characteristics of the watershed. When the drainage density is low, it means that most of the water percolates into the subsurface and that not many channels have developed to carry the surface runoff that is generated. Increased surface water flow in the area due to higher drainage density increases the area's susceptibility to drought conditions. The highest drainage density was 0.68-1.2097 Km/Km^2 , with the least range being 0.00-0.97 km/km^2 , with an area coverage of 1.33% and 66.30% of

the watershed, respectively, as shown in Table 4.6. The southern part of the watershed is covered with the highest drainage density range class (Figure 4.4b).

4.3.1.3. Index-Based Parameters: NDVI, LST, TWI and MNDWI

The highest NDVI was 0.70-0.78, with the lowest range being 0.17-.40, with area coverages of 22.94% and 3.44% of the watershed, respectively, as shown in Table 4.6. 32.62% (highest coverage) of the watershed covered with the average temperature range of 26.13-27.23⁰C. Areas with the lowest NDVI values have the highest danger of drought, so they were given high weights and low rankings. Due to its application in reaction to the drought, the NDVI is viewed as an indirect component in the assessment of droughts (Zagade and Umrikar, 2021).

Another essential environmental indicator is LST, especially when it comes to monitoring droughts (Adi Nugraha et al., 2019). Through its monitoring of the earth's energy balance, the LST offers information on the physical characteristics and climate of the surface. Lower rainfall conditions brought by the higher LST results in a decrease in vegetation cover. There is less surface water remaining as a result of increased evaporation brought by the higher temperature, which dries out the soil and vegetation and results in drought. The highest LST was 38 - 42 ⁰C, with the lowest range being 22 - 26 ⁰C, with an area coverage of 25.54% and 9.69% of the watershed, respectively, as shown in Table 4.6.

TWI correlates positively with soil moisture at the 0-1 m soil surface and is calculated by integrating the upper and local slopes area, both of which reflect the location's wetness (Olii et al., 2021). Therefore, drought is more likely to occur in areas with lower TWI. The highest TWI was 13.7-24.0, with the lowest range being 2.03-5.75, with an area coverage of 2.03% and 39.68% of the watershed, respectively, as shown in Table 4.6.

Plant water stress can be predicted using NDWI because of its strong correlation with both plant water content (Alharbi et al., 2022) and rainfall (Adi Nugraha et al., 2019). However, compared to the NDWI, the MNDWI can show more information about the open water (Xu, 2006). Hence, drought is more likely to occur when there is lower MNDWI. The highest MNDWI was -0.078- -0.37, with the least range being -0.68- -0.26, with an area coverage of 0.65% and 26.92% of the watershed, respectively, as shown in Table 4.6. The central and eastern part of the watershed was covered with the lowest MNDWI range class (Figure 4.4a).

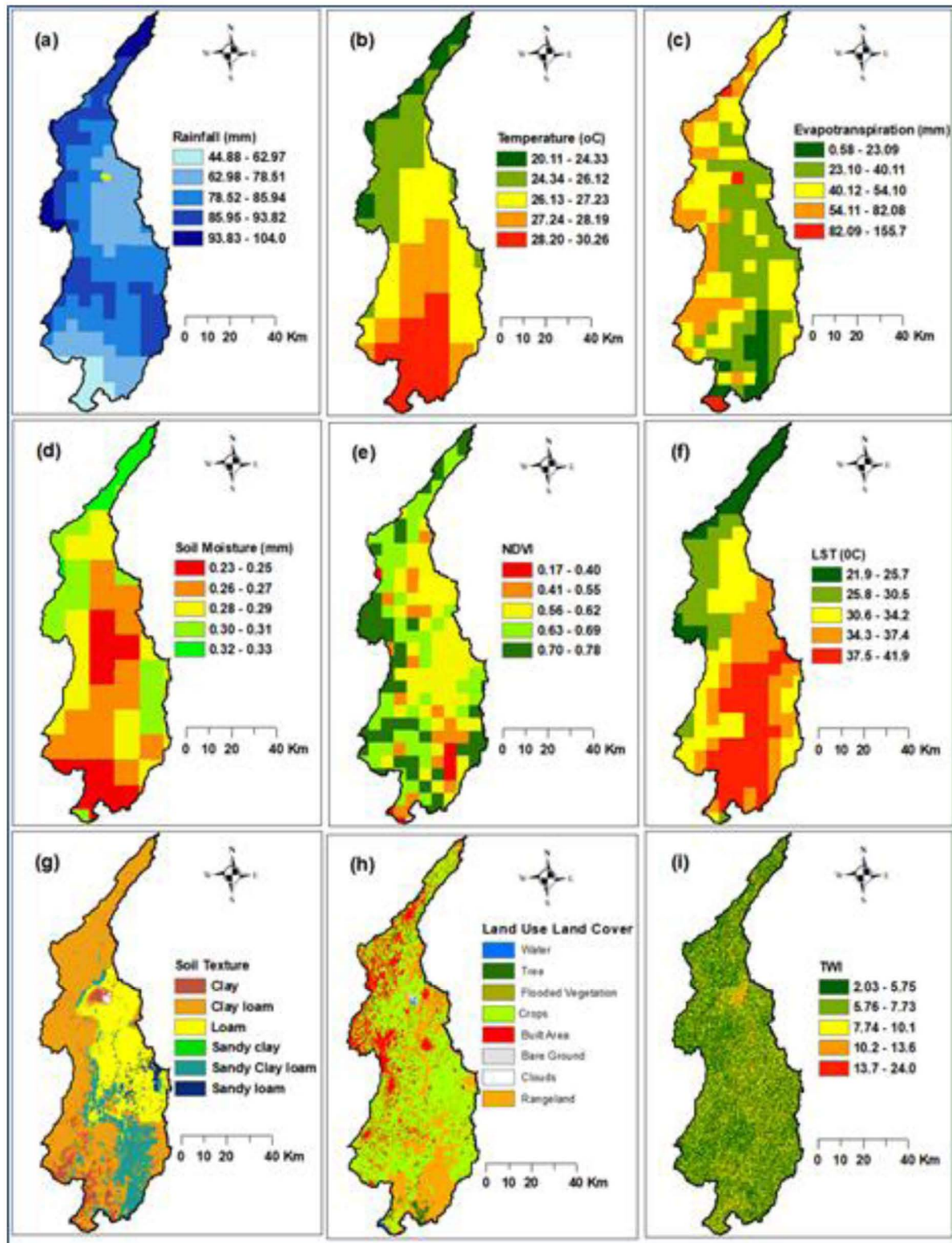


Figure 4.3: Raster layers (parameters): (a) R, (b) T, (c) ET, (d) SM, (e) NDVI, (f) LST, (g) ST, (h) LULC, and (i) TWI

4.3.1.4. Topographic and Environmental Parameters

4.3.1.4.1. Slope, Elevation and Aspect

Figure 4.4c presents the slope classes of the study area. The northern, western and southwestern parts of the watershed covered the highest slope class. The highest slope was 26.0-66.0 in degree, with the least range being 0.00 - 0.97 in degree, with an area coverage of 1.50% and 54.28% of the watershed, respectively as shown in Table 4.6. The land's slope has a significant role in generating runoff and promoting rainwater infiltration. Higher slope gradients will result in less rainwater infiltration, which will assist in the drought situation. Water flow over steeper terrain is substantially higher than it is at the nearby ground surface (Alharbi et al., 2022). Areas with steep slopes are thought to be more vulnerable to drought than areas with gentle slopes or flat terrain (Wu et al., 2017). Therefore, it is believed that places with lower slopes are less likely to experience drought than areas with intermediate or higher slopes (Zagade and Umrikar, 2021).

Table 4.6 displays the highest elevation range (2701-3400 m) and lowest elevation range (1200-1600 m), corresponding to an area coverage of 4.16% and 19.40% of the watershed, respectively. The watershed's middle region, which is within the elevation class of 1600-1900 m, has the highest coverage (45.95%), whereas the southern portion of the watershed has the lowest elevation class (Figure 4.4d). Water availability greatly depends on relative elevation of the place in the watershed (Jain et al., 2015). When compared to the nearby ground surface, water runoff is significantly higher over steeper terrain (Alharbi et al., 2022). In comparison to lower elevations, higher altitudes are unable to hold as much water.

Majority (27.88 %) of the watershed occupied by the aspect of flat (-1) where the west (247.5-292.5) and the east (67.5-112.5) have a coverage of 16.27% and 16.02%, respectively (Table 4.6 and Figure 4.4f). Thus, after a thorough analysis of relevant literature, susceptibility classes of various aspect ranges have been discovered, and ranks and weight have been assigned in accordance with these findings. Aspect is the orientation of the slope; different aspects get varied amounts of solar radiation, which affects hydrology of the research area (Alharbi et al., 2022). According to Ekrami et al., (2016), aspects were analyzed, and susceptibility classes were generated.

4.3.1.4.2. Land Use Land Cover

LULC is one of the most important variables to consider when determining how a particular area is affected by droughts. The degree of drought is largely influenced by land use and land cover (Zagade and Umrikar, 2021). High vegetation cover areas are more vulnerable to droughts than low vegetation cover areas in terms of land cover. Majority of the watershed (60.25%) covered with crops indicating the watershed is dominated by cultivating land (Figure 4.3h). Range land and built up area have 20.56% and 16.52 % coverage, respectively. The southern tip of the watershed is covered with cultivated and grazing lands.

4.3.1.5. Socio-economic Parameter

4.3.1.5.1. Population Density

Table 4.6 presents the highest population density (9101-1700 person/Km²) and lowest elevation range (0-390 person/Km²), corresponding to an area coverage of 0.18% and 56.20% of the watershed, respectively. The watershed's western, northwestern and southwestern parts, which is within the density class of 1401-4200 persons/Km², has area coverage 1.81% (Figure 4.4e). The areas with less population and hence low water demand category are comparatively less susceptible to drought (Jain et al., 2015). Places with dense populations are more susceptible to drought than those with smaller populations because of their higher levels of water demand and use (Alharbi et al., 2022).

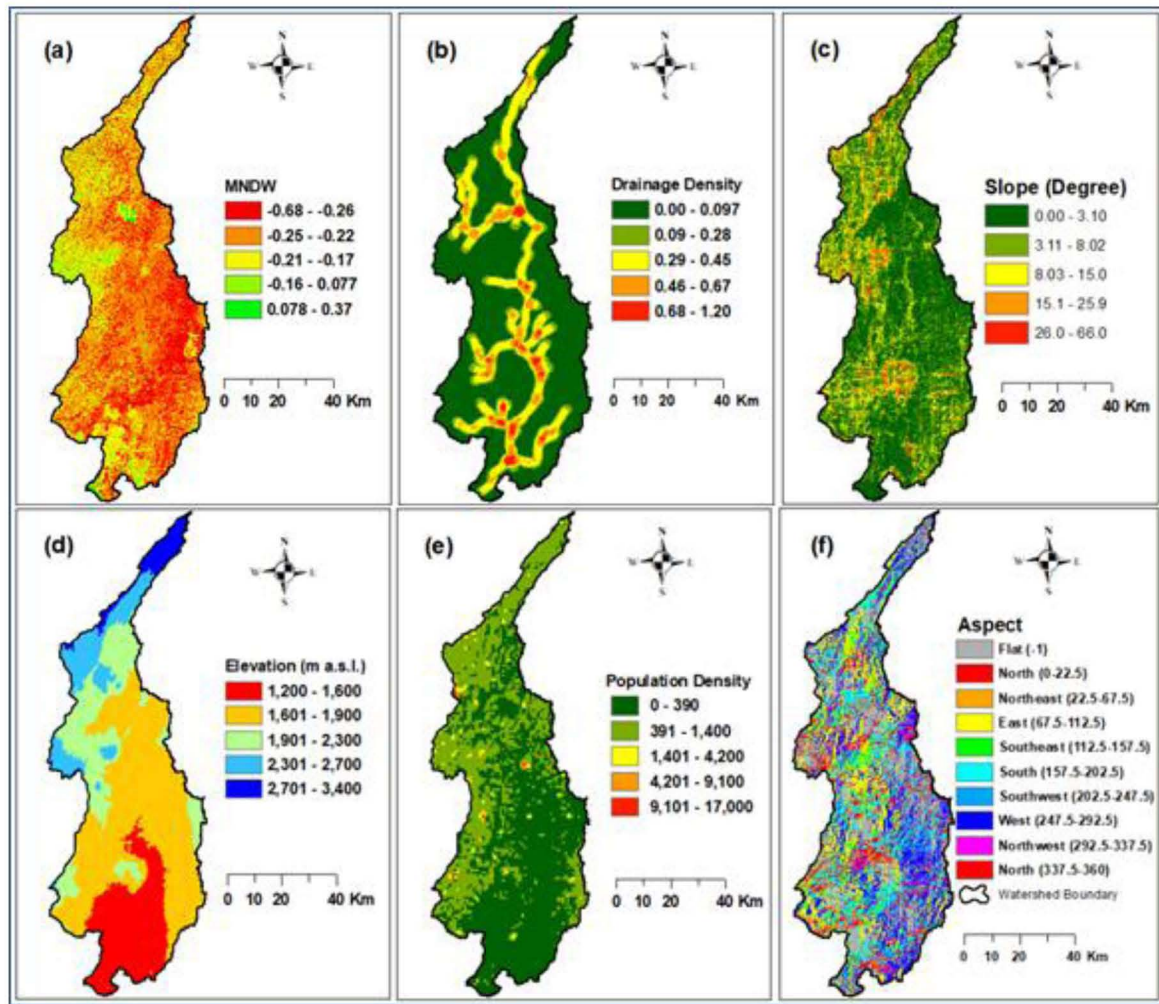


Figure 4.4: Raster layers (parameters): (a) MNDWI, (b) DD, (c) S, (d) E, (e) PD, and (f) A

4.3.2. AHP Weight Allocation

The pairwise comparison matrix (Table 4.3) and normalized vector for the drought susceptibility (Table 4.4) for each parameter shows the weight of each parameter calculated according to its importance. The random index Table 4. and consistency index Table 4. are simultaneously checked whether the model will be accepted or not. If the consistency ratio value is less than 0.1, the weighted model is correct for subsequent analysis (Table 4.5a and 4.5b). Weight and rating are given according to the importance of each parameters (Saaty, 2008) (Table 4.2). Therefore, the predicted model for drought susceptibility can be accepted because the consistency ratio value in the AHP analysis of the current research is 0.03.

Table 4.3: Pairwise comparison matrix of selected parameters for drought susceptibility modeling.

Parameters	RAINFALL	T	ET	SM	NDVI	LST	ST	LULC	TWI	MNDWI	DD	S	E	PD	A
RF	1	1	1	2	3	3	5	5	5	7	7	7	9	9	9
T	1	1	1	1	3	3	3	5	5	5	7	7	7	8	9
ET	1	1	1	1	1	2	2	3	5	5	7	7	8	8	8
SM	1/2	1	1	1	1	1	2	3	3	3	4	5	5	7	8
NDVI	1/3	1/3	1	1	1	1	1	3	3	5	5	4	4	6	7
LST	1/3	1/3	1/2	1	1	1	1	2	3	3	3	3	4	5	7
ST	1/5	1/3	1/2	1/2	1	1	1	1	2	3	3	3	4	5	5
LULC	1/5	1/5	1/3	1/3	1/3	1/2	1	1	1	2	3	3	3	4	5
TWI	1/5	1/5	1/5	1/3	1/3	1/3	1/2	1	1	1	2	3	4	4	4
MNDWI	1/7	1/5	1/5	1/3	1/5	1/3	1/3	1/2	1	1	1	2	4	3	4
DD	1/7	1/7	1/7	1/4	1/5	1/3	1/3	1/3	1/2	1	1	1	2	3	3
S	1/7	1/7	1/7	1/5	1/4	1/3	1/3	1/3	1/3	1/2	1	1	1	2	3
E	1/9	1/7	1/8	1/5	1/4	1/4	1/4	1/3	1/4	1/4	1/2	1	1	1	2
PD	1/9	1/8	1/8	1/7	1/6	1/5	1/5	1/4	1/4	1/3	1/3	1/2	1	1	1
A	1/9	1/9	1/8	1/8	1/7	1/7	1/5	1/5	1/4	1/4	1/3	1/3	1/2	1	1

Note: RF (Rainfall), T (Temperature), ET (Evapotranspiration), SM (Soil Moisture), NDVI (Normalized Difference Vegetation Index), LST (Land Surface Temperature), ST (Soil Texture), LULC (Land Use and Land Cover), TWI (Topographic Wetness Index), MNDWI (Modified Normalized Difference Water Index), DD (Drainage Density), S (Slope), E (Elevation), PD (Population Density), and A (Aspect).

Table 4.4: Normalized pairwise comparison matrix.

Parameters	RF	T	ET	SM	NDVI	LST	ST	LULC	TWI	MNDWI	DD	S	E	PD	A	Normalized Weight	Weight (%)
RF	0.180879	0.159625	0.135244	0.212363	0.232988	0.207955	0.275482	0.192678	0.163488	0.1875	0.154982	0.146341	0.156522	0.134328	0.118421	0.177	17.7
T	0.180879	0.159625	0.135244	0.106181	0.232988	0.207955	0.165289	0.192678	0.163488	0.133929	0.154982	0.146341	0.121739	0.119403	0.118421	0.156	15.6
ET	0.180879	0.159625	0.135244	0.106181	0.077663	0.138637	0.110193	0.115607	0.163488	0.133929	0.154982	0.146341	0.13913	0.119403	0.105263	0.132	13.2
SM	0.090439	0.159625	0.135244	0.106181	0.077663	0.069318	0.110193	0.115607	0.098093	0.080357	0.088561	0.10453	0.086957	0.104478	0.105263	0.102	10.2
NDVI	0.060293	0.053208	0.135244	0.106181	0.077663	0.069318	0.055096	0.115607	0.098093	0.133929	0.110701	0.083624	0.069565	0.089552	0.092105	0.090	9.00
LST	0.060293	0.053208	0.067622	0.106181	0.077663	0.069318	0.055096	0.077071	0.098093	0.080357	0.066421	0.062718	0.069565	0.074627	0.092105	0.074	7.40
ST	0.036176	0.053208	0.067622	0.053091	0.077663	0.069318	0.055096	0.038536	0.065395	0.080357	0.066421	0.062718	0.069565	0.074627	0.065789	0.062	6.20
LULC	0.036176	0.031925	0.045081	0.035394	0.025888	0.034659	0.055096	0.038536	0.032698	0.053571	0.066421	0.062718	0.052174	0.059701	0.065789	0.047	4.70
TWI	0.036176	0.031925	0.027049	0.035394	0.025888	0.023106	0.027548	0.038536	0.032698	0.026786	0.04428	0.062718	0.069565	0.059701	0.052632	0.040	4.00
MNDWI	0.02584	0.031925	0.027049	0.035394	0.015533	0.023106	0.018365	0.019268	0.032698	0.026786	0.02214	0.041812	0.069565	0.044776	0.052632	0.032	3.20
DD	0.02584	0.022804	0.019321	0.026545	0.015533	0.023106	0.018365	0.012845	0.016349	0.026786	0.02214	0.020906	0.034783	0.044776	0.039474	0.025	2.50
S	0.02584	0.022804	0.019321	0.021236	0.019416	0.023106	0.018365	0.012845	0.010899	0.013393	0.02214	0.020906	0.017391	0.029851	0.039474	0.021	2.10
E	0.020098	0.022804	0.016905	0.021236	0.019416	0.01733	0.013774	0.012845	0.008174	0.006696	0.01107	0.020906	0.017391	0.014925	0.026316	0.017	1.70
PD	0.020098	0.019953	0.016905	0.015169	0.012944	0.013864	0.011019	0.009634	0.008174	0.008929	0.00738	0.010453	0.017391	0.014925	0.013158	0.013	1.30
A	0.020098	0.017736	0.016905	0.013273	0.011095	0.009903	0.011019	0.007707	0.008174	0.006696	0.00738	0.006969	0.008696	0.014925	0.013158	0.012	1.20
Total	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	100

Note: RF (Rainfall), T (Temperature), ET (Evapotranspiration), SM (Soil Moisture), NDVI (Normalized Difference Vegetation Index), LST (Land Surface Temperature), ST (Soil Texture), LULC (Land Use and Land Cover), TWI (Topographic Wetness Index), MNDWI (Modified Normalized Difference Water Index), DD (Drainage Density), S (Slope), E (Elevation), PD (Population Density), and A (Aspect).

Table 4.5: Random index (RI) for drought susceptibility, RI for n values to calculate the CR (Saaty 2008).

(a) Random index (RI) for n values to calculate the consistency ration (Saaty, 2008)															
n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

Table 4.6: Consistency index (CI) and consistency ratio (CR) for drought susceptibility modeling.

λ_{max}	n (parameters)	RI	CI	CR	Consistency Check
15.73907894	15	1.59	0.052791353	0.033202109 = 3 %	CR < 0.1(Acceptable)

Table 4.7: Ranks of parameter classes based on their capability of drought susceptibility and area (Km²)

Categories	Parameters	Ranking of Drought Susceptibility				
		Extreme (1)	Severe (2)	Moderate (3)	Mild (4)	No Drought (5)
Climatic Parameter	Rainfall	44.88 - 62.97	62.98 - 78.51	78.52 - 85.94	85.95 - 93.82	93.83 - 104
	Area (Km ²)	259.33	1460.33	1974.28	1372.25	266.61
	Temperature	28.20-30.26	27.24-28.19	26.13-27.23	24.34-26.12	20.11-24.33
	Area (Km ²)	1042.90	1010.51	1739.36	1165.23	374.99
	Evapotranspiration (mm)	82.09-155.7	54.11-82.08	40.12-54.10	23.10-40.11	0.58-23.09
Soil and Hydrological Parameters	Area (Km ²)	83.16	1006.21	1766.55	1968.70	508.23
	Soil moisture	0.23-0.25	0.26-0.27	0.28-0.29	0.30-0.31	0.32-0.33
	Area (Km ²)	980.83	1454.22	1401.13	1174.07	321.64
	Soil Texture	C	CL	L	SCL	SL
	Area (Km ²)	338.54	2790.72	1263.88	820.41	90.53
Index Based Parameters	Drainage Density	0.68-1.20	0.46-0.67	0.29-0.45	0.098-0.28	0.00-0.97
	Area (Km ²)	70.94	321.05	873.42	530.41	3533.57
	NDVI	0.17-.40	0.41-0.55	0.56-0.62	0.63-0.69	0.70-0.78
	Area (Km ²)	183.45	581.65	1785.23	1554.00	1221.53
	LST	38-42	35-37	32-34	27-31	22-26
	Area (Km ²)	1362.18	1270.35	1355.17	828.41	516.66
	TWI	2.03-5.75	5.76-7.73	7.74-10.1	10.2-13.6	13.7-24.0
	Area (Km ²)	1612.90	1363.47	679.44	326.86	82.41
Topographic and Environmental Parameters	MNDWI	-0.68- -0.26	-0.25- -0.22	-0.21- -0.17	-0.16- -0.077	-0.078- -0.37
	Area (Km ²)	1435.24	2156.80	1267.70	436.62	34.42
	Elevation (m)	2701-3400	2301-2700	1901-2300	1601-1900	1200-1600
	Area (Km ²)	221.61	554.32	1071.50	2449.43	1033.93
	Slope	26.0-66.0	15.1-25.9	8.03-15.0	3.11-8.02	0.00-3.10
	Area (Km ²)	79.74	265.00	656.70	1427.90	2884.07
	Aspect	S	SW-SE	WE	NE-NW	N
	Area (Km ²)	575.05	304.31	778.95	702.38	127.04
Socio-economic parameter	LULC	CR	BA	RL	FV	T
	Area (Km ²)	3211.64	880.80	1096.01	0.94	111.00
	Population Density	9101-1700	4201-9100	1401-4200	391-1400	0-390
	Area (Km ²)	9.69	21.89	96.69	2206.79	2995.76

Note: S=South, SW-SE=Southwest-Southeast, WE=Westeast, NE-NW=Northeast-Northwest=North, CR=Crops, BA= Built Area, RL=Rangeland, FG= Flooded Vegetation, T=Tress, C= Clay, CL= Clay Loam, L= Loam, SCL=Sandy Clay Loam, and SL= Sandy Loam

4.3.3. Drought Susceptibility of Bilate River Watershed

Different drought susceptibility categories were generated after the modeling of susceptibility as shown in Figure 4.5. According to Figure 4.5a, approximately 70.23% (3694.92 km²) and 23.16% (1218.67 km²) of the watershed are susceptible to moderate and severe droughts, respectively. The sum of these drought categories covered 93.39% (4913.59 km²) of the study watershed, implying that the majority of the watershed is susceptible to drought. The extreme drought category covers insignificant areal coverage 6.60% (347.05 km²) in the watershed (Table 4.7a). The study area's central, southern, and southwestern regions, particularly Alaba, Kembata, west Arsi, Wolayta zonal administration and Sidama regional administration are covered by moderate-to-severe drought categories.

Areas at severely susceptible to droughts are found in parts of Wolayta zone (54.12%), Alaba zone (13.80%) and Sidama region (16.04%) which covers 83.96% (972.88 km²) of the watershed. Areas at moderately susceptible to droughts are found in some parts of Hadiya (24.59%), Wolayta (17.13%), west Arsi (13.85%) zones and Sidama region (16.26%) which cover 71.83% (1062.69 km²) of the total watershed (Figure 4.5b). Conversely, areas susceptible to mild droughts found in Silte 51.08 % (176.85 km²) and Gurage 19.22% (66.55 km²) zones which comprise 70.3% (243.4 km²) of the watershed. The mild drought areas are found in higher elevation class of the watershed. These areas (mild drought) are observed in the western part of Hadiya and northern part of Gurage zones, and some portion of Silte Zone. Wolayta and Hadiya zones covered with high percentage of severe and moderate drought in the watershed, respectively (Figure 4.6a and 4.6b).

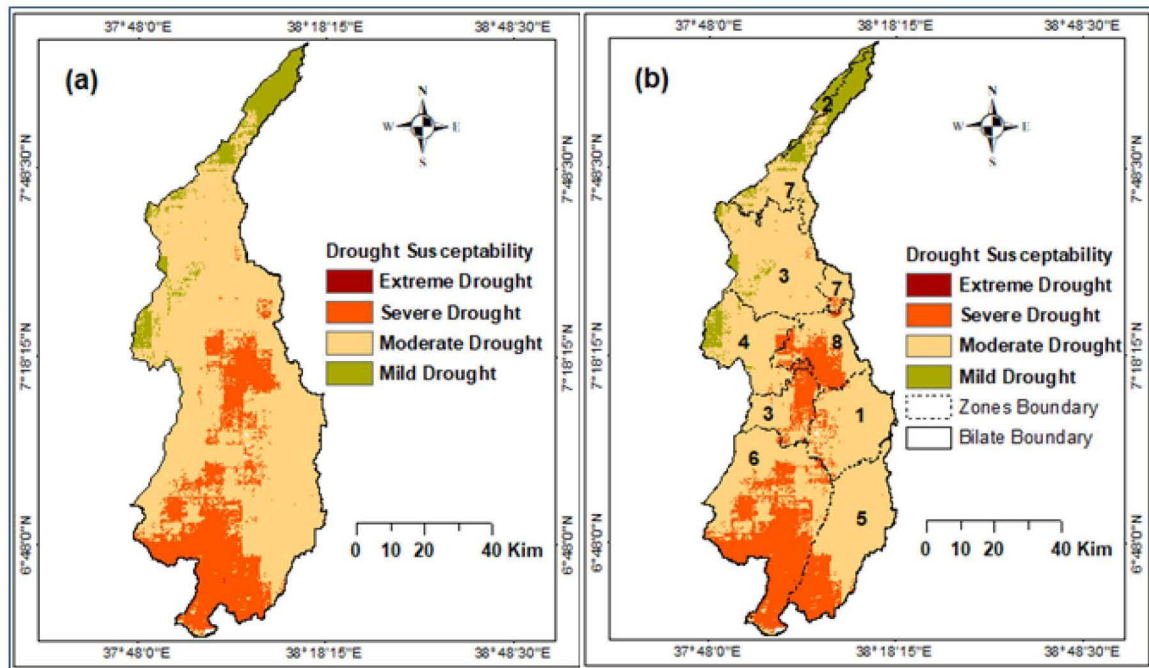


Figure 4.5: Drought Susceptibility map: (a) in a watershed, and (b) Zonal administration (1 = West Arsi, 2 = Gurage, 3 = Hadiya, 4 = Kembata, 5 = Sidama, 6=Wolayta, 7 = Silte, and 8=Alaba).

The central and southern parts of the Bilate River watershed, which is primarily agricultural area, have a high risk of drought (Figure 4.5a). The present study's findings are consistent with those of (Hessebo, Woldeamanuel and Tadesse, 2021), who found that over the last three decades, the central and lower catchment areas have experienced warming and increased susceptibility to drought. These areas, which are characterized by severe drought category, are high in temperature and relatively low in elevation. Figure 4.3b and 4.4d show the high temperature and low elevation, respectively. Apart from variations in drought categories this finding indicates that drought happens everywhere in the watershed. The result of Haile et al., (2022), showed that drought events occurred in all areas of the watershed, although to varying degrees, is consistent with the occurrence of drought in this research modeling. Moreover, the outcomes of this research indicate that rainfall, temperature, soil moisture, land surface temperature, and elevation had a significant impact on the watershed's drought susceptibility modeling. According to Figure 4.3a and 4.3b, severe drought occurs in areas with low rainfall and high temperatures. Bouabdelli et al., (2022) verified that high temperatures and low rainfall are associated with drought occurrences. Figure 4.3d illustrates how severe droughts also happen in low-moisture areas (Yu et al., 2023), additionally agree with this, stating that low soil moisture levels are an indicator of drought. Furthermore, the low altitude portion of the

watershed experienced the severe drought that was noted in the watershed's central and southern regions (Figure 4.4d). This is also supported by the fact that droughts typically happen at low altitudes (Karnieli et al., 2010; Wolteji et al., 2022).

Overall, the watershed has a spatial coverage of 23.16% (1218.67 Km²) and 70.23% (3694.92 Km²) for severe and moderate drought, respectively (Table 4.7a). This showed that the entire watershed is susceptible to droughts, which could have a negative effect on the livelihood of the local community. Parts of the Wolayta zone, Alaba zone, and Sidama region are seriously covered by severe drought on zonal administration basis (Figure 4.5b). In comparison to other areas of the watershed, the Wolayta zone has a high spatial coverage of severe drought, 54.12% (659.28 Km²) Table 4.7b). This is also consistent with the finding made of (Haile et al., 2022), that the Wolayta zone is suffering from a severe drought. The study's findings provide valuable new insights into the process of identifying drought-prone regions within the watershed. Communities and governmental organizations will be able to implement different practices and assist the efforts in mitigation of drought with the use of this information. This research has practical implications at all levels, from local to regional, since it can improve drought response and mitigation plans, aid in decision-making, and promote sustainable drought management strategies.

Table 4.8: Drought class and its area coverage in Bilate River Watershed and its Zonal administration.

Drought classification in Bilate River Watershed										
No.	Study area	Extreme Drought		Severe Drought		Moderate Drought		Mild Drought		Total (Km ²)
		Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	Area (Km ²)	Area (%)	
1	BRW	1.23	0.02	1218.67	23.16	3694.94	70.22	347.13	6.60	5261.96
Drought classification in Zonal administration within BRW										
No.	Zones	Extreme Drought		Severe Drought		Moderate Drought		Mild Drought		Total (Km2)
		Area (Km2)	Area (%)	Area (Km2)	Area (%)	Area (Km2)	Area (%)	Area (Km2)	Area (%)	
1	Gurage	0.00	0.00	0.00	0.00	7.07	0.19	66.55	19.22	73.62
2	Hadya	0.00	0.00	118.18	9.70	908.86	24.59	42.51	12.28	1069.56
3	Kembata	0.00	0.00	29.33	2.41	423.07	11.45	59.98	17.33	512.39
4	Sidama	0.00	0.00	195.42	16.04	600.91	16.26	0.30	0.09	796.63
5	Wolayta	0.32	99.72	659.28	54.12	632.99	17.13	0.02	0.01	1292.61
6	Silte	0.00	0.00	7.98	0.65	353.06	9.55	176.85	51.08	537.88
7	Alaba	0.00	0.00	168.11	13.80	258.30	6.99	0.00	0.00	426.41
8	West Arsi	0.00	0.00	39.88	3.27	511.97	13.85	0.01	0.00	551.87
	Total	0.32	99.72	1218.18	100.00	3696.24	100.00	346.23	100.00	5261.97

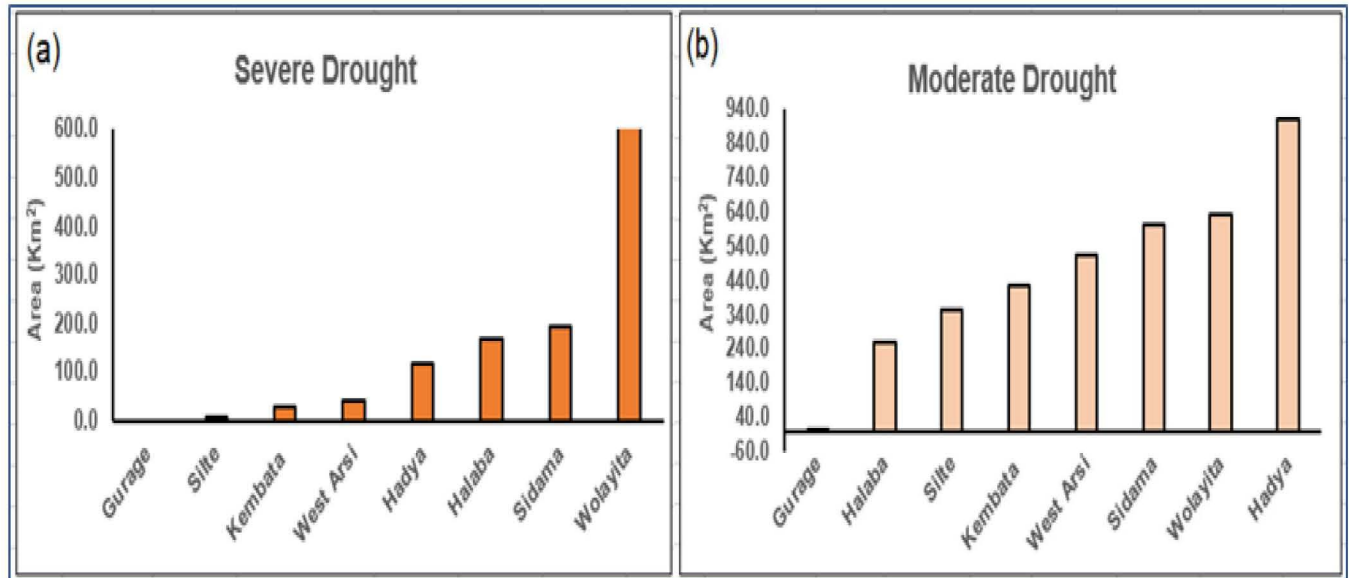


Figure 4.6: Drought area coverage in zonal administration of BRW: (a) Severe drought, & (b) moderate drought.

4.3.4. Model performance

The drought susceptibility model was validated through the receiver operating characteristic (ROC) analysis by comparing the stratified random samples of VHI data. The ROC curve of the drought susceptibility model obtained shown on Figure 4. 7. The curve indicate that model has $AUC=0.701(70.1\%)$. Thus, As can be observed, the AHP model used in this study demonstrated acceptable level of accuracy in the spatial prediction of possible drought susceptibility. An additional indication that the model can account for some of the major variables influencing drought conditions is the modest strength of the correlation ($r = 0.52$) between the DSM and VHI. In addition, the association implies that the drought model may not properly account for some of the other variables or factors that affect the change in DSM.

Overall, a more thorough understanding of the model's strengths and weaknesses can be attained by combining the correlation and AUC results. This information can then be used to lead future model improvements, the addition of new variables, or the investigation of alternative modeling strategies to improve the model's overall capacity for drought monitoring and prediction

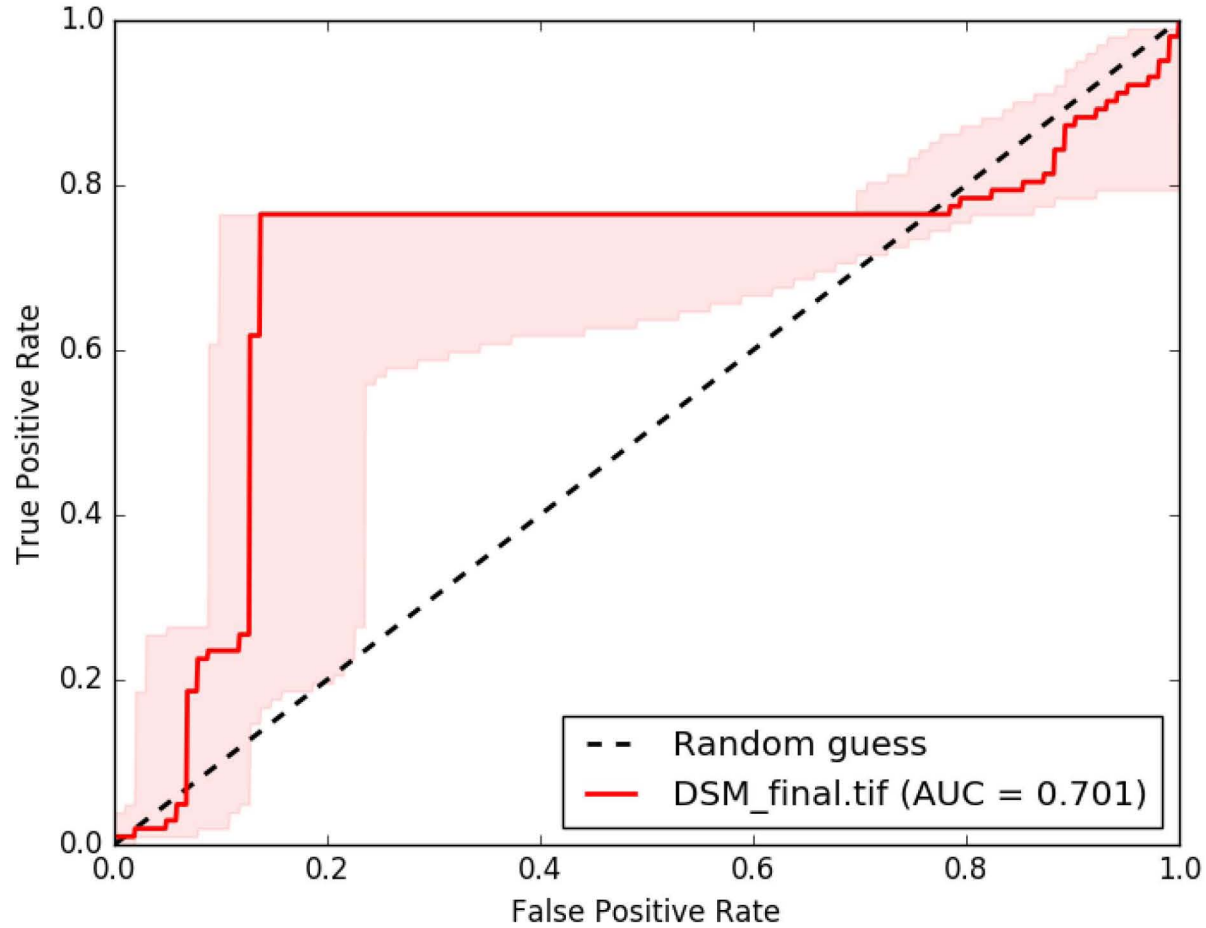


Figure 4.7: ROC-AUC of drought susceptibility model (DSM)

In general, numerous factors contribute to the complexity of drought susceptibility modeling utilizing the AHP model and geospatial approaches. First, obtaining, compiling, and processing the required data which comprises climate, environmental and socioeconomic data can be a laborious procedure. The AHP model also calls for the selection of pertinent criteria (socioeconomic, environmental, and climatic), which can be a difficult and subjective process. Each criterion must then be assigned a weight depending on its relative importance. Finally, the process of combining the AHP model with geospatial techniques can further complicate the modeling process. Using spatial analysis techniques, such as overlay analysis, raster calculations, and spatial modeling, and integrating the geospatial data can be computationally demanding, particularly for high-resolution datasets. In addition, the availability and quality of the input data affect the scalability of the drought vulnerability modeling approach, which in turn can significantly impact the model's ability to scale and provide accurate results. Scalability can also

be impacted by the complexity of the AHP model and the use of geospatial approaches; more sophisticated techniques may offer better scalability but come with a higher learning curve and more processing resources.

When used in conjunction with geographic information systems, the AHP offers a reliable method of disaster monitoring (Palchaudhuri and Biswas, 2016). The AHP methodology's hierarchical structure makes it easy to merge the individual components into a whole by measuring and synthesizing many aspects of a complicated decision-making process in a hierarchical way (Russo and Camanho, 2015). Because of its simplicity, AHP is one of the most widely used techniques that highlights the MCDM process (Sivakumar, Radha Krishnappa and Nallanathel, 2021). The most crucial step in the hierarchical analytical process is thought to be transforming the problem under study into a hierarchical structure (Fathi et al., 2015). Additionally, the AHP offers statistical metrics to assess judgment inconsistencies (Fernández and Lutz, 2010).

Overall, drought vulnerability modeling benefits from the application of geospatial techniques and AHP model, which can be used to spatially represent and analyze a variety of data sources, support scenario analysis, enable multi-criteria decision-making through a hierarchical structure, and provide flexibility and adaptability to regional contexts and vulnerability hotspot identification. These methods can be combined to create thorough and reliable evaluations of drought susceptibility, which are essential for developing focused mitigation and adaptation plans, allocating resources, and managing drought risks.

4.4. Conclusion

The geospatial techniques and AHP model were used to develop a drought susceptibility model involved in different pertinent parameters from climatic, soil, hydrology, environmental and socio-economic variables. The results indicated that the main causes of the severe and moderate droughts are rainfall, temperature, evapotranspiration and soil moisture according their weight given in the modeling process. The findings show the central and southern parts of the watershed are the most susceptible areas to severe and moderate drought categories, covering for 23.16% and 70.23% of the watershed, respectively. In line with this, on the basis of administration zones, Wolayta is the main hot spot of severe droughts (54.12%) while Hadiya zone is the main susceptible area to moderate drought (24.59%) within the watershed. Hence, the southern and central parts of the watershed, specifically parts of Wolayta and Hadiya zones need priorities in implementing

intervention related to drought mitigation strategies in the watershed. Besides, information generated from this research can guide decision-making processes related to drought mitigation strategies, water resource management, land use planning, and agricultural practices. The outcome derived from this research can inform decision makers, water managers, and stakeholders in developing targeted interventions and strategies to mitigate the impacts of droughts, which in turn enhance adaptations to reduce susceptibility and enhance resilience to drought events. Decision-makers can use the susceptibility hotspot visualization to prioritize effective mitigation and adaptation measures. Water resource managers and agricultural planners can utilize the drought susceptibility model created by this research to make well-informed decisions about crop selection, irrigation techniques, water allocation, and other drought-related initiatives. However, inadequacies need to be addressed, such as low spatial resolution data accessibility, and absence of previously documented historical drought events information for model validation. Therefore, improving data quality, looking into additional parameters, and validating the model should be the main goals of future research in order to enhance the accuracy and utility of drought susceptibility modeling. Hence, addressing these suggestions and limitations could further improve the understanding of drought susceptibility and the utility of geospatial techniques and AHP models for effective drought management planning.

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CHAPTER FIVE

FUTURE DROUGHT PROJECTION IN BILATE RIVER WATERSHED, CENTRAL RIFT VALLEY OF ETHIOPIA: INSIGHT FROM THE STATE-OF-THE-ART GLOBAL CLIMATE MODELS

ABSTRACT

Future droughts are likely to be central to climate adaptations as well as water resource management in a region as vulnerable as Ethiopia's Central Rift Valley (CRV). This study assessed future droughts in the Bilate River Watershed in the CRV for the period 2015-2100 using CMIP6 model outputs under two emissions scenarios (SSP2-4.5 and SSP5-8.5). Droughts were analyzed at 3, 6, 9, and 12-month time scales described using the Standardized Precipitation Evapotranspiration Index (SPEI). A decadal pattern evaluation was carried out in addition to power spectral analysis and change-point detection with the Pettitt test; return period estimation; EOF analysis; and characterization of drought events regarding frequency, duration, and severity. Results show a steady increase in drought occurrence, with repeated moderate, severe, and possibly extreme drought events expected across all timescales, increasing greatly under SSP5-8.5. Longer SPEI timescales show less regular but more drawn-out and severe cumulative hydrological droughts. Statistically significant change points show an abrupt move towards increased drought conditions, mainly in the second half of the century. Power spectral analysis hints at a possible enhancement of multi-year drought periods (3.75-7.5 years) under SSP5-8.5. In this watershed, EOF analysis provides the leading spatially coherent drought mode along with contrasts that are persistent in secondary patterns. Compared to SSP2-4.5, the scenario of SSP5-8.5 introduces much greater variability and extremes of droughts. An even more significant amplification is projected for mid-century (2045-2054) also in terms of drought severity and frequency for the entire. The study shows both short-term and long-term adaptation strategies are needed to mitigate negative impacts of the increasing drought and climate change in general.

Keywords: Drought, CMIP6, SPEI, Change point detection, High-emission scenarios (SSP5-8.5), Climate adaptation, Bilate River watershed, Central Rift Valley of Ethiopia

5.1. Introduction

One of the severe and enduring environmental hazards that significantly affects livelihood and productivity is drought (Wang et al., 2021). Drought is environmental danger that can negatively impact both natural and human systems (Degefie et al., 2019; An et al., 2022). This natural disaster is invisible until it reaches its most severe stage (Mahdavi et al., 2021). Droughts usually begin as a lack of precipitation (meteorological drought), then move through the hydrologic cycle over a period of days to years to affect soil moisture which is agricultural drought), and lastly, go to streamflow, runoff, and storage in aquifers and surface reservoirs known as hydrological drought (Cook et al., 2018). In the twenty-first century, drought's characteristics and impacts are expected to change due to global warming (Degefie et al., 2019). Even though it is critical to demonstrate

and assess the current condition of drought from the past to the present using the data that is now available, predicting future droughts in light of climate change is key to minimizing droughts (An et al., 2022).

In order to improve climate modeling, the IPCC is providing a wide range of climate projections under different scenarios through its Coupled Model Intercomparison Project Phase 6 (CMIP6). In CMIP6 projections, common socio-economic paths (SSPs) are the scenarios considered. Potential future socioeconomic trends that affect greenhouse gas emissions and the effects of climate change are reflected in the SSPs. Because each pathway specifies distinct paths for economic growth, population expansion, and technology improvement, researchers are able to evaluate a range of possibilities. GCM projections help with planning, preparing for potential extreme weather events, and mitigating the effects of climate change (Hamed et al., 2022). In addition to the current idea of representative concentration pathways (RCP), the SSP scenario was presented in the sixth evaluation report most recently released by the Intergovernmental Panel on Climate Change (IPCC). It takes into account "future socioeconomic changes" and "efforts to mitigate climate change" (An et al., 2022). Without a doubt, one of the major issues facing the world in the twenty-first century is climate change (Kim and Jehanzaib, 2020). In extreme situations, droughts can put unseen strain on natural ecosystems and pose a major threat to the food, water, and biological systems that humans rely on for survival (Wang et al., 2021).

While droughts occur naturally, climate change has typically hastened the hydrological processes leading to them occurring more severely and rapidly, with a number of implications (Mukherjee, et al., 2018). Recent studies have indicated that climatic changes and anthropogenic practices are making the droughts more severe and prolonged. The lack of clarity in rainfall trends and rising temperature aggravates the frequency of droughts. The research will establish future changes of significant climate factors of concern in the context of drought, e.g., precipitation and temperature, from the most up-to-date CMIP6 data. These variables determine the onset, duration, and intensity of drought, thus enabling one to conduct a more sensitive risk estimation. Drought affects more people compared to any other nature-related disaster (Degefie et al., 2019). To help decision-makers comprehend and make adaptation strategies for future climate change, the GCMs, particularly the recently released (CMIP6), are extremely important (Feyissa et al., 2023).

Future droughts must be explored by accounting for climate change in addition to the current drought using observed data (An et al., 2022). Despite Ethiopia's increasing drought frequency and intensity, not much research has been done to forecast future drought events in the watershed of the Bilate River. The main objective of this study was to evaluate the Bilate River Watershed's potential drought conditions using CMIP6 models. This study uses the latest SSP scenarios under CMIP6 over BRW to analyze the expected future changes in drought characteristics. To analyze drought risk between 2015 and 2100, the most recent climatic CMIP6-based climatic data (Shrestha et al., 2020) will be utilized. Thus, this study's objectives are to: (1) Examine the frequency, severity, and occurrence of drought events over the Bilate River Watershed under moderate (SSP2-4.5) and high (SSP5-8.5) emission scenarios. (2) To analyze the Bilate River Watershed's decadal drought trends and pinpoint the change point. (3) To perform EOF analysis to identify leading spatial and temporal modes of variability in characteristics of drought, which would provide information regarding underlying climatic drivers and how they affect the watershed.

5.2. Material and Methods

5.2.1. Study Area Description

Bilate river watershed is located in the South-Western Escarpment of the Main Ethiopian Rift Valley region (Figure 5. 1). Geographically, it is located 6°32'40'' to 8°09'29'' N and 37°46'11'' to 38°18'43'' E. The area of the watershed is about 5324 Km². The watershed is confined to Abiyata and Shala Lakes from the east, Omo Gibe basin from the west, and Lake Abaya and Chamo from the South. The North and Northeastern part of the watershed has steep slopes and the center and the south part has gentle slopes. The altitude of the watershed ranges from 1116 to 3373 m a.s.l. The watershed has a bimodal rainfall characteristic with a short and main rainy season. The watershed receives annual average rainfall that ranges from 1068.79 to 1276.68mm at lower altitude and higher altitude of the watershed. Bilate river is the main river of the watershed that drains into lake Abaya with its tributaries (Burka et al., 2024b).

Table 5.1: Meteorological Stations used in Bilate River watershed

No	Station Name	Latitude	Longitude	Altitude	AP (mm)	Minimum MAT (°C)	Maximum MAT(°C)
1	Alaba	7.31	38.09	1772	1070.2	12.4	23.4
2	Bilate	6.92	38.12	1496	1068.8	12.5	23.4
3	Hossna	7.50	37.87	2200	1202.6	11.3	22.4
4	Boditi	6.95	37.96	2043	1121.6	15.5	25.3
5	Shone	7.13	37.95	1959	1360.9	15.6	26.6
6	Wolayta	6.81	37.73	2022	1398.9	15.9	25.4
7	Wulbareg	7.74	38.12	1992	1245.0	12.39	23.2

5.2.2. Data types and sources

The current and future climates are often simulated using general circulation models (GCMs) (Enayati et al., 2021). Following climate change, GCMs are essential instruments for tracking droughts (Shrestha et al., 2020). There are no set rules or suggested method for choosing a GCM (Hamed et al., 2022). For instance, Salehie et al., (2022) used the simulated precipitation, maximum, and minimum temperature (Pr, Tmax, and Tmin) GCMs from CMIP6 to choose the top models. Similarly, the availability of desired climate data (precipitation, minimum and maximum temperature) and the emission scenarios employed served as a reference for the selection of GCMs in the research (Tibangayuka et al, 2024). Models that consider these many possibilities give academics a thorough picture of how climate change can worsen drought conditions by enabling them to investigate a variety of possible futures. According to Shafiei et al, (2023), GCMs are crucial tools for climate prediction and attribution, forecasting future climate change, and replicating past climate conditions. Therefore, in this research 14 GCMs were retrieved from the CMIP6 climate data database (Table 5. 2) (<https://cds.climate.copernicus.eu/>). However, Single GCM projections frequently contain uncertainties (Ahmed et al., 2019). Therefore, multi-model ensembles (MMEs) are frequently suggested as a useful strategy for lowering the uncertainty related to climate projections (Ahmed et al., 2019). Accordingly, this study assesses the ensemble model's performance to determine whether it merits selection based on its superiority over other models.

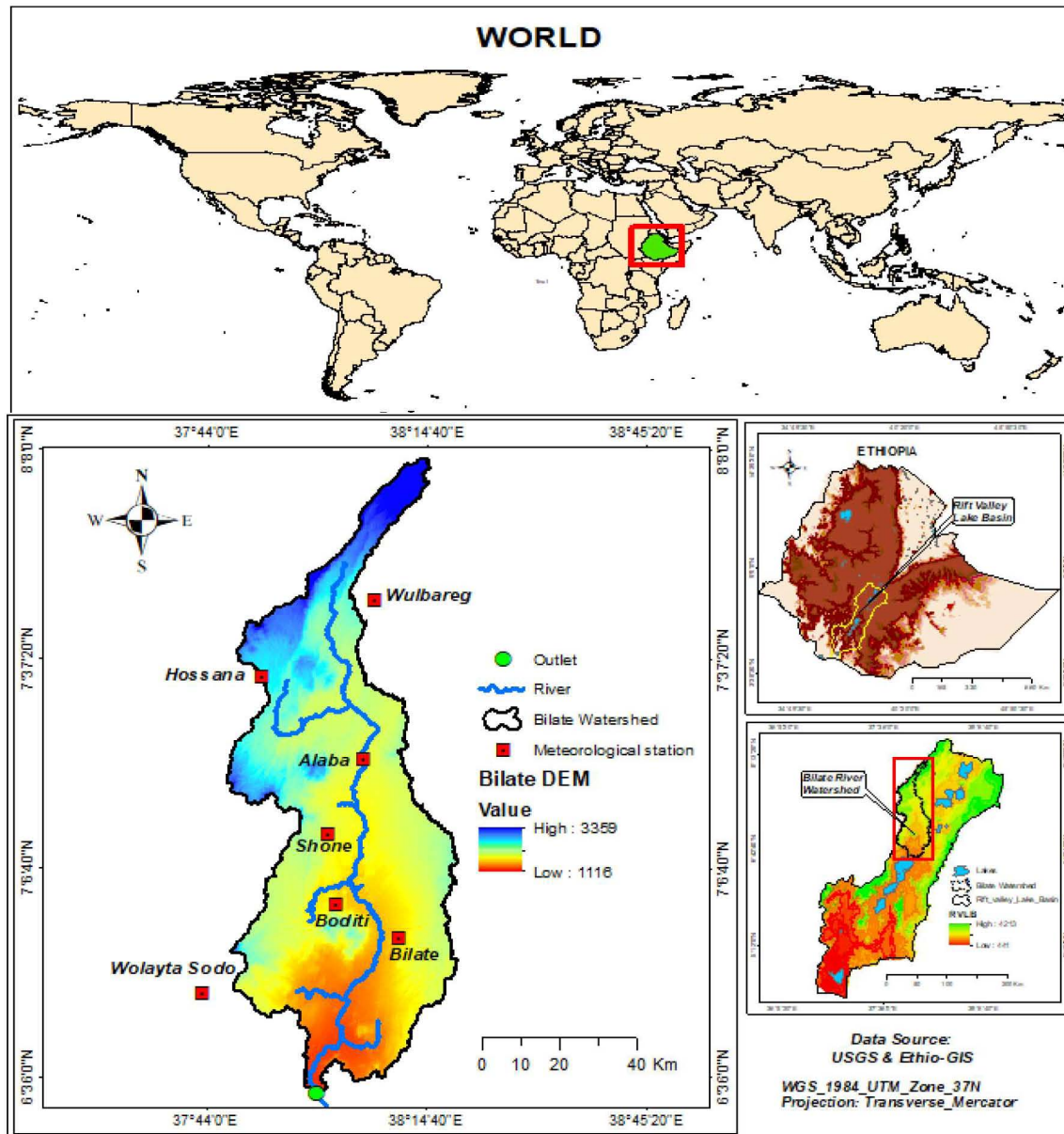


Figure 5.1: Location map of Bilate River Watershed. (Data Source: Ethio-GIS and USGS)

Table 5.2: CMIP6 Models with variant level “r1i1p1f1” with historical, SSP2- 4.5 and SSP5- 8.5 projection

No	Model	Institution	Country	Horizontal Resolution (Long x Lat)	Variables		
					Tmin	Tmax	Pr
1	ACCESS-CM2	Australian Community Climate and Earth System Simulator (ACCESS)	Australia	$1.875^0 \times 1.250$	✓	✓	✓
2	CMCC-ESM2	Centro Euro-Mediterraneo sui Cambiamenti Climatici	Italy	1.25×1.875	✓	✓	✓
3	CNRM-ESM2-1	Centre National de Recherches Météorologiques, Toulouse 31 057	France	$1.41^0 \times 1.41^0$	✓	✓	✓
4	EC-Earth3-CC	EC-Earth-Consortium	Europe	$0.7^0 \times 0.7^0$	✓	✓	✓
5	EC-Earth3-Veg	EC-Earth Consortium	Europe	$0.7^0 \times 0.7^0$	✓	✓	✓
6	INM-CM5-0	Institute for Numerical Mathematics	Russia	$2^0 \times 1.5^0$	✓	✓	✓
7	MIROC6	Japan Agency for Marine-Earth Science and Technology (JAMSTEC), Kanagawa	Japan	$1.4^0 \times 1.4^0$	✓	✓	✓
8	MPI-ESM1-2-LR	Max Planck Institute for Meteorology (MPI-M)	Germany	$1.875^0 \times 1.86^0$	✓	✓	✓
9	MRI-ESM2-0	Meteorological Research Institute, Ibaraki	Japan	$1.12^0 \times 1.12^0$	✓	✓	✓
10	INM-CM4-8	Institute for Numerical Mathematics (INM)	Russia	$2.0^0 \times 1.5^0$	✓	✓	✓
11	NorESM2-MM	NorESM Climate modeling Consortium	Norway	$1.3^0 \times 0.9^0$	✓	✓	✓
12	NSEM3	Nanjing University of Information Science and Technology Earth System Model	China	$1.87^0 \times 1.87^0$	✓	✓	✓
13	BCC-CM2-M	Beijing Climate Center (BCC)	China	$1.15^0 \times 1.15^0$	✓	✓	✓
14	GFDL-ESM4	NOAA Geophysical Fluid Dynamics Laboratory	USA	$1.3^0 \times 1.0^0$	✓	✓	✓
15	MMME	-	-	-	✓	✓	✓

5.2.3. CMIP6 datasets and SSPs for Future Drought Risk Analysis

Climate models can be used to reliably forecast future climate change (Guo et al., 2022). Temperature, precipitation, and other climate variable projections under various scenarios of greenhouse gas concentrations are among the crucial datasets produced by CMIP6 models. Simplifying data collection and output, CMIP6 enables inter-model comparison, making climate projections more accurate and implications on the world and regional climate change. For climate-related hazard understanding, particularly floods and droughts, future rainfall estimates under the updated CMIP6 are crucial (Abduljaleel et al., 2024). Under 2100, for instance, SSP245 represents a medium-range socioeconomic development pathway with an average radiative forcing of 4.5 W m^{-2} , while SSP585 accounts for high-intensity fossil fuel-driven development with high radiative forcing of 8.5 W m^{-2} (Colín-García et al., 2024). Shared Socioeconomic Pathways (SSPs) consider a number of dimensions, such as population change, economic growth, and technological advancement, that can have deep implications for greenhouse gas emissions and climate vulnerabilities. Five distinct SSPs exist, ranging from pathways of sustainable development (SSP1) to those with high challenges for mitigation and adaptation (SSP5).

Utilization of CMIP6 data sets and SSPs is vital in order to conduct future drought risk assessment at the watershed level. Applying high-resolution future climate projections of CMIP6 models, is possible to identify how future changes in temperature and precipitation trends may influence water supply and hydrologic processes within the watershed. For instance, such data sets can be used for the simulation of such extreme climatic events like severe dry spells that have the potential to intensify droughts. In order to provide a complete picture of potential drought hazards, analysts can also investigate how other socioeconomic trajectories such as urbanization, changes in land use, and agricultural practices might affect the dynamics of water demand and supply by combining multiple SSP scenarios. Numerous analytical techniques based on SSP have been presented in recent literature (Ahn et al., 2023).

The selection GCMs for future projection of drought on the study area should be guided by a series of key requirements. In order to reasonably resolve fine-scale climate characteristics, including land use and topography, which play a significant role in precipitation and evaporation processes, higher resolution models could be chosen. In addition, the models are tried against their performance in the past to simulate the past climate conditions so that they can project reliably for

the future. It is also important that the models can simulate a variety of greenhouse gas emission scenarios and socio-economic scenarios so that future climate conditions vary widely and are thoroughly assessed. The CMIP6 models are extensively intercomparing tested in order to make them well-established and tested on numerous climate metrics.

5.2.4. Methodology

5.2.4.1. Downscaling and Bias Correction

Downscaling procedures are employed by researchers to post-process and recalibrate the raw estimates from To improve the coarse resolution, the GCMs must downscale in order to extract the local future climate conditions (Shrestha et al., 2020). This research uses quantile mapping (QM), which is based on the gamma distribution bias correction technique, to increase the accuracy of CMIP6 data in forecasting changes in drought characteristics (Ayugi et al., 2021) .

Quantile mapping (QM) approaches are among the most significant and widely used methods of correcting bias (Enayati et al., 2021). Several methods, including quantile mapping, are used in the raw climate model output to measure and eliminate this bias (Shrestha et al., 2020). To rectify the bias, Gupta et al., (2019) created the Climate Data prejudice Corrector (Enayati et al., 2021) tool .The QM techniques post-process the results of climate modeling by implementing statistical transformations (Enayati et al., 2021). As cited by Gupta et al., (2019), the precipitation used Gamma distribution which is indicate on equation 1 (Ines and Hansen, 2006) and temperature used normal distribution as indicated on equation 2 (Li et al., 2010) for bias correction using CDBC. According to Gupta et al, (2019), the equations for precipitation and temperature that works for bias correction in CDBC are:

$$\text{Precipitation: } \bar{x}_{ms.corr} = \begin{cases} F_{oh}^{-1}(F_{mh}(x_{ms})), & x_{ms} \geq x_{th} \\ 0, & x_{ms} < x_{th} \end{cases} \quad (1)$$

$$\text{Temperature: } \bar{x}_{ms.corr} = x_{ms} + F_{oh}^{-1}(F_{ms}(x_{ms})) - F_{oh}^{-1}(F_{ms}(x_{ms})) \quad (2)$$

Note: where x is climatic variable, $x_{ms.corr}$ is bias corrected model simulated data; to categories between the wet and the dry day threshold value x_{th} is used (day with precipitation greater than 1 mm is assumed to be a wet day); F is CDF, whereas F^{-1} is its inverse. (o = observed, m = model,

h = historical period, and s = simulation period). Here, the simulated period can either be historical or a future period.

Climate Data Bias Corrector (CDBC) is a program developed by Gupta et al., (2019), with the aim of giving more precise climate data, particularly when it comes to precipitation, temperature, and solar radiation records. The program is primarily aimed at the correction of biases in climate datasets that may have occurred as a result of measurement errors, changes in instrumentation, and site relocations. This research used the CDBC program for bias correction.

5.2.4.2. Evaluations of CMIP-6 climate model outputs

The performance of the results of CMIP6 climate models needs to be tested to identify their relevance and accuracy. The testing commonly occurs as a comparison of model simulations with historical observations of climate records to identify their capability to simulate key climate variables, including temperature and precipitation. The Nash-Sutcliffe Efficiency (NSE), which estimates the match between predicted values and observations, and the Root Mean Square Error (RMSE), which estimates the average magnitude of calculated minus observed value discrepancies, are the usual statistical metrics employed here. Additionally, numbers like bias, quantifying systematic discrepancy between forecasted and true values, and correlation coefficients quantifying the amount of association between forecasted and observed data have an important role to ascertain particular areas where climate variables are being overestimated or underestimated by the models.

5.2.4.3. Drought Index for Drought Characterization

Since drought indices serve as stand-ins for tracking and measuring droughts, it's critical to create reliable drought indices in order to study drought characteristics in light of climate change (Mukherjee et al., 2018). A drought index is an essential tool for characterizing and monitoring drought since it simplifies complicated climate processes (An et al., 2022). SPEI integrates both precipitation and potential evapotranspiration into its calculations, providing a more holistic view of moisture availability than indices that focus solely on precipitation levels. Several drought indices have been developed to appropriately depict the features of drought in accordance with requirements and objectives, and they have been used in several research (An et al., 2022).

Future droughts brought on by climate change are also frequently predicted using drought indices (Ta et al., 2022). One of the primary advantages of SPEI is its ability to be computed over various time scales, ranging from a single month to several years. Precipitation is the sole or combined with additional meteorological factors in the majority of drought indexes (Mukherjee et al., 2018). . SPEI addresses SPI's shortcomings while providing an enhanced supplemental drought record (Badji et al., 2023). As science continues to develop, SPEI will increasingly be at the forefront of tracking and controlling world drought, offering information leading to sustainable agriculture practices, water resource planning, and environmental conservation. Drought is still mostly caused by evapotranspiration (Wang et al., 2021). Because it is applicable across different time scales and can be used to analyze droughts that are both short-term and long-term (Bae et al., 2018; Hui-Average et al., 2018; Lee et al., 2017; Vicente-Serrano et al., 2010), the SPEI uses the monthly difference between precipitation and PET. The SPEI, which adds evapotranspiration variables to SPI and considers the PDSI characteristic that evapotranspiration is temperature-sensitive, describes the degree of divergence of dry and wet conditions from climatological average conditions by normalizing the difference between potential evapotranspiration and precipitation (Zhao et al., 2017; Vicente-Serrano et al., 2010).

Vicente-Serrano et al. (2010) suggest that SPEI is easy to calculate and is derived from the original SPI computation process. The SPEI uses the monthly difference between potential evapotranspiration (PET) and precipitation. With a value for PET , the difference between the precipitation (P) and PET for the month i is calculated: $D_i = P_i - PET_i$ which provides a simple measure of the water surplus or deficit for the analyzed month. After standardizing the variable through a series of computations, SPEI is finally determined using the formula below (Vicente-Serrano et al., (2010):

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

where $W = \sqrt{-2\ln(P)}$ for $P \leq 0.5$, P is the probability of exceeding a determined D_i value and is given as $P = 1 - F(x)$. If $P > 0.5$, P is replaced by $1 - P$ and the sign of the resultant SPEI is reversed.

The constants are: $C_0=2.515517$, $C_1=0.802853$, $C_2=0.010328$, $d_1=1.432788$, $d_2=0.189269$, $d_3=0.001308$. The average value of the SPEI is 0, and the standard deviation is 1.

SPEI could be calculated using the SPEI package of R statistical software (Vicente-Serrano et al., 2010) and the classification is indicated in Table 5. 2

Table 5.3: Drought classification of SPEI drought Indices

Category	SPEI Values
Extreme wet	≥ 2.00
Severe wet	1.5 -1.99
Moderate wet	1-1.49
Normal	-0.99 - 0.99
Moderate Drought	-1.49- -1
Severe Drought	-1.99 - 1.5
Extreme Drought	≤ -2

5.2.4.4. Pettitt Test, Power Spectral and Empirical Orthogonal Function Analysis

5.2.4.4.1. Pettitt Test (Change Point Analysis)

The Pettitt test, a robust non-parametric statistical method, is widely applied to identify change points in time series data, giving information on potential changes in climatic or environmental trends. A specific version of the non-parametric test created by Pettitt (1979) and based on the U_t statistic was used to determine the time of any abrupt shift (Myronidis et al., 2018). The Pettitt Test is a non-parametric method for the identification of a change point in a time series, which can signal a significant change in drought patterns when interpreting SPEI results. The Pettitt Test uses a rank-based method. It calculates the test statistic U_t at each time step t (Myronidis et al., 2018):

$$U_t = \sum_{i=1}^t \sum_{j=t+1}^N \text{sgn}(X_i - X_j) \quad (4)$$

Where X_i and X_j are value of timeseries, N is total number of observation and $\text{sgn}(X)$ is the sine function defined as:

$$\text{sgn}_x = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \\ -1, & \text{if } x < 0 \end{cases} \quad (4.1)$$

Then the test statistic K is the maximum absolute value of U_t :

$$K = \max|U_t| \quad (4.2)$$

So, the point where K occurs is the estimated change point. Moreover, the significance of the change point is tested using the following approximate formula for the p-value:

$$p \approx 2\exp\left(-\frac{6K^2}{N^3 + N^2}\right) \quad (4.3)$$

Therefore, if p-value is smaller than the chosen significance level (e.g., 0.05), the null hypothesis is rejected, indicating a significant change point.

5.2.4.4.2 Power Spectral analysis

Using a spectrum analysis on a main component, peaks describing the interannual, decadal, and interdecadal variability were found (Moreira et al., 2015). On any time, scale, spectral analysis can be used to determine the periodic features of a drought pattern (Dabanlı et al., 2017). Power spectral analysis (PSA) is used in drought research with SPEI results to identify periodicities or dominant frequencies in drought occurrences. Power spectral analysis is used to ascertain the drought episode's periodicity and One term for periodicities is a frequent occurrence in a trend (Ogunrinde et al., 2020). This analysis helps in understanding cyclical patterns and drivers of drought, such as links to climate phenomena like El Niño-Southern Oscillation (ENSO). Then, using the SPEI time series the power spectral density (PSD) is will be computed to show the distribution of variance across different frequencies. Finally, The PSD highlights the dominant frequencies and their corresponding period. Drought cycle analysis is done via spectral analysis (Kim et al., 2011). The mathematical expression of PSA is indicated below: First, Discrete Fourier Transform (DFT) converts a time-domain signal $x(t)$ into its frequency-domain representation (Ogunrinde et al., 2020):

$$X(f) = \sum_{t=0}^{N-1} X_t \cdot e^{-i2\pi ft} \quad (5)$$

Where, $X(f)$ is Fourier coefficient for frequency (f), N is number of data points, t is time index, and $e^{-i2\pi ft}$ is complex exponential (Euler's formula)

Using the power spectrum, one may find primarily powerful oscillations, which are represented by relatively large amplitude frequency peaks, and scaling behavior, which is shown by a power-law form of the power spectrum at specific frequency bands (Telesca et al., 2013).

The, the power spectral density (PSD) represents the power content of the signal as a function of frequency. It is computed using the magnitude squared of the Fourier Transform:

$$P(f) = |X(f)|^2 \quad (5.1)$$

Where $P(f)$ is power at frequency f and $|X(f)|$ is magnitude of Fourier Transform

Finally, the frequency resolution depends on the sampling interval Δt and the number of data points NN :

$$f_{resolution} = \frac{1}{N\Delta t} \quad (5.2)$$

5.2.4.4.3. Empirical Orthogonal Function (EOF) Analysis

A principal component analysis (PCA) called the EOF analysis is used to examine a collection of time series data (Adi-Kusumo et al., 2016). EOF analysis is a statistical method used to identify patterns of variability in spatial and temporal data, like drought time series. It involves in anomaly calculation, covariance matrix, eigenvalue and decomposition, and principal component time Series. The principal component (PC) time series, which depict the temporal evolution of every spatial pattern, are obtained by projecting the original data onto the EOFs (Wu et al., 2022).

Hence, in EOF analysis, first, compute the anomalies by subtracting the mean of each column (spatial location) from the corresponding time series (Wu et al., 2022):

$$X = X' - \tilde{X} \quad (6)$$

where $\tilde{X}$ is the mean of X along the time dimension. Next, calculate the covariance matrix CC of the anomalies:

$$C = \frac{1}{m-1} X'^T X' \quad (6.1)$$

Where X'^T is the transpose of X' . Then, the eigenvalue decomposition on the covariance matrix conducted:

$$C = V\Lambda V^T \quad (6.2)$$

where V is the matrix of eigenvectors (spatial patterns or EOFs), and Λ is the diagonal matrix of eigenvalues (variance explained by each EOF). Finally, the principal components (PC) analysis conducted which project the original data onto the EOFs to obtain the principal components:

$$PC = X'V \quad (6.3)$$

Where the PCs represent the temporal evolution of the spatial patterns.

5.2.4.4.4. Return Period analysis

The average amount of time that passes between two comparable drought events is known as the return period (Urías et al., 2007). This knowledge is helpful for estimating the danger of droughts over a specific time period and their chance of recurrence. Carrying out return period analysis involves fitting some statistical distribution to the data and estimating the return period. Start by fitting the occurrence of drought events, in this case represented by SPEI values, to a probability distribution, which could either be Generalized Extreme Value (GEV) or Weibull distribution. Then, return period RT is defined based on some probability P of the drought event happening within a given year (Urías et al., 2007):

$$RT = \frac{1}{P} \quad (7)$$

5.2.4.4.5. Decadal drought pattern analysis

Decadal analysis involves calculating the average SPEI for every decadal period from 2015 to 2100. The analysis begins with the initial decadal period of 2015–2024 and continues sequentially up to the end of the study period (2100). Decadal averages are used by the analysis to compare drought conditions over different time periods systematically. The average SPEI value for every decadal period represents overall drought conditions for that interval. By comparing these averages, trends in drought severity can be established and decades of worst conditions delineated. Decadal trend refers to a comparison of the differential differences in SPEI values and reflects

significant drought pattern changes, allowing for educated inference of drought development over the study period. The strategy gives precedence to the long-term trends and makes it possible to identify the decades when drought will be most visible, particularly against the background of the potential impact of climate change.

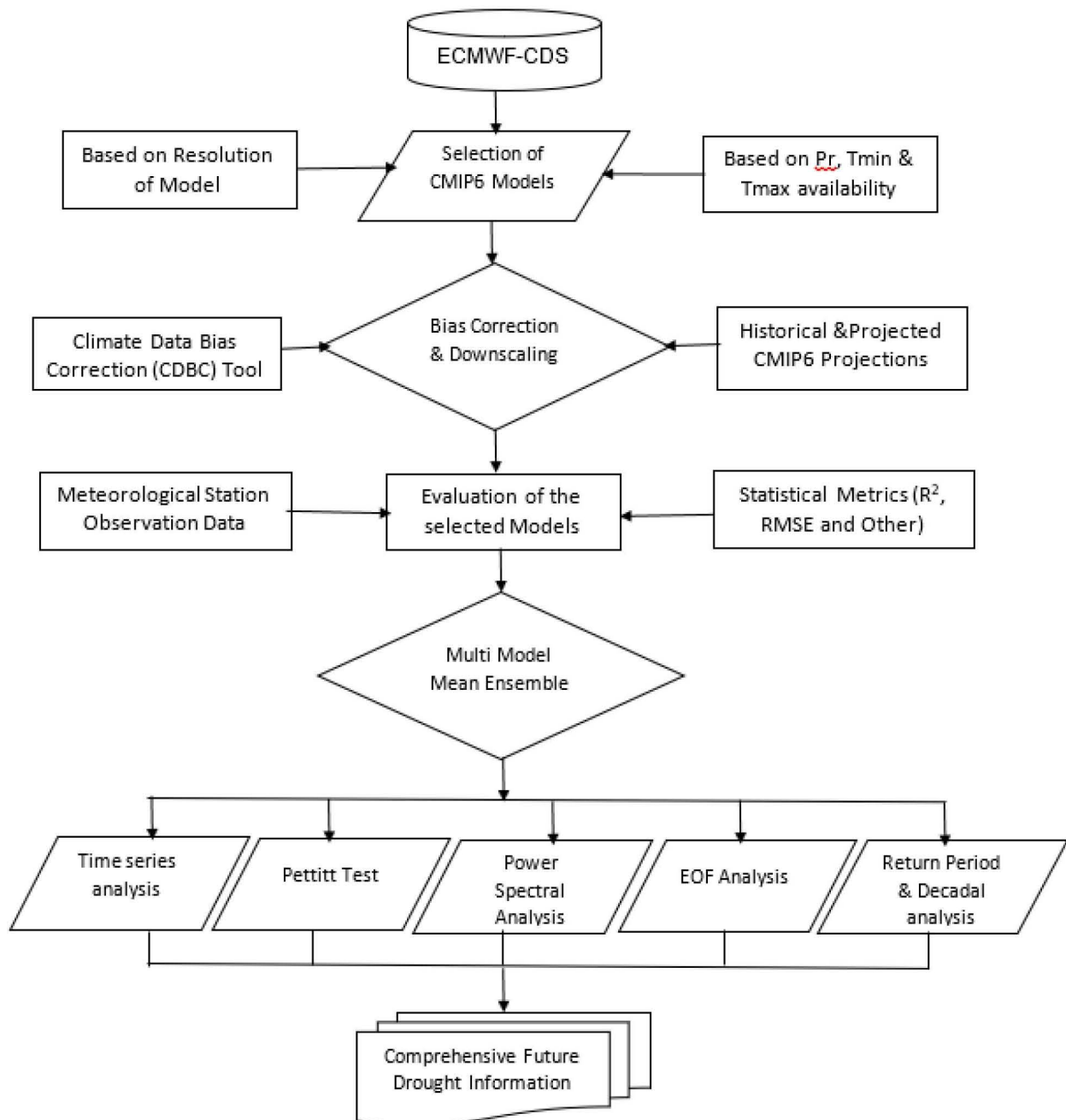


Figure 5.2: Methodological workflow followed in this research.

5.3. Result and Discussion

5.3.1. Evaluations of CMIP-6 climate model outputs

The precipitation data showed the metrics shown in Table 5. 4 for its evaluation. The composite performance score is calculated by combining normalized metrics. Metrics like MAE, RMSE, MAPE, and Bias penalize models with higher errors, while R^2 , NSE, and Willmott's Index reward models with better predictive accuracy.

The model with the highest score reflects the most balanced and accurate performance across all metrics. Goodness of Fit (R^2 and NSE) of MMME explains the highest proportion of variance in the observed data (R^2) and shows the greatest efficiency compared to the observed mean. MMME in Error Metrics (MAE, RMSE, MAPE) likely has the lowest average errors in predicting the observed values, indicating it closely aligns with the actual data. Agreement (Willmott's Index) of MMME is a higher Index of Agreement suggests the MMME's predictions are in strong alignment with observed values. In summary, MMME performs consistently well across all metrics, representing the most reliable and accurate fit for the data. The minimum and maximum temperature also a similar pattern of metrics in its evaluation.

Table 5.4: Evaluation of metrics' statistics for selected GCMs for this research.

Model	MAE	RMSE	MAPE	R2	NSE	Bias	Willmott Index	PBIAS	Performance Score	Rank
EC-Earth3-CC	0.857335	1.103022	5.02961	0.22651	-0.04805	0.00044	0.691265	0.002575	-6.12326	2
EC-Earth-CC-Veg-LR	0.938301	1.194884	5.506668	0.148373	-0.22989	-0.00033	0.63669	-0.00195	-7.08697	15
INM-CM4-8	0.882472	1.124119	5.179014	0.207803	-0.08853	-0.00017	0.677048	-0.00101	-6.39046	5
INM-CM-5-8	0.877771	1.115947	5.149482	0.215296	-0.07276	3.7E-05	0.684224	0.000217	-6.31669	4
MRI-ESM2-0	0.892971	1.148369	5.239028	0.186701	-0.136	-0.00059	0.66057	-0.00346	-6.57315	11
NorESM2-MM	0.88637	1.133207	5.193529	0.200049	-0.1062	0.000295	0.671339	0.001726	-6.44994	8
MPI-ESM1-1-LR	0.898069	1.140722	5.262879	0.193548	-0.12092	-0.0002	0.666862	-0.00115	-6.56353	10
MIROC6	0.886811	1.13844	5.210079	0.195325	-0.11644	0.000464	0.669318	0.002717	-6.49031	9
NESM3	0.87498	1.108232	5.136686	0.222051	-0.05798	-0.00014	0.688299	-0.00082	-6.26849	3
CMCC-ESM2	0.882285	1.129847	5.176574	0.202702	-0.09965	-0.00012	0.67235	-0.00068	-6.4141	6
CNRM-ESM2-1	0.902756	1.149384	5.297293	0.185734	-0.13801	-6E-05	0.659256	-0.00035	-6.64286	12
ACCESS-CM2	0.904223	1.152179	5.307312	0.183517	-0.14355	-0.00017	0.660418	-0.00101	-6.66451	13
BCC-CM2-M	0.886544	1.130483	5.194917	0.202317	-0.10089	0.000544	0.67336	0.003188	-6.44089	7
GFDL-ESM4	0.898447	1.163488	5.273023	0.174231	-0.16611	-0.0006	0.652107	-0.00351	-6.67884	14
MMME	0.652668	0.833849	3.833585	0.464572	0.461051	-4.3E-05	0.764743	-0.00025	-3.75003	1

5.3.2. Drought Event Identification and Characterizations

In certain parts of this sections, the results were presented from only the most representative stations. As a result, the stations that had the highest elevation at Hossana and the lowest elevation at Bilate were chosen to display the findings. Time series analysis of projected SPEI at 3,6,9 and 12-month time scales for Bilate station under SSP2-4.5 scenario shows a recurrent drought pattern in varying intensity throughout 21st century (2015-2100). Throughout all time scales that were analyzed, the projection shows a high frequency of moderate drought. These drought events characterized by SPEI, represent an obvious deviation from the normal conditions. Visual examination suggests such periods happen occasionally throughout the projection, for instance, around the late 2020s, mid-2050s, and late 2090s, among numerous other instances (Figure 5. 3).

SPEI time series within the study period (2015-2021) shows a decreasing pattern in SPEI values particularly from 1995–2000 and 2015–2020, indicating the occurrence of severe and prolonged drought events (Figure 5. 3). For instance, the values of SPEI below -1.5 constantly dropping during these intervals indicate the existence of severe drought. Extreme drought peak (SPEI value below -2.0) were observed in the period of 1998 and 2017.

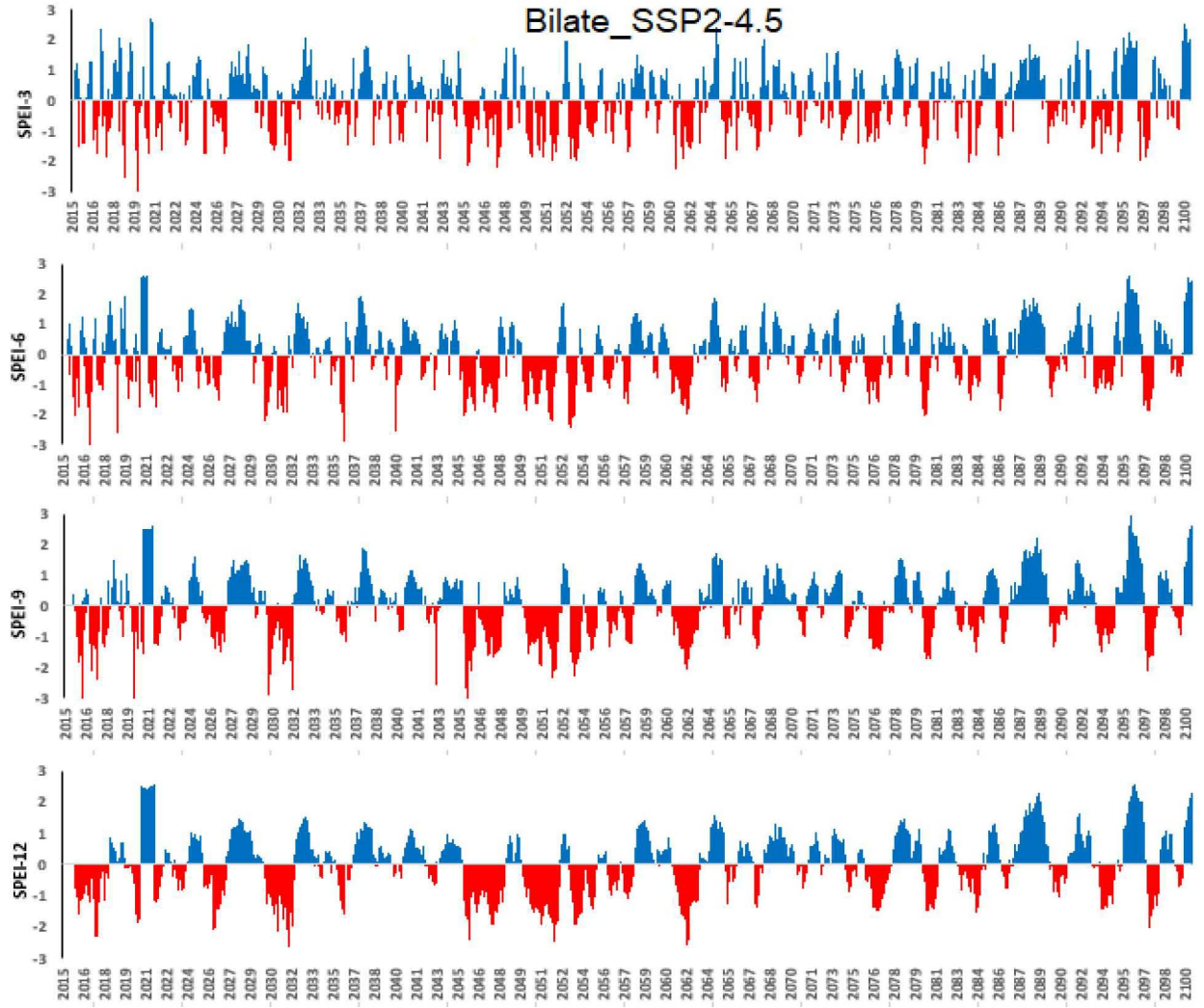


Figure 5.3: Plot of SPEI-3, SPEI-6, SPEI-9, and SPEI-12 of Bilate Station under SPP2-4.5 emission scenario.

A severe drought occurred in 2030–2031; 2052–2053; and 2064–2065. The major periods occurred around 2082–2084; values appear to regularly fall within or pass through this range over a variety of time ranges. On longer time scales, such as SPEI-9 and SPEI-12, the prevalence of severe drought conditions suggests the emergence of hydrological drought.

In the case of extreme drought, the analysis indicates the potential for extreme drought events ($\text{SPEI} \leq -2.0$). Projected extreme drought condition observed particularly in two periods: The period (~2048–2049), and this period shows a pronounced depression across all timescales, with SPEI values showing to fall significantly below the -2.0, particularly sustained in the SPEI-9 and SPEI-12. This indicates a major multi-year drought event with a high likelihood of severe impacts

on agriculture and water sources. The period (~2082-2084), perhaps peaking slightly less intensely than (~2048-2049) event in Figure 5. 3, this period also clearly shows SPEI values dropping into the extreme drought category (≤ -2.0) across multiple timescales, indicating another episode of major hydroclimatic stress. Overall, the SPEI projections under SSP2-4.5 indicates that Bilate station will likely face a future characterized by substantial hydroclimatic variability, including frequent moderate droughts, recurrent severe droughts, and occasional potentially devastating extreme drought events.

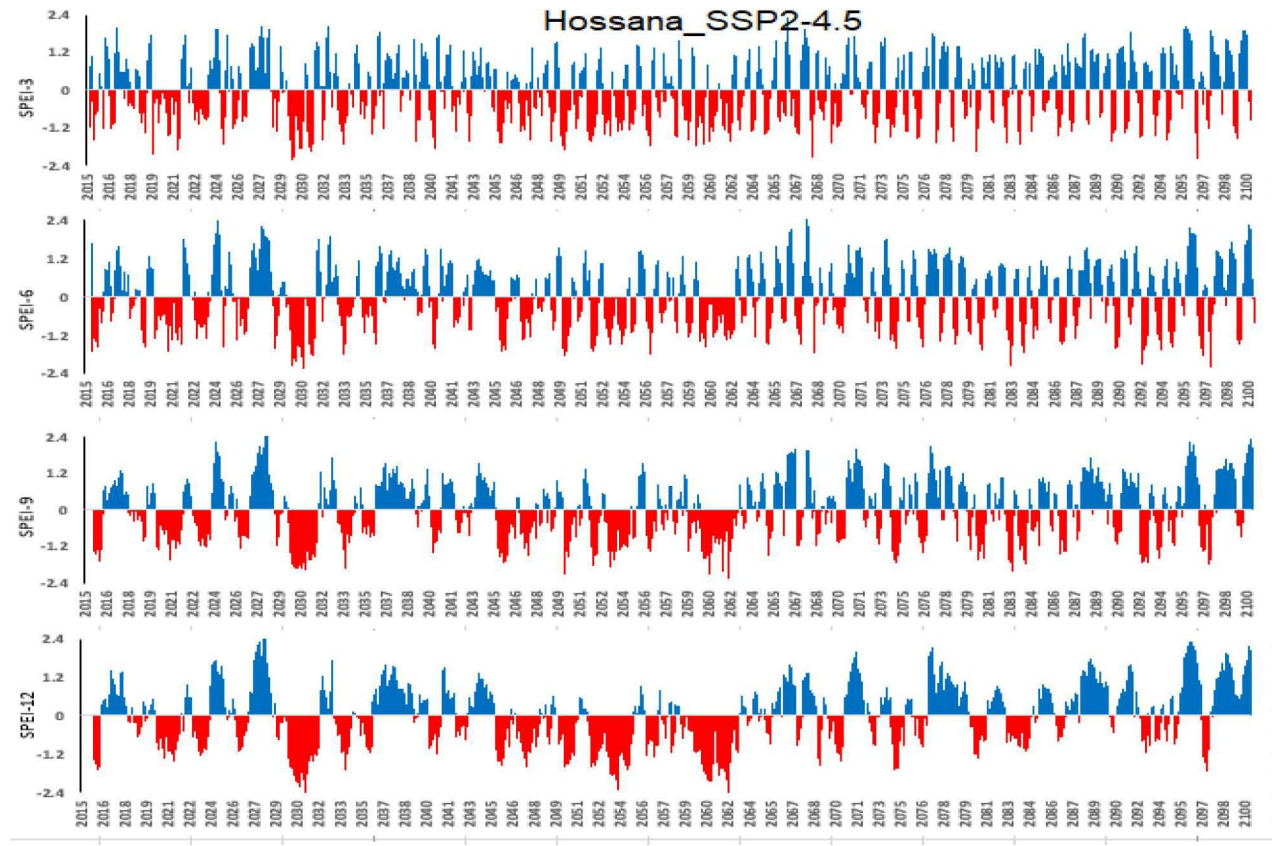


Figure 5.4: Plot of SPEI-3, SPEI-6, SPEI-9, and SPEI-12 of Hossana Station under SSP2-4.5 emission scenario.

In Hossana station under SSP2-4.5, events of moderate drought are typically observed across all time scales, particularly in the SPEI-3 (Figure 5. 4), reflecting recurrent short-term drought. These short-term droughts typically last a few months at the SPEI-3 scale. For longer timescales (SPEI-9, SPEI-12), moderate droughts characterize more longer periods of drought, sometimes lasting for a year or more (e.g., observed in the early 2040s, mid-2060s, and late 2080s in the SPEI-12 (Figure 5. 4). Major periods where severe drought conditions are indicated include 2030-2032 which shows strong negative peaks reaching severe levels across multiple timescales (SPEI-6,

SPEI-9, SPEI-12). Mid-2050s (2055-2057): where severe drought conditions are predictable , noticeable especially in SPEI-9 and SPEI-12 (Figure 5.4). Extreme drought events, are also projected, although less frequently than moderate or severe droughts. These are identifiable as the sharpest negative peaks in Figure 5. 4. Based on visual inspection: the period around 2030-2031 indicates values exceeding the extreme drought threshold, particularly evident in the SPEI-6, SPEI-9, and potentially SPEI-12 (Figure 5. 4). In general, the analysis of projected SPEI under the SSP2-4.5 scenario for Hossana station indicates a future characterized by significant hydroclimatic variability, interrupted by recurrent droughts of varying intensity and duration. The frequent occurrence of moderate short-term droughts (SPEI-3) suggests ongoing challenges for rainfed agriculture. The projected severe and extreme drought events, particularly those identified around the early 2030s and mid-2050s which manifest across multiple time scales, indicates periods of vulnerability.

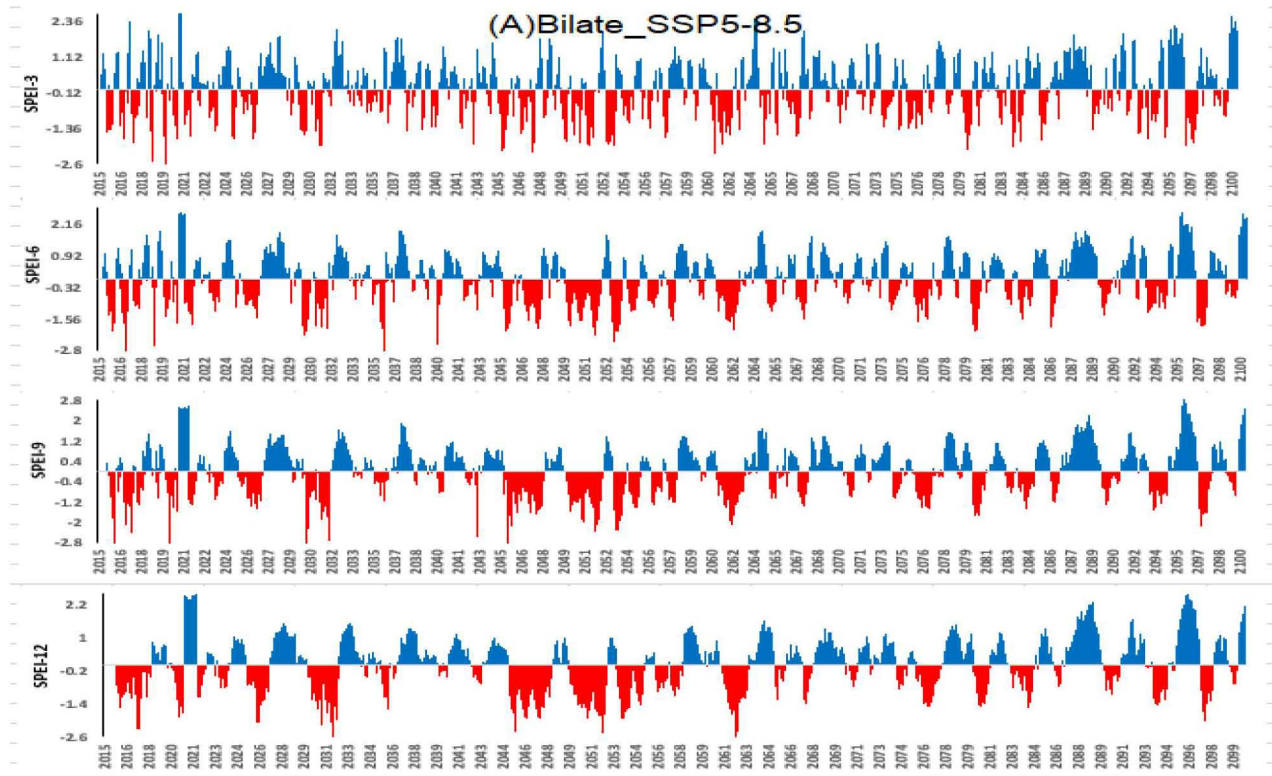


Figure 5.5: Plot of SPEI-3, SPEI-6, SPEI-9, and SPEI-12 of Bilate Station under high SPP5-8.5 emission scenario.

The Bilate Station under the high-emission SSP5-8.5 scenario, moderate drought is often observed across all four-time scales and these events commonly occurred, indicating recurrent periods of

moderate drought. The frequency of these drought events appears particularly high in the shorter-term SPEI-3 and SPEI-6. Although their frequency is smaller than moderate drought, severe drought is visible in the projection of all-time scale. Severe drought recognized visually in the periods of 2030s, mid-2040s, early 2050s, late 2070s, and the mid-2080s. The persistence of these events tends to increase with longer SPEI timescales. Extreme drought is relatively more frequent, though often shorter-lived, at the SPEI-3 timescale. However, extreme droughts are also observed at the SPEI-6, SPEI-9, and SPEI-12-time scales, expected impacting water resources. Distinguished extreme drought periods are observed around 2032, 2045-2046, 2052, and 2085-2086, visible across one or more-time scales (Figure 5. 5). Bilate Station under the SSP5-8.5 scenario strongly suggest a future marked by significant hydro-climatic stress, characterized by the recurrent onset of moderate, severe, and extreme drought conditions throughout the study period. The frequent moderate and severe droughts showed by SPEI-3 and SPEI-6 indicate towards persistent vulnerability in sectors sensitive to short-to-medium term moisture availability, such as rain-fed agriculture.

Similarly, in Hossana station under SSP5-8.5, SPEI-3 indicates frequent moderate drought events (SPEI below -1.0) are projected throughout the study period. Severe drought events (SPEI below -1.5) are also frequent, observed as relatively short period. Particularly, multiple incidents of extreme drought ($\text{SPEI} \leq -2.0$) are observed, indicating recurrent periods of intense short-term water deficit potentially impacting rain-fed agriculture. The extreme events observed distributed across the study period, for example, visible around the mid-2020s, mid-2040s, late 2050s, mid-2070s, and late 2090s (Figure 5. 6). Similar patterns are observed in SPEI-6, SPEI-9 and SPEI-12 in Figure 5. 4.

In general, the SPEI value projection under the SSP5-8.5 scenario indicates a future of recurring and intense drought at the Hossana Station on different time scales. High frequency of moderate, severe, and extreme droughts at the short-term (SPEI-3, SPEI-6) suggests vulnerable sensitivity for agriculture relying on seasonal rainfall. The persistence of droughts, particularly extreme droughts, in the longer-term indices (SPEI-9, SPEI-12) signifies serious water resource management issues. There are some significant multi-year drought events observed, particularly in the middle part of the century (late 2040s-mid 2050s) and at the end of the century (late 2090s), that merit particular attention for long-term adaptation planning.

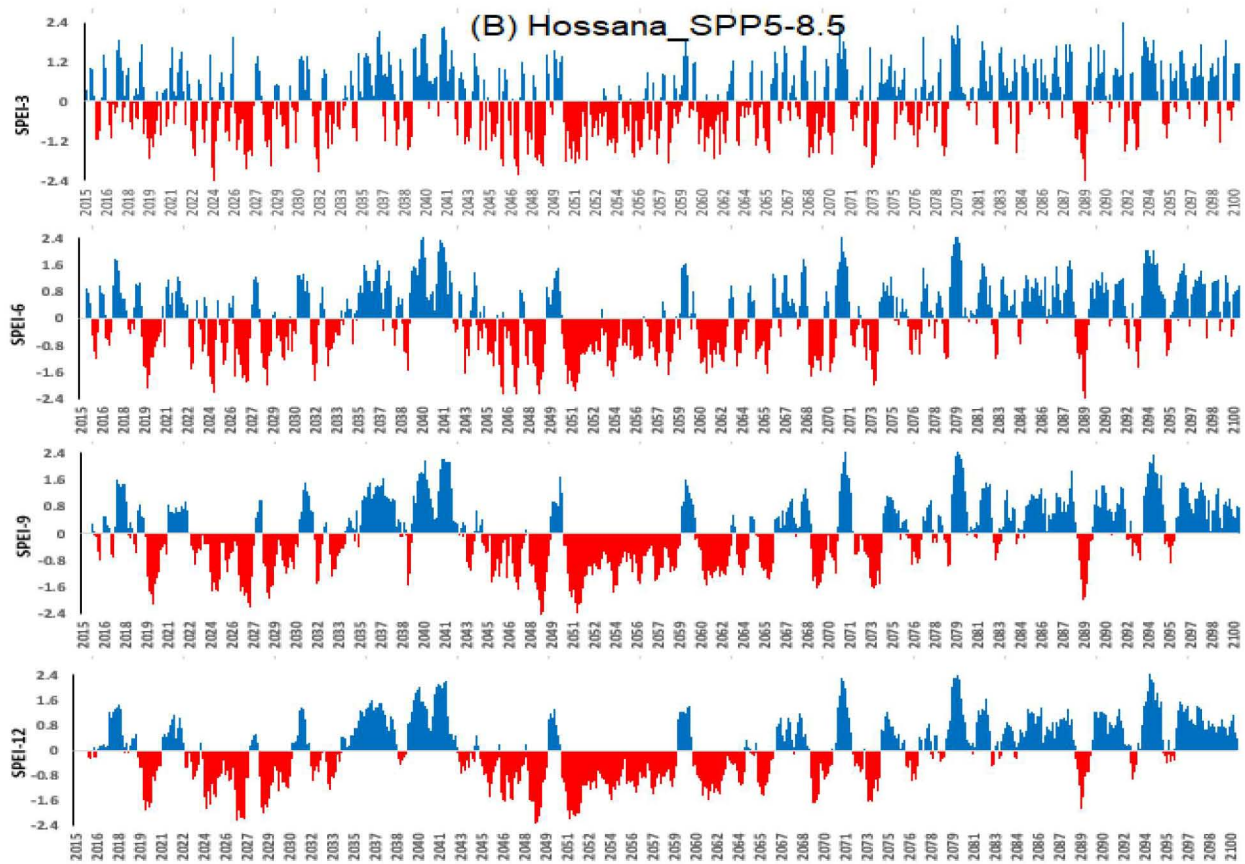


Figure 5.6: Plot of SPEI-3, SPEI-6, SPEI-9, and SPEI-12 of Hossana Station under high SPP5-8.5 emission scenario.

In Bilate under SSP2-4.5, the magnitudes of identified drought occurrences were indicated by drought severity, which is defined as cumulative deficiency and intensity. Although intense droughts can occur across all timescales (e.g., -2.51 for SPEI-3, -2.20 for SPEI-9), the most severe events in terms of total cumulative deficit were observed in the longer-term indices. For example, SPEI-9 event (2053-2054) with a severity of -14.79 over 8 months and an SPEI-12 event (2052) reaching a severity of -16.55 over 9 months, indicating substantial accumulated water stress during these periods (Table 5. 5).

Across time scale, there is a trend for the length of drought occurrences to increase. For instance, SPEI- shows about 3-5 months, but in the case of SPEI-9 and SPEI-12 shows range sustained duration with a value of 4 up to 8/9 months (Table 5. 5). This result is similar with the expectation as longer time scales assimilate condition for extended period of time. Thus, drought events in this case identified represent more prolonged that affects agriculture and hydrology of the watershed. Drought frequencies significantly varies across the time scales considered in this analysis (Table

5. 5). For instance, SPEI-3 is the most occurring approximately 0.48 times per year (41 drought events), showing a meteorological drought. SPEI-6 droughts are relatively less frequent at 0.42 events per year (36 total events) representing agricultural drought. The longer drought events captured by SPEI- and SPEI-12 were less often with a frequency of 0.27 and 0.28 events per year, respectively. When the focus is the timing of major events, the mid-2045 and late-2047 periods appear as prominent drought intervals captured by several SPEI indices. However, the early-to-mid 2050s (approximately 2050-2054) stand out prominently, covering multiple major drought events listed across all SPEI timescales, including some of the most severe and extreme drought events presented in Table 5. 5. The recurrence of drought signals across SPEI-3, -6, -9, and -12 during this timeframe strongly suggests a critical multi-year period of pervasive drought conditions affecting agricultural systems and longer-term hydrological resources in the watershed.

In summary, the watershed experiences frequent short-term meteorological droughts (SPEI-3) roughly every two years, while less frequent but often longer-lasting and potentially more cumulatively severe agricultural and hydrological droughts (SPEI-9, SPEI-12) occur approximately every 3-4 years. While high drought intensity (rapid deficit accumulation) can manifest on any timescale, the largest total water deficits (severity) tend to be associated with the longer-duration events captured by SPEI-9 and SPEI-12. Critically, periods like the early-to-mid 2050s, where major drought events were identified concurrently across all SPEI timescales, highlight times of profound and widespread water stress impacting the watershed from immediate soil moisture levels through to long-term water storage systems.

Table 5.5: Selected major Drought events at Bilate Station in intermediate emission (SPP2-4.5) scenario

Drought	Start Date	End Date	Duration (Months)	Severity	Intensity	Total No of Events	Frequency (Events per year)
SPEI-3	12/1/2019	2/1/2020	3	-7.53272	-2.510907	41	0.4767442
	9/1/2031	11/1/2031	3	-5.482317	-1.827439		
	6/1/2045	8/1/2045	3	-5.754583	-1.918194		
	10/1/2047	12/1/2047	3	-5.603561	-1.867854		
	3/1/2050	5/1/2050	3	-5.330515	-1.776838		
	8/1/2053	12/1/2053	5	-8.682835	-1.736567		
	6/1/2080	9/1/2080	4	-6.83807	-1.709518		
SPEI-6	5/1/2030	9/1/2030	5	-9.4943	-1.89886	36	0.4186047
	7/1/2045	10/1/2045	4	-7.7	-1.925		
	12/1/2047	2/1/2048	3	-5.24363	-1.74788		
	1/1/2052	5/1/2052	5	-9.66895	-1.93379		
	7/1/2053	1/1/2054	7	-14.0876	-2.01252		
	7/1/2080	11/1/2080	5	-9.15304	-1.83061		
	7/1/2097	11/1/2097	5	-8.71029	-1.74206		
SPEI-9	8/1/2045	1/1/2046	6	-13.2299	-2.20499	23	0.2674419
	3/1/2051	6/1/2051	4	-7.27972	-1.81993		
	3/1/2052	7/1/2052	5	-10.2531	-2.05062		
	9/1/2053	4/1/2054	8	-14.7886	-1.84858		
	5/1/2062	9/1/2062	5	-9.55724	-1.91145		
	9/1/2080	1/1/2081	5	-8.13311	-1.62662		
	8/1/2097	2/1/2098	7	-12.0744	-1.72491		
SPEI-12	6/1/2017	9/1/2017	4	-8.00657	-2.00164	24	0.2790698
	9/1/2045	1/1/2046	5	-9.8182	-1.96364		
	8/1/2047	12/1/2047	5	-8.54167	-1.70833		
	4/1/2051	8/1/2051	5	-8.33295	-1.66659		
	1/1/2052	9/1/2052	9	-16.5521	-1.83913		
	12/1/2053	7/1/2054	8	-13.8858	-1.73572		
	3/1/2062	10/1/2062	8	-15.4816	-1.9352		

In Hossana under SSP2-4.5 with SPEI-3, which typically reflects short-term meteorological or agricultural drought conditions, and Table 5. 6 indicates the highest frequency of 0.4767 per year (total 41 events). The drought is commonly characterized by shorter durations, ranging from 2 to 4 months. While frequent, the individual event severities (e.g., -3.1 to -7.4) and intensities (around -1.55 to -2.01) are relatively lower than some of the more extreme events observed at longer

timescales in Table 5. 6. This suggests frequent, relatively short-lived periods of precipitation deficit mainly affecting the early stages of agriculture.

SPEI-6 and SPEI-9 show indicate frequencies of 0.3837 and 0.3605 events per year, respectively compared to SPEI-3. Drought events identified by SPEI-6 and SPEI-9 often have longer durations, ranging from 3 to 6 months for SPEI-6 and 2 to a prominent 13 months for SPEI-9 (Table 5. 6). The severity and intensity values can also increase; for instance, the 13-month SPEI-9 event starting in April 2030 exhibited a significant severity of -23.5847. The increased duration and potential for higher severity under these indices suggest impacts that extend beyond short-term agricultural concerns, likely affecting stream flows, soil moisture at deeper levels, and surface water supplies more substantially.

SPEI-12 shows the lowest frequency value of 0.2093 events per year with only 18 events in Table 5. 6. However, these events often display significantly longer durations, for example lasting 16, 9, and 10 months. Correspondingly, the cumulative severity can be substantial, intensified by the 16-month event starting June 2030 with a severity of -30.7693 and a high average intensity of -1.92308. These characteristics signify prolonged periods of water deficit with major implications for groundwater levels, and overall water resource management, representing the most persistent drought conditions captured in this analysis.

Overall, the SPEI-3, SPEI-6, SPEI-9, and SPEI-12 examination of drought occurrences reveals unique drought features. Short-term SPEI-3 droughts are most frequent (0.48 events/year) but typically brief (2-4 months duration) with moderate severity, reflecting agricultural stress. In contrast, long-term SPEI-12 droughts are least frequent (0.21 events/year) but can endure significantly longer (e.g., 16, 10, 9 months duration) and accumulate substantial severity (e.g., -30.8) and high intensity (e.g., -1.93), indicating major hydrological impacts on water resources. Intermediate SPEI-6 and SPEI-9 indices show characteristics bridging these extremes. Overall, Table 5. 6 present a trade-off: higher frequency for shorter, less severe droughts (SPEI-3) versus lower frequency for potentially much longer and more severe hydrological droughts (SPEI-12).

Table 5.6: Selected major Drought events at Hossana Station in intermediate emission (SPP2-4.5) scenario.

Drought	Start Date	End Date	Duration (Months)	Severity	Intensity	Total No of Events	Frequency (Events per year)
SPEI-3	7/1/2015	8/1/2015	2	-3.10987	-1.55493	41	0.4767442
	3/1/2030	5/1/2030	3	-6.02154	-2.00718		
	9/1/2030	11/1/2030	3	-5.36186	-1.78729		
	6/1/2031	9/1/2031	4	-7.35807	-1.83952		
	8/1/2040	9/1/2040	2	-3.35451	-1.67726		
	6/1/2045	8/1/2045	3	-4.92469	-1.64156		
	2/1/2050	4/1/2050	3	-5.36381	-1.78794		
SPEI-6	3/1/2030	8/1/2030	6	-11.2123	-1.86872	33	0.3837209
	10/1/2030	1/1/2031	4	-7.47928	-1.86982		
	7/1/2031	10/1/2031	4	-6.75624	-1.68906		
	8/1/2045	11/1/2045	4	-6.40544	-1.60136		
	3/1/2050	5/1/2050	3	-5.20029	-1.73343		
	4/1/2052	7/1/2052	4	-6.40255	-1.60064		
	11/1/2083	2/1/2084	4	-6.52395	-1.63099		
SPEI-9	4/1/2030	4/1/2031	13	-23.5847	-1.81421	31	0.3604651
	7/1/2031	9/1/2031	3	-4.92192	-1.64064		
	11/1/2045	12/1/2045	2	-3.43215	-1.71607		
	8/1/2050	9/1/2050	2	-3.09619	-1.5481		
	6/1/2052	8/1/2052	3	-4.9212	-1.6404		
	9/1/2074	11/1/2074	3	-4.91068	-1.63689		
	2/1/2083	4/1/2083	3	-5.38131	-1.79377		
SPEI-12	2/1/2016	5/1/2016	4	-6.46118	-1.6153	18	0.2093023
	6/1/2030	9/1/2031	16	-30.7693	-1.92308		
	11/1/2053	7/1/2054	9	-17.3588	-1.92876		
	1/1/2055	4/1/2055	4	-6.40549	-1.60137		
	9/1/2060	6/1/2061	10	-18.3491	-1.83491		
	12/1/2061	8/1/2062	9	-17.2514	-1.91682		
	10/1/2074	11/1/2074	2	-3.34879	-1.6744		

Similarly, Bilate under SSP5-8.5, on the shorter-term droughts, SPEI-3 exhibits the highest frequency, with an average of 0.488 events per year, totaling 42 events in the analysis period (Table 5. 7). These events are typically shorter, often lasting 3 months, though some extend to 5 months (e.g., 8/1/2053-12/1/2053). The severity and intensity values, while indicating drought conditions, are generally less extreme compared to longer timescales. SPEI-6 are somewhat less frequent (0.407 events/year, 35 total events) but show a tendency for longer durations (up to 7 months) and potentially greater severity, as seen in the 7/1/2053 event (-14.0876 severity).

SPEI-9 and SPEI-12 point to longer droughts. Less frequent is the occurrence, at 0.279 events/year (24 events) for SPEI-9 and 0.291 events/year (25 events) for SPEI-12. Although less frequent than

the short-term droughts, they occur much longer (up to 7 months for SPEI-9, and up to 9 months for SPEI-12) and reach much higher severity and intensity values (Table 5. 7). For instance, the SPEI-9 event that began on 8/1/2045 had a severity of -13.2281, and a particularly severe SPEI-12 drought that began on 1/1/2052 lasted for 9 months with a severity of -16.5521.

The different time scales indicate a consistent pattern: when the integration period of the SPEI increases, the number of drought events observed will decrease. However, the potential duration, severity, and intensity of the droughts taking place will increase. This is to say that while relatively frequent short meteorological droughts (SPEI-3) can happen, extensive, longer hydrological droughts (more appropriately captured by SPEI-9 and SPEI-12) are less frequent but far more far-reaching in impact when they do happen, being a greater burden due to the longer time and build-up water deficit. The study presents an upward trend with recurrent drought events on various timescales. The region can be expected to experience recurring, short-lived droughts (SPEI-3) and less frequent but potentially much more severe and longer-duration droughts (SPEI-9, SPEI-12). This compound drought hazard of both short-duration dryness and long-duration large-scale water shortage emphasizes the need for resilient water resource management and adaptation measures capable of addressing impacts across both temporal scales in the next few decades.

Bilate station under SSP5-8.5 scenario suggests a future facing significant and intensifying drought. The projected high frequency of shorter droughts (SPEI-3) combined with the occurrence of severe, multi-season droughts (SPEI-9, SPEI-12), including events lasting 8-9 months with high severity (e.g., -16.55 in 2052, -15.48 in 2062 for SPEI-12) (Table 5. 7), aligns with expectations of increased climate variability and extreme events under SSP5-8.5 scenario. This pattern points towards rising water stress, impacting agriculture, water sources, reinforcing the critical need for proactive adaptation measures to cope with the harsh hydroclimatic conditions projected under this high-warming future.

Table 5.7: Selected major drought events in Bilate Station in high emission (SSP5-8.5) Scenarios

Drought	Start Date	End Date	Duration (Months)	Severity	Intensity	Total No of Events	Frequency (Events per year)
SPEI-3	12/1/2019	2/1/2020	3	-7.49413	-2.49804	42	0.4883721
	9/1/2031	11/1/2031	3	-5.48143	-1.82714		
	6/1/2045	8/1/2045	3	-5.75268	-1.91756		
	10/1/2047	12/1/2047	3	-5.60356	-1.86785		
	3/1/2050	5/1/2050	3	-5.33052	-1.77684		
	8/1/2053	12/1/2053	5	-8.68284	-1.73657		
	6/1/2080	9/1/2080	4	-6.83807	-1.70952		
SPEI-6	5/1/2030	9/1/2030	5	-9.49095	-1.89819	35	0.4069767
	7/1/2045	10/1/2045	4	-7.69788	-1.92447		
	12/1/2047	2/1/2048	3	-5.24363	-1.74788		
	1/1/2052	5/1/2052	5	-9.66895	-1.93379		
	7/1/2053	1/1/2054	7	-14.0876	-2.01252		
	7/1/2080	11/1/2080	5	-9.15304	-1.83061		
	7/1/2097	11/1/2097	5	-8.71029	-1.74206		
SPEI-9	8/1/2045	1/1/2046	6	-13.2281	-2.20469	24	0.2790698
	10/1/2047	1/1/2048	4	-6.34435	-1.58609		
	3/1/2051	6/1/2051	4	-7.27972	-1.81993		
	3/1/2052	7/1/2052	5	-10.2531	-2.05062		
	5/1/2062	9/1/2062	5	-9.55724	-1.91145		
	9/1/2080	1/1/2081	5	-8.13311	-1.62662		
	8/1/2097	2/1/2098	7	-12.0744	-1.72491		
SPEI-12	9/1/2045	1/1/2046	5	-9.82105	-1.96421	25	0.2906977
	8/1/2046	12/1/2046	5	-8.54167	-1.70833		
	8/1/2047	12/1/2047	5	-8.54167	-1.70833		
	4/1/2051	8/1/2051	5	-8.33295	-1.66659		
	1/1/2052	9/1/2052	9	-16.5521	-1.83913		
	12/1/2053	7/1/2054	8	-13.8858	-1.73572		
	3/1/2062	10/1/2062	8	-15.4816	-1.9352		

Table 5.8: Selected major drought events in Hossana Station in high emission (SSP5-8.5) Scenarios

Drought	Start Date	End Date	Duration (Months)	Severity	Intensity	Total No of Events	Frequency (Events per year)
SPEI-3	11/1/2026	2/1/2027	4	-6.70827	-1.67707	35	0.4069767
	4/1/2032	6/1/2032	3	-5.41647	-1.80549		
	1/1/2047	5/1/2047	5	-9.85833	-1.97167		
	8/1/2048	11/1/2048	4	-6.84168	-1.71042		
	1/1/2049	3/1/2049	3	-5.77375	-1.92458		
	8/1/2051	10/1/2051	3	-5.13488	-1.71163		
	4/1/2089	7/1/2089	4	-7.96845	-1.99211		
SPEI-6	12/1/2019	2/1/2020	3	-5.28143	-1.76048	24	0.2790698
	9/1/2024	12/1/2024	4	-7.6702	-1.91755		
	1/1/2027	7/1/2027	7	-11.9526	-1.70752		
	9/1/2028	12/1/2028	4	-6.86092	-1.71523		
	11/1/2048	4/1/2049	6	-11.8428	-1.97381		
	5/1/2051	1/1/2052	9	-16.8442	-1.87158		
	6/1/2054	8/1/2054	3	-4.80308	-1.60103		
SPEI-9	12/1/2019	5/1/2020	6	-10.6041	-1.76734	19	0.2209302
	12/1/2026	7/1/2027	8	-15.4091	-1.92613		
	9/1/2028	1/1/2029	5	-8.85903	-1.77181		
	10/1/2048	5/1/2049	8	-15.8593	-1.98241		
	4/1/2051	4/1/2052	13	-24.6253	-1.89426		
	6/1/2054	9/1/2054	4	-6.51517	-1.62879		
	9/1/2073	1/1/2074	5	-7.79039	-1.55808		
SPEI-12	2/1/2020	8/1/2020	7	-12.2797	-1.75424	17	0.1976744
	12/1/2026	8/1/2027	9	-18.1615	-2.01795		
	11/1/2028	3/1/2029	5	-8.90318	-1.78064		
	9/1/2048	7/1/2049	11	-20.7259	-1.88418		
	6/1/2051	6/1/2052	13	-25.125	-1.9327		
	8/1/2069	12/1/2069	5	-8.03943	-1.60789		
	10/1/2073	1/1/2074	4	-6.44988	-1.61247		

Similarly, in Hosamane station under SSP5-8.5 scenario, analysis of the SPEI-3 data shows the highest frequency of drought events (35 events, ~0.41 events/year). These short-term droughts, reflecting conditions over 3 months, typically have shorter durations (ranging from 3 to 5 months shown in Table 5. 8) and comparatively lower cumulative severity scores than those identified by longer-term indices. For instance, the most severe SPEI-3 event listed (-9.85833) occurred over 5 months. This indicates frequent occurrences of relatively short dry spells, which could primarily impact rain-fed agriculture.

SPEI-6 and SPEI-9 both show a decreasing number of events (24 events/~0.28 per year for SPEI-6; 19 events/~0.22 per year for SPEI-9). The events detected, however, have longer durations and

much larger cumulative severity. SPEI-6 detects events with durations as long as 9 months with a severity of -16.8442, while SPEI-9 detects droughts with durations of up to 13 months with severity values as high as -24.6253 (Table 5.8). These indices record longer dryness that affects seasonal water supplies like streamflow. SPEI-12 identifies the fewest drought events (17 events, ~0.20 events/year), consistent with its 12-month timescale. However, these events are the longest-lasting droughts, with durations shown lasting up to 13 months and with the largest cumulative severity values for instance, -25.125 for the 2051-2052 event. These multi-decadal droughts constitute extreme hydrological stress, with probably severe impacts on major water bodies and groundwater recharge over extended periods. The simulations show notable drought activity at all time scales, with the most severe events simulated in the middle of the present century (e.g., 2048-2052).

Overall, these simulated drought characteristics, based on climate model simulations, give a picture if interpreted through the prism of SSP5-8.5. The results, showing recurring short-term droughts (SPEI-3) coupled with less common but extremely intense and prolonged hydrological droughts (SPEI-9, SPEI-12), particularly the massive events predicted near mid-century—are firmly in performance with the increased frequency/severity of extremes foreseen under SSP5-8.5. This kind of drought regime under this scenario implies water resource management challenges, widespread agricultural damage, and potentially intense socio-economic vulnerabilities due to the lack of water, indicating the severe effects of greenhouse gas emissions as evidenced in the SSP5-8.5 future.

5.3.3. Change Point Analysis (Pettitt Test)

The change point analysis (Pettitt test) consistently shows low p-values ranging from 0.00291 down to 2.2×10^{-16} in all stations and all SPEI time scales shown change point statistics (U^*) in Table 5. 9. In Table 5. 9 the change point value consistently shows negative values for all stations. The magnitude of the negative value indicates the intensity of this shift, with values like -1.42 (Hossana SPEI-6) and -1.27 (Wulbareg SPEI-3) showing pronounced transitions to drier condition compared to values closer to zero (e.g., -0.045 for Wolayta SPEI-12).

The change points analysis identified are projected to occur mainly in the latter half of the 21st century, grouped between the mid-2060s and the late 2080s (Table 5. 9). For instance, stations like Bilate, Hossana, and Wolayta Sodo show change points mainly occurring in the 2060s (e.g., 2063,

2066, 2067). Shone and Wulbareg exhibit change points concentrated around the year 2077. Boditi's change points are clustered around 2078-2080. Alaba shows slightly later change points, mostly occurring in the 2080s (2077-2087). Therefore, the consistent detection of statistically significant future change observed towards drier conditions across, all stations and SPEI timescales under the moderate SSP2-4.5 scenario.

The Pettitt test under the SSP2-4.5 scenario, reveals statistically highly significant ($p < 0.01$) abrupt change points across all locations and drought timescales. The consistently negative change point values strongly indicate a projected shift towards significantly drier conditions (lower SPEI values) following these change points. These abrupt transitions to a potentially more arid regime are predominantly projected to occur between the mid-2060s and the late 2080s. The timing often shows consistency across different SPEI timescales within individual stations, suggesting fundamental hydro-climatic shifts impacting meteorological, agricultural, and hydrological drought characteristics around the same future periods.

Table 5.9: Pettitt Test for all stations under intermediate emission (SSP2-4.5) scenario.

Station	Drought Category	Pettitt Test Statistics			
		CP Statistics (U*)	P-value	CP Value	CP Month, Year
Alaba	SPEI-3	44336	4.56E-05	-0.89838	Feb,2084
	SPEI-6	59162	1.08E-08	-0.396	May, 2077
	SPEI-9	72140	1.03E-12	-0.51066	Dec,2086
	SPEI-12	81426	4.39E-16	-0.3323	Jan, 2087
Bilate	SPEI-3	34660	0.00291	-1.01095	Dec, 2067
	SPEI-6	45308	2.84E-05	-0.2681	Jun, 2063
	SPEI-9	55070	1.38E-07	-0.18265	Jun, 2063
	SPEI-12	65486	1.49E-10	-0.16208	Jul, 2063
Hossana	SPEI-3	42656	0.000101	-0.82172	Aug, 2076
	SPEI-6	37832	0.000834	-1.42391	Aug,2063
	SPEI-9	57274	3.58E-08	-0.41609	Sep, 2063
	SPEI-12	93258	2.20E-16	-0.63996	May, 2063
Boditi	SPEI-3	42300	0.000119	-0.52701	Dec, 2080
	SPEI-6	56802	4.80E-08	-0.93979	Jan, 2078
	SPEI-9	63138	7.70E-10	-0.22927	Mar, 2078
	SPEI-12	69214	9.71E-12	-0.27713	Feb,2078
Shone	SPEI-3	37476	0.000964	-0.89062	Sep, 2084
	SPEI-6	45336	2.80E-05	-0.66562	Jan, 2077
	SPEI-9	55226	1.25E-07	-0.19299	May,2077
	SPEI-12	61404	2.49E-09	-0.46747	May, 2077
Wolayta	SPEI-3	50716	1.69E-06	-0.9565	Sep, 2067
	SPEI-6	64326	3.38E-10	-0.9668	Jun, 2066
	SPEI-9	74418	1.67E-13	-0.20742	Jul, 2066
	SPEI-12	85658	2.20E-16	-0.04534	Jul, 2066
Wulbareg	SPEI-3	61368	2.55E-09	-1.27259	Jan,2077
	SPEI-6	85180	2.20E-16	-0.16003	Apr, 2077
	SPEI-9	100056	2.20E-16	-0.3261	May, 2077
	SPEI-12	113440	2.20E-16	-0.89615	May, 2077

Note: CP = Change Point

Similarly, the Pettitt test under SSP5-8 scenario, results consistently indicate the existence of statistically significant change points in all stations and time scales considered. The extremely low p-values, predominantly 2.2e-16 underscore the high statistical confidence in the detected shifts. Even the slightly higher p-values observed for Bilate (e.g., 0.005273 for SPEI-3) remain well below conventional significance levels (e.g., $\alpha = 0.05$), confirming the robustness of the detected changes. The uniformly negative sign of the Change point Value noted as a critical finding for all entries.

Table 5.10: Pettitt Test for all stations under high emission (SSP5-8.5) scenario

Station	Drought Category	Pettitt Test Statistics			
		CP Statistics (U*)	P-value	CP Value	CP Month, Year
Alaba	SPEI-3	90108	2.20E-16	-0.6987944	Oct, 2070
	SPEI-6	116606	2.20E-16	-0.1801206	Jan, 2071
	SPEI-9	134892	2.20E-16	-0.5279848	Jan, 2071
	SPEI-12	143922	2.20E-16	-0.08048661	Dec, 2070
Bilate	SPEI-3	33046	0.005273	-1.010952	Dec, 2067
	SPEI-6	44498	4.22E-05	-1.592179	Jun, 2063
	SPEI-9	55928	8.20E-08	-0.182652	Jun, 2063
	SPEI-12	65794	1.20E-10	-0.1620811	Jul, 2063
Hossana	SPEI-3	68694	1.44E-11	-0.9498955	Oct, 2070
	SPEI-6	92542	2.20E-16	-0.2428506	Mar, 2074
	SPEI-9	108350	2.20E-16	-0.04983827	Jun, 2074
	SPEI-12	117058	2.20E-16	-0.1980475	Jul, 2074
Boditi	SPEI-3	79020	3.59E-15	-0.6443944	Jan, 2066
	SPEI-6	99892	2.20E-16	-0.2333433	Mar, 2066
	SPEI-9	112434	2.20E-16	-0.7216315	Apr, 2066
	SPEI-12	124190	2.20E-16	-0.00421639	Jul, 2066
Shone	SPEI-3	80830	7.44E-16	-0.4903844	Jan, 2070
	SPEI-6	102140	2.20E-16	-0.09250332	Apr, 2074
	SPEI-9	117750	2.20E-16	-0.2512192	Jun, 2074
	SPEI-12	127706	2.20E-16	-0.195207	Oct, 2070
Wolayta	SPEI-3	78998	3.65E-15	-0.08076415	Mar, 2066
	SPEI-6	99782	2.20E-16	-0.1952007	May, 2066
	SPEI-9	100518	2.20E-16	-0.1952007	May, 2066
	SPEI-12	124290	2.20E-16	-0.03715721	Dec, 2074
Wulbareg	SPEI-3	83208	2.20E-16	-0.4866149	Nov, 2070
	SPEI-6	101648	2.20E-16	-0.6513414	Jan, 2071
	SPEI-9	115184	2.20E-16	-0.01143936	Mar, 2071
	SPEI-12	124288	2.20E-16	-0.384281	May, 2071

Note: CP = Change Point

The SPEI is structured such that lower values represent drier conditions. Therefore, a negative change point value represents an abrupt shift in the mean SPEI towards lower values after the identified change point year/month, compared to the previous period. This collectively implies a future characterized by an increase in drought or a rise in severity/frequency of dry periods at all the sites and drought time scales under the SSP5-8.5 scenario. The 'Change point year/month' for these observed changes is largely imagined to occur in the latter part of the 21st century, largely clustered between 2063 and 2074. For instance, stations such as Bilate, Boditi, and Wolayta Sodo show change points around the mid-2060s, while Alaba, Hossana, Shone, and Wulbareg exhibit change points extending to the early 2070s (Table 5.10). Some variability is observed by station and SPEI timescale, reflecting potential differences in regional climate responses and in the time

scale of drought being considered. The SSP5-8.5 scenario is a high greenhouse gas emission and high global warming future. The simulated trend of increased dryness is consistent with expectations under such scenarios in most regions, due to processes that include increased evapotranspiration due to rising temperatures and potential shifts in precipitation regimes.

5.3.4. Power Spectral Analysis

In power spectral analysis under SSP2-4.5 scenario, there is variability in stations and time scales. For instance, for Alaba and Bilate, a consistent sub-annual cycle of 0.42 years (approx. 5 months) dominates across all time scales (Table 5. 11 and Figure 5. 7). This indicates strong intra-annual variability (perhaps related to distinct wet/dry seasons) is the primary driver of fluctuations at these locations. Shone also shows mainly sub-annual cycles (0.31-0.83 years). But in the case of Hossana, very short cycles (~1 month) for short-term SPEI, shifting to ~10 months (0.83 years) for SPEI-9 and a long multi-year cycle (7.5 years) for SPEI-12 (Table 5. 11 and Figure 5. 8). This implies different processes dominate variability depending on the time scale considered – short-term for seasonality vs. longer-term for climate cycles (Table 5. 11). The dominant cyclical behavior of drought/wet periods is complex and highly dependent on both the location and the timescale being considered. Sub-annual variability is prominent at several stations, while multi-year cycles (potentially related to climate phenomena like ENSO, often manifesting in the 2-7-year band) appear dominant only for specific timescales at certain locations (e.g., 7.5 years for SPEI-12 at Hossana, or 3.75 years for SPEI-9/12 at Boditi).

Under SSP5-8.5 scenario, there is appearance of strong multi-year cycles. For instance, For Alaba, Boditi, Shone, and Wulbareg, a 7.5-year cycle becomes the dominant period in all time scales. For instance, at Hossana, a 3.75-year cycle dominates across all SPEI time scales. Wolayta Sodo shows mostly a 7.5-year cycle, with a 3.75-year cycle for SPEI-9. This scenario suggests a potential establishment of multi-year climate variability (cycles of 3.75 or 7.5 years) that strongly influences drought/wet patterns across multiple time scales at most stations (Table 5. 11). This could imply that longer-term climate drivers become more dominant over local, sub-annual factors under higher warming levels.

Overall, the power spectral analysis discloses significant differences in the temporal characteristics of drought variability between the intermediate (SSP2-4.5) and high-emission (SSP5-8.5)

scenarios. While the SSP2-4.5 scenario exhibits a complex picture with mixed sub-annual and multi-year dominant cycles varying by location and time scale, the SSP5-8.5 scenario indicates a strong tendency towards the dominance of multi-year cycles (particularly 7.5 years, but also 3.75 years) across most stations and time scales. This suggests that under a high-emission future, drought patterns might become more strongly governed by periodic multi-year climate rhythms. The station Bilate provides a counter example, highlighting that local factors can still dominate under certain conditions (Figure 5.). These findings have implications for water resource management and adaptation planning, suggesting potentially different dominant frequencies of drought recurrence under different future scenarios.

Table 5.11: Results of Power Spectral analysis at SSP2-4.5 and SSP5-8.5 emission scenarios

Station	SSP2-4.5				SSP5-8.5			
	Dominant period (Years)				Dominant period (Years)			
	SPEI-3	SPEI-6	SPEI-9	SPEI-12	SPEI-3	SPEI-6	SPEI-9	SPEI-12
Alaba	0.42	0.42	0.42	0.42	7.5	7.5	7.5	7.5
Bilate	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42
Hossana	0.08	0.08	0.83	7.5	3.75	3.75	3.75	3.75
Boditi	0.3	7.5	3.75	3.75	7.5	7.5	7.5	7.5
Shone	0.31	0.31	0.31	0.83	7.5	7.5	7.5	7.5
Wolayta	7.5	0.3	0.3	0.3	7.5	7.5	3.75	7.5
Wulbareg	7.5	7.5	0.44	7.5	7.5	7.5	7.5	7.5

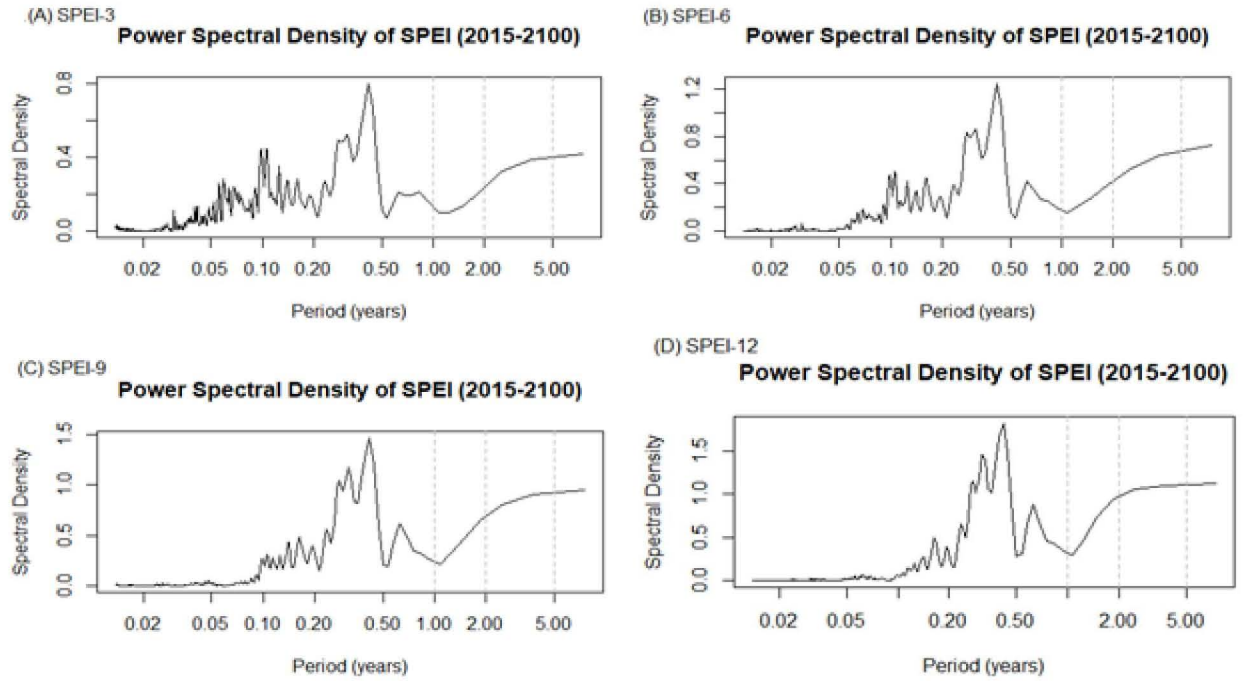


Figure 5.7: PSD at Bilate Station under SSP2-4.5 scenario: (A) SPEI-3, (B) SPEI-6, (C) SPEI-9, and (D) SPEI-12

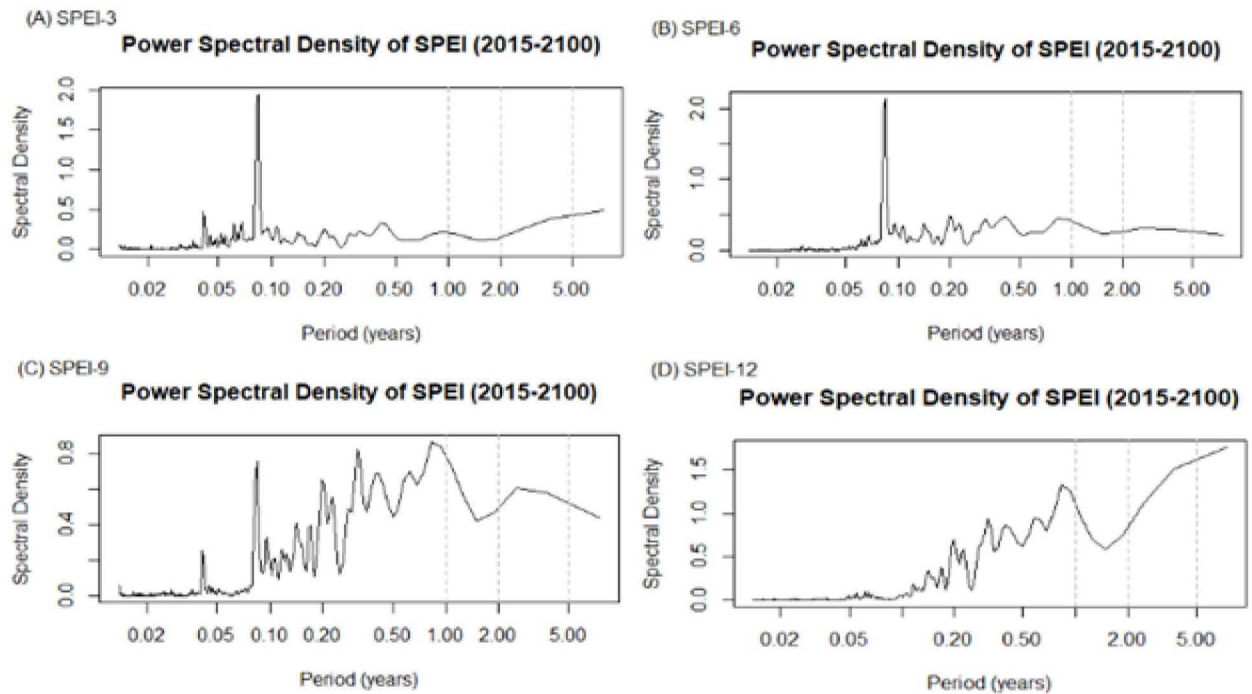


Figure 5.8: PSD at Hossana Station under SSP2-4.5 scenario: (A) SPEI-3, (B) SPEI-6, (C) SPEI-9, and (D) SPEI-12

5.3.5. Empirical Orthogonal Function (EOF) Analysis

In all time scales, the first EOF mode (EOF1, shown in Figure 5. 9) shows a consistent spatial pattern showing a negative loading for EOF1 in all stations. This shows that the dominant mode of variability in drought conditions, irrespective of the time scale considered, is spatially coherent across Bilate watershed. When this EOF1 is active, all stations tend to experience similar anomalies simultaneously – either all tending towards drier conditions (negative SPEI) or all tending towards wetter conditions (positive SPEI), depending on the sign of the corresponding principal component time series. The magnitudes of the loadings vary slightly among stations (e.g., Bilate often shows a stronger negative loading compared to Wulbareg in SPEI-3), suggesting some spatial variation in the intensity of response to this dominant mode, but the overall consistency is the key feature (Figure 5. 9). This spatial coherence strongly indicate that the primary driver of drought variability projected under SSP2-4.5 for this region is likely related to large-scale climatic factors or atmospheric circulation patterns that influence the area relatively uniformly.

The second EOF mode (EOF2, shown in Figure 5. 9) represents the second most significant pattern of variability, orthogonal to EOF1. Unlike EOF1, EOF2 indicates a pattern of spatial contrast across all time scales. This mode characterizes the stations with positive loadings and others with negative loadings, indicating that when this mode is active, some parts of the region experience anomalies opposite to others (e.g., some stations becoming drier while others become wetter). This outcome is consistent with Wang et al., (2015), who found that the second EOF mostly depicts the positive and negative variations related to the north and south arid regions, which are influenced by variations in pertinent terrain and atmospheric circulation.

For instance, For SPEI-3 (Figure 5. 9 A), EOF2 shows positive loadings primarily at Hossana, Wolayta Sodo, and Wulbareg, while Alaba, Bilate, Boditi, and Shone show negative loadings. This suggests a contrast primarily between the northwestern/northeastern and southwestern stations and the western/central stations for short-term variability. For SPEI-6, SPEI-9, and SPEI-12 (Figure 5. 9 B, C, D), the EOF2 pattern appears relatively Table 5., though a little different from SPEI-3. In these longer time scales, Bilate, Boditi, and Wolayta Sodo in general exhibit positive loadings, while Alaba, Hossana, Shone, and Wulbareg tend to display negative loadings (with Alaba having a particularly strong negative loading in SPEI-12). This repeated pattern in EOF2 reflects region-

scale forcing like topography, differential response to seasonal precipitation patterns, or mesoscale meteorological conditions that create contrasting conditions within the watershed. These results suggest that while region-scale drought events triggered by large-scale climate signals are the ubiquitous characteristic, intra-regional heterogeneity in drought severity triggered by EOF2 is also a repeated characteristic of projected hydroclimate under SSP2-4.5.



Figure 5.9: Empirical Orthogonal Function in intermediate (SSP2-4.5) emission scenario: (A) SPEI-3, (B) SPEI-6, (C) SPEI-9, and (D) SPEI-12

Similarly, the first EOF mode (EOF1, shown in Figure 5. 10) displays a consistent spatial pattern, showing negative loadings of similar magnitude (ranging approximately from -0.25 to -0.4) in all stations. This uniformity in sign and comparable magnitude across stations signifies that the dominant mode of drought variability in this watershed, under the SSP5-8.5 scenario, is characterized by strong spatial coherence. It implies that the primary driver of SPEI fluctuations tends to affect the entire study area relatively uniformly; the stations are likely to experience synchronous shifts towards wetter or drier conditions. The persistence of this spatially coherent pattern across short-term (SPEI-3) to longer-term (SPEI-12) drought indicators suggests that the

large-scale climatic factors influencing moisture availability under this high-emission future scenario dominate the regional drought signal regardless of the timescale considered.

The second EOF mode (EOF2, in Figure 5. 10), representing the next most significant pattern of variability orthogonal to EOF1, discloses spatial contrasts within the watershed. While EOF1 indicates homogeneity, EOF2 shows spatial differentiation in drought response. For SPEI-3 (Figure 5. 10A), EOF2 shows positive loadings for Alaba, Boditi, and Wulbareg (highest positive loading), while Hossana and Wolayta Sodo display negative loadings. Bilate and Shone show near-zero loadings, indicating minimal participation in this mode. This indicates a contrast primarily between the Wulbareg/Alaba/Boditi group and the Hossana/Wolayta Sodo group for short-term drought variability.

For SPEI-6, SPEI-9, and SPEI-12 (Figure 5. 10B, C and D), the EOF2 pattern stabilizes. In these longer timescales, Alaba, Boditi, Hossana, and Wulbareg show positive loadings, while Wolayta Sodo shows a strong negative loading. Bilate and Shone maintain relatively weak (near-zero or slightly negative) loadings. This persistent pattern for medium-to-long-term drought indicates a constant spatial gradient. It primarily contrasts the behavior of Wolayta Sodo against a cluster of stations including Hossana and Wulbareg.

EOF2 might reflect the influence of more localized factors, such as topography, land cover differences, or differential susceptibility to specific atmospheric circulation patterns that become more clearly expressed over longer accumulation periods (Figure 5.10). The stability of this pattern from SPEI-6 onwards suggests that the factors driving this spatial contrast are particularly relevant for multi-seasonal to annual drought dynamics. These findings underscore the importance of considering both dominant coherent patterns and secondary contrasting patterns when assessing future regional drought risk and developing adaptation strategies under high-emission climate change scenarios.



Figure 5.10: Empirical Orthogonal Function in high (SSP5-8.5) emission scenario: (A) SPEI-3, (B) SPEI-6, (C) SPEI-9, and (D) SPEI-12

5.3.6. Return period of Drought

In the return period analysis, under SSP2-4.5 scenario, the total number of projected drought events ranges from a minimum of 8 (Shone, SPEI3) to a maximum of 15 (Alaba, SPEI9) over the study period (Table 5. 12). This indicates significant spatial variation in drought susceptibility. Stations like Alaba (SPEI9), Boditi (SPEI3), and Wulbareg (SPEI6) show higher incidences (15, 14, and 12 events respectively) (Table 5. 12). The average return periods vary. The shortest return period is observed for Alaba SPEI9 at 5.7 years, suggesting relatively frequent moderate-term droughts at this station (Figure 5.). The longest return period is observed for Shone SPEI3 at 10.8 years, implying less frequent short-term (meteorological/agricultural) drought events at this station compared to others. Generally, return periods group between approximately 6 and 10 years. For

instance, SPEI12 (indicative of longer-term hydrological drought) shows return periods ranging from 7.2 years (Shone) to 9.6 years (Hossana, Wulbareg) (Table 5. 12).

Similarly, under SSP5-8.5 scenario, the number of drought events ranges from 5 (Boditi, SPEI9) to 14 (Bilate, SPEI3) (Table 5. 12) . While the maximum number of drought events (14 at Bilate SPEI3) is comparable to the SSP2-4.5 maximum, the minimum is notably lower. Return periods exhibit greater fluctuation under SSP5-8.5. The shortest return period is 6.1 years (Bilate, SPEI3), indicating a high frequency of short-term droughts (Table 5. 12). However, this scenario also characterizes significantly longer return periods for certain station-time scale combinations, particularly 17.2 years for Boditi SPEI9 and 12.3 years for both Bilate SPEI9 and Wolayta Sodo SPEI9. These values indicate that while some types of droughts might become more frequent (like SPEI3 at Bilate), others, particularly at the 9-month timescale in specific locations, might become considerably less frequent, potentially implying longer intervening periods but not necessarily lower severity when events do occur. Hydrological drought indicators (SPEI12) show return periods generally between 6.6 years (Hossana, Boditi, Wulbareg) and 8.6 years (Wolayta Sodo) (Table 5. 12).

There is no universal trend of return periods becoming consistently shorter or longer under the higher emission scenario (SSP5-8.5) compared to the moderate one (SSP2-4.5). The direction of change depends heavily on the station and the timescale of SPEI. For some station-time scale combinations, SSP5-8.5 leads to shorter return periods (more frequent droughts). For instance, SPEI3 for Bilate: 6.1 years (SSP5-8.5) vs. 7.8 years (SSP2-4.5) Hossana SPEI6 & SPEI12: 9.6 years vs. 6.6 years, Alaba SPEI6 & SPEI12: 6.6/8.6 years vs. 7.2 years (mixed signal here, SPEI6 slightly longer, SPEI12 shorter) (Table 5. 12). Therefore, the SSP5-8.5 scenario seems to introduce greater variability and more extreme return periods (both shorter and significantly longer) compared to the more constrained range observed under SSP2-4.5. Hence, SSP5-8.5 is arguably "worse" because it introduces greater extremes and unpredictability.

Table 5.12: Return period (years) in SSP2-4.5 and SSP5-8.5 scenarios for all stations

SSP2-4.5 Scenario			SSP5-8.5 Scenario		
Station	Total number of Drought events	Return period (Years)	Station	Total number of Drought events	Return period (Years)
Alaba			Alaba		
SPEI3	12	7.2	SPEI3	11	7.8
SPEI6	13	6.6	SPEI6	12	7.2
SPEI9	15	5.7	SPEI9	11	7.8
SPEI12	10	8.6	SPEI12	12	7.2
Bilate			Bilate		
SPEI3	11	7.8	SPEI3	14	6.1
SPEI6	10	8.6	SPEI6	10	8.6
SPEI9	9	9.6	SPEI9	7	12.3
SPEI12	10	8.6	SPEI12	12	7.2
Hossana			Hossana		
SPEI3	9	9.6	SPEI3	11	7.8
SPEI6	9	9.6	SPEI6	13	6.6
SPEI9	11	7.8	SPEI9	11	7.8
SPEI12	9	9.6	SPEI12	13	6.6
Boditi			Boditi		
SPEI3	14	6.1	SPEI3	11	7.8
SPEI6	11	7.8	SPEI6	9	9.5
SPEI9	13	6.6	SPEI9	5	17.2
SPEI12	13	6.6	SPEI12	13	6.6
Shone			Shone		
SPEI3	8	10.8	SPEI3	12	7.2
SPEI6	10	8.6	SPEI6	8	10.8
SPEI9	11	7.8	SPEI9	12	7.2
SPEI12	12	7.2	SPEI12	11	7.8
Wolayta			Wolayta		
SPEI3	9	9.6	SPEI3	11	7.8
SPEI6	9	9.6	SPEI6	8	10.8
SPEI9	11	7.8	SPEI9	7	12.3
SPEI12	11	7.8	SPEI12	10	8.6
Wulbareg			Wulbareg		
SPEI3	11	7.8	SPEI3	10	8.6
SPEI6	12	7.2	SPEI6	8	10.8
SPEI9	9	9.6	SPEI9	12	7.2
SPEI12	9	9.6	SPEI12	13	6.6

5.3.7. Decadal Drought Pattern

In a decadal average value of SPEI analysis under SSP2-4.5., a projected intensification of drought conditions peaking around the middle of the 21st century, specifically within the 2045-2054 decade neatly in all stations. SPEI values for all four timescales tend to dip significantly into

negative territory, suggesting a period of heightened drought risk across multiple temporal scales during this period. This indicates a potential vulnerability for both short-term water availability (agriculture) and longer-term water resources (hydrology) during this mid-century timeframe under the SSP2-4.5 scenario. Figure 5. 11 demonstrate that while the general decadal trends are similar across the different SPEI timescales for a given station, the magnitude of the SPEI values can differ. Often, during the peak drought decade (2045-2054), the longer timescale SPEI-12 shows the most pronounced negative values (Figure 5. 11B, C, D, E, F, and G), indicating that the projected mid-century drought could be characterized by sustained, year-long deficits in the water balance.

While the temporal pattern (mid-century dip, late-century recovery/wetting) is broadly consistent, the absolute magnitude of the projected SPEI values varies between stations. For instance, Hossana (Figure 5. 11C) and Boditi (Figure 5. 11D) appear to show a wider range of SPEI values, with Hossana exhibiting a particularly deep negative excursion during the 2045-2054 decade across all time scales. Wulbareg (Figure 5. 11G) also shows a substantial dip. In contrast, stations like Alaba (Figure 5. 11A) and Wolayta Sodo (Figure 5. 11F) show similar patterns but potentially with less extreme negative peaks compared to Hossana. This highlights potential spatial variability in drought severity within the watershed, even under the same climate scenario. Similar pattern of return period analysis was observed in SSP5-8.5 scenarios across all station which is annexed as a supplementary information.

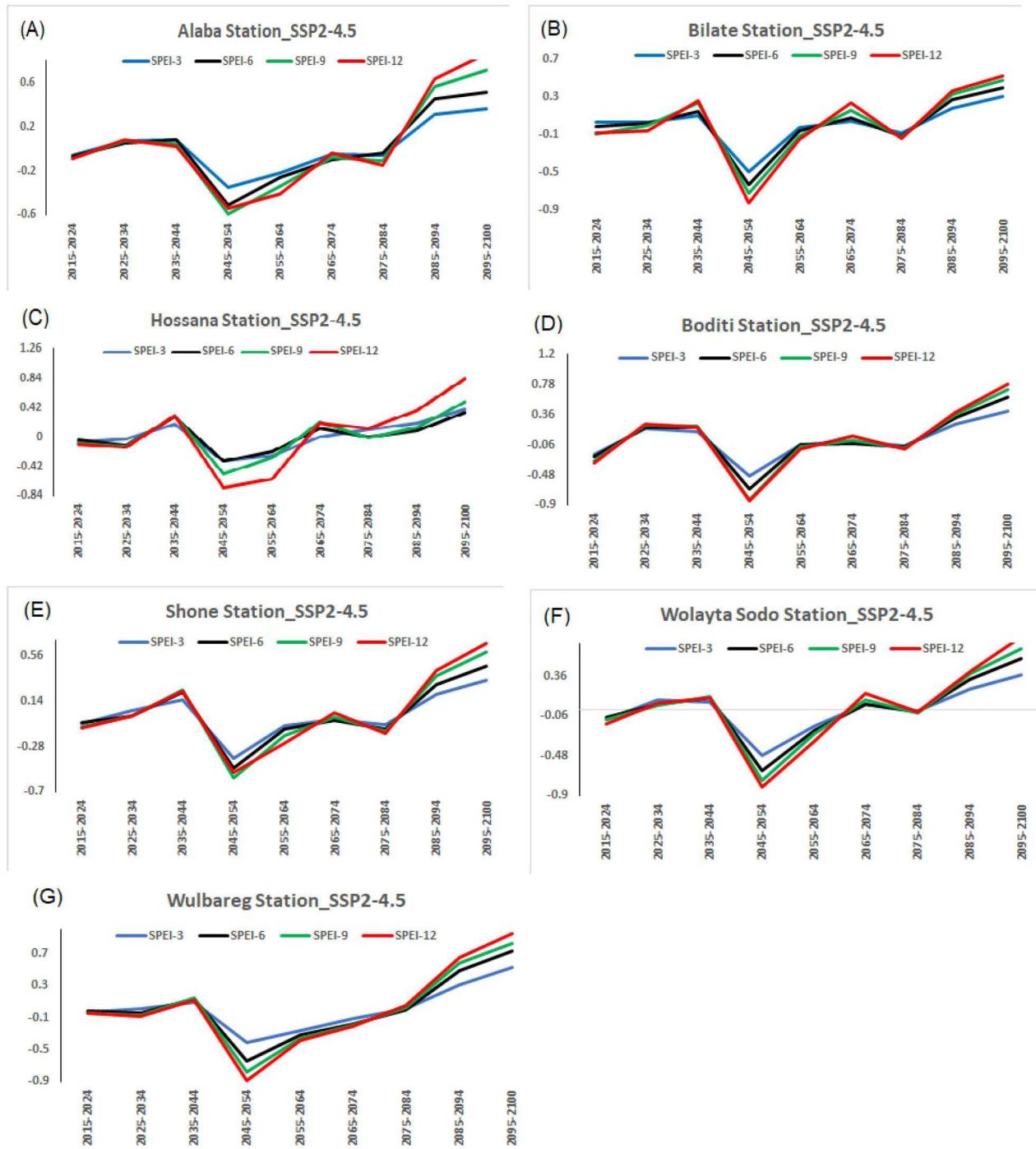


Figure 5.11: Decadal Drought pattern in intermediate (SSP2-4.5) emission scenario at each station: (A) Alaba, (B) Bilate, (C) Hossana, (D) Boditi, (E) Shone, (F) Wolayta Sodo, and (G) Wulbareg

5.4. Conclusion

The research analyzed future projections of droughts over the Bilate river Watershed, using CMIP6 model simulations under SSP2-4.5 and SSP5-8.5 scenarios and multi-scalar SPEI drought index (SPEI-3, -6, -9, -12) for 2015-2100. The research assessed future drought events, identified temporal shifts, analyzed spatial patterns, and estimated recurrence intervals.

Together, these results suggest that the Bilate River Watershed is projected to face a strongly enhanced drought risk over the coming decades, particularly in a high-emission future (SSP5-8.5). The results emphasize the utmost need for multi-dimensional anticipatory climate adaptation and water resource management planning to mitigate the adverse impacts of growing drought frequency, intensity, and duration in local ecosystems, water supplies, and agriculture.

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CHAPTER SIX

SYNTHESIS OF KEY FINDINGS, CONCLUSION AND RECOMMENDATIONS

6.1. Key findings

Drought is a natural hazard that impacts a wide range of sectors, but primarily water management and agriculture. Formulating appropriate adaptation and mitigation strategies requires an understanding of the various aspects of drought, including its characteristics, spatial variability, and future direction due to climate change. This PhD research combined results from four separate but related chapters to conduct an integrated, multi-methods analysis of BRW drought dynamics. Using several weather variables, chapter two described previous droughts from 1981 to 2019 and evaluated patterns. In Chapter 3, the Google Earth Engine (GEE) platform was used to map the spatial occurrence, distribution, and frequency of droughts using satellite remote sensing based on vegetation health indicators (2000-2022). Chapter 4 identified spatial patterns and located areas that are highly vulnerable to drought by combining the Analytic Hierarchy Process (AHP) with fifteen different geographical characteristics to create a model of drought susceptibility. In Chapter 5, future drought characteristics (2015–2100) are predicted using the results of the CMIP6 climate model under two socioeconomic paths (SSPs). Here, the main conclusions from these chapters are integrated, highlighting methodological overlaps, convergent findings, and general implications for BRW drought management.

The methodological technique used in this study is sequential and complimentary, with each chapter filling in specific information gaps and building on the findings of the previous ones. This is the study's strongest point. By examining past drought periods using long-term (39-year) station-based meteorological information, chapter two introduced the baseline of this research. It conducted a thorough comparison of the performance of five distinct drought indices (SPI, SPEI, RDI, eRDI, and scPDSI), which is often absent from regional research. The conclusion that scPDSI was more appropriate for short-term droughts, whereas SPI, SPEI, RDI, and eRDI performed similarly at 6- and 9-month timescales, offered helpful direction for index selection in later analyses (e.g., SPEI in Chapter Five of drought prediction). The application of the Theory of Run made it possible to identify years with severe drought (1984/85, 1999/2000, 2002/3, 2009),

quantify the intensity, duration, and frequency of previous drought occurrences, and identify early spatial changes (e.g., Bilate Tena vs. Hossana/Wulbareg). The basis for future projections was established by the Mann-Kendall trend test, which confirmed the presence of a statistically significant positive trend in drought conditions across a large portion of the watershed. However, this chapter also emphasized the intrinsic drawback of recording fine-scale spatial patterns using only sparse point-based data (seven points denoting BRW).

However, Chapter Three overcomes the spatial constraint observed in chapter two by using the GEE platform to make use of optimally processed remotely sensed satellite data (MODIS vegetation and LST products). It has used the Vegetation Health Index (VHI), Vegetation Condition Index (VCI), and Temperature Condition Index (TCI) from 2000 to 2022 to track the prevalence and severity of drought monthly over the crucial May–October period. A more comprehensive picture of the condition of vegetative health in relation to drought was provided by the VHI, or the integration of moisture (VCI) and heat stress (TCI). As proof for the early indicators in Chapter two.

Chapter Five confirmed the spatial vulnerability of the south and west portion of the BRW both qualitatively and statistically. It found years of severe drought in the recent past (2002, 2009, 2015, 2022), which overlapped with Chapter two in part but took the study further into the recent past. Additionally, spatial autocorrelation analysis (Moran's I) suggested underlying geographic controls by clustering drought patterns in a statistically significant way, especially in years with high drought like 2009 and 2015. Indicators and environmental factors (temperature, precipitation, LST, elevation) were correlated to reveal the physical mechanisms behind the observed VHI patterns.

Chapter Four tried to explain why some places are more vulnerable to drought by measuring innate susceptibility, whereas Chapters Two and Three tried to explain where and when droughts have happened. The study went beyond the scope of single-indicator analysis by incorporating fifteen distinct parameters, including topographic (slope, elevation, aspect, topographic water index (TWI), modified normalized difference water index (MNDWI), hydrological (drainage density), climatic (rainfall, temperature, ET), soil (moisture, texture), vegetation (NDVI, LULC), and socio-economic (population density). It was found that the two most significant drivers were soil moisture and climate variables. The AHP technique offered a systematic way to assign weights to

the relative significance of such elements from the literature and expert opinion (a low consistency ratio of 0.03 verifying it). A spatially explicit map classifying the watershed into mild, moderate, severe, and extreme susceptibility levels was produced by the resultant Drought Susceptibility Model (DSM). With its clear demarcation of the central, southern, and southwestern regions as being susceptible to moderate-to-severe levels due to factors like reduced rainfall, extreme temperatures, and a lower altitude covered in the preceding chapters, this map supported the findings in Chapters Two and Three. An AUC of 0.701 was obtained from cross-validation using a Receiver Operating Characteristic (ROC) curve utilizing VHI data (Chapter Four). This suggests that the model performed quite well and that there is a significant correlation between intrinsic vulnerability (DSM) and drought effects seen (VHI). This chapter described an operational tool for identifying drought hotspots that should receive the highest priority for intervention, such as the administrative areas of Wolayta and Hadiya.

Then, utilizing the globally accepted SPEI (based on the comparison and relevance to record climate change impacts in Chapter 2), Chapter Five used bias-adjusted CMIP6 climate model outputs for the 21st century (2015-2100) to project the observed historical trends and weaknesses into the future. Through forecasts under both high-emission (SSP5-8.5) and intermediate-emission (SSP2-4.5) scenarios, the chapter provided insight into the possible range of drought threats in the future. Future drought frequency, duration, severity, temporal change, spatial behavior, and recurrence intervals were defined at multiple timescales (SPEI-3, -6, -9, -12) using sophisticated statistical techniques such as change (Pettitt test), power spectral density, Empirical Orthogonal Function (EOF) analysis, and recurrence. In addition to projecting an intensification of drought on all indices, especially under high-emission scenarios, Chapter Five qualitatively testified to a catastrophic future, completing the upward trend that emerged in Chapter Two. The findings indicated the presence of an early peak intensity drought event in the middle of the twenty-first century (c. 2045–2054), followed by statistically significant changes toward conditions that were consistently drier in the latter half of the century.

A consistent picture of increasing drought risk in the BRW is provided by the temporal analysis conducted throughout the chapters. Significant past historical climatic droughts were highlighted in Chapter Two, including the famous 1984–85 catastrophe (the well-known famine year) and significant occurrences in the early 2000s and 2009. Based on satellite VHI data from 2000

onward, Chapter Three confirmed the importance of the 2000s, particularly 2002 and 2009, and named 2015 and 2022 as more recent years with widespread drought coverage, which significantly affected the health of the vegetation during crucial months. Since meteorological and vegetation indices measure different aspects of dryness (precipitation/ET deficiency vs. vegetation response), it is not surprising that they differ slightly in identifying specific peak years (Chapter 2 vs. Chapter 3). Future estimates are placed in historical context by the rising trend in drought conditions identified in Chapter Two based on data up to 2019.

The forecast in Chapter Five indicated that this historical trend will continue and become more pronounced. Drought frequency, intensity, and duration are expected to rise across all SPEI timescales (3, 6, 9, and 12 months) in both SSP scenarios, but significantly more in SSP5-8.5. This suggests serious risks to longer-term hydrologic systems and water resources (SPEI-9, SPEI-12) as well as short-term rain-fed agriculture (SPEI-3, SPEI-6). The Pettitt test found statistically significant transition spots, mostly after the 1960s, where the watershed abruptly shifts to a potentially drier climatic regime. This makes it imperative that long-term adaptation planning be done as soon as possible. The mid-21st century (2045–2054) was identified by decadal analysis as the time of high vulnerability, during which drought levels are expected to peak on many timescales. Additionally, power spectrum analysis showed a possible shift toward both relatively low emissions and stronger multi-year dry periods of larger scale (3.75–7.5 years) at high emissions. This could alter the pace of drought recurrence over higher-scale and apparently deeper/longer-duration episodes compared to previous history.

Throughout the dissertation, a consistent conclusion about drought's geographical patterns is drawn. The abstract mentioned harsh droughts in the south, and the Theory of Run utilized in Chapter 2 showed that the drought at the southern Bilate Tena station was more severe and lasted longer than at highland stations. Through the use of VHI maps, Chapter Three offered much more definitive spatial data, constantly showing that during drought, the southern, central, and southwestern regions of the BRW experienced the highest frequency and degree of vegetative stress. These areas of higher temperatures and less rainfall were associated with this spatial trend. The drought frequency study presented in Chapter Three further supported the southern segment's significantly higher incidence of drought events over the 2000–2022 timeframe.

Susceptibility modeling in Chapter Four gave these patterns their explanatory link. The central and southern regions of the DSM map were clearly the most susceptible (moderate to severe), which corresponded precisely to the regions that were found to be most commonly impacted in Chapters Two and Three. According to AHP weighting, the main drivers were low soil moisture, high ET, high temperature, and little rainfall—all of which are typical of such southern and central lower-altitude zones. Finding the Wolayta and Hadiya zones to be hotspots of severe and moderate susceptibility, respectively, offers useful information for administrative priority measures.

The spatial dynamics under future climate change were further described by the EOF analysis of Chapter 5. Throughout the watershed, the dominant mode (EOF1) had a spatially uniform pattern, indicating that large-scale climate forces are mainly acting on the entire area rather uniformly over extended drought. However, despite the presence of strong climate change signals, the second mode (EOF2) revealed persistent spatial differences, frequently separating northern/western stations from southern/central ones. This demonstrated the ongoing influence of intra-regional influences (likely topography, differential sensitivity to weather regimes as suggested in Chapter 3 correlations with altitude/LST). Accordingly, adaptation techniques will need to be spatially varied, and internal diversity in severity (EOF2) is likely to persist even as overall drought risk increases watershed-wide (EOF1). This is supported by Chapter Three's spatial autocorrelation test (Moran's I), which demonstrates that drought is spatially clustered, supporting the idea of discrete sensitive zones.

Several methodological contributions to the assessment of drought in the central rift valley are made by this research. First, Chapter Two's direct comparison of various meteorological drought indices offers helpful recommendations for further research in the Rift Valley that goes beyond the use of a single index. Second, beyond the limitations of point interpolation, the use of GEE to analyze satellite data in near-real time (Chapter Three) shows a practical tool for spatial drought monitoring in data-poor environments like Ethiopia. Third, compared to the BRW, the combined drought susceptibility modeling employing AHP and a broad range of 15 geographic characteristics (Chapter Four) provides a more comprehensive analysis of intrinsic drought risk. ROC analysis is employed to compare and validate the DSM against satellite-derived VHI, enhancing robustness. Last but not least, the most recent evaluation of the future risk of drought is represented by the use of the most recent CMIP6 projections for the SSP scenarios (Chapter Five),

which employ a number of novel statistical techniques (change point, spectral analysis, EOF, and return periods) to gather multifaceted information about future drought characteristics. New analytical stages in the field of drought study in this area include the creation of spatial statistics data (Chapter 3, Moran's I) and validation data (Chapter 4, ROC-AUC utilizing VHI).

It is important to recognize the limitations in each chapter, even with the comprehensive framework. The limited number of ground stations (seven) and their spatial distribution limited the feasibility of the meteorological study (Chapter Two). The resolution of MODIS products can still be too coarse to catch highly localized fluctuations, and VHI still reflects vegetation response rather than actual water availability, despite Chapter Three's improvement of spatial coverage using satellite data. Since there were no extensive historical impact data available, the validation of the drought susceptibility model in Chapter Four was restricted to correlation with VHI and ROC analysis. The model is based on the AHP approach with some weight assignment subjectivity as well as the resolution and quality of input geospatial data to be accurate. The inherent uncertainties of GCM forecasts, the bias-correction method selection, and the dependence on SPEI as the primary future drought indicator are addressed in Chapter 5.

These limitations invariably suggest new research directions. Spatial observation could be improved by using higher-resolution satellite images (such as Sentinel) and adding soil moisture products from radar (addressing the restrictions of Chapter 3). More locally relevant future estimates could be obtained by including downscaled CMIP6 data (addressing Chapter 5 constraints). Investigating machine learning methods for drought susceptibility modeling and forecasting may provide substitutes or additions to AHP (addressing the limitations of Chapter 4). More investigation would link the effects of meteorological drought (SPEI) on water resources by statistically representing hydrological dryness from streamflow observations and hydrological model simulations. The socioeconomic effects of past and future droughts should be quantified, and the adaptive capacity of local populations to contextualize the corresponding vulnerability estimations should be determined. Examining the viability and efficacy of certain adaptation choices in the context of BRW is also crucial.

The combined results have significant implications for the Bilate River Watershed's drought management and adaptation plans. The necessity of resource investment and actions that are

regionally focused is highlighted by the constant identification of the southern and central regions—in particular, the Wolayta and Hadiya zones—as drought hotspots. Concerning future projections, including the mid-century intensification and the late-century transition to circumstances of dryness, as well as the confirmation of a worsening historical pattern underscore the limitations of reactive attempts to combat drought. Proactive long-term planning is essential, considering both scenarios of moderate and large emissions from climate change.

Short-term agricultural drought (represented by SPI/SPEI-3/6 and VHI variability) and long hydrological drought (represented by SPEI-9/12 predictions and vulnerability indicators like drainage and soil moisture) need to be dealt with by management measures. This involves a multi-scalarity of measures including: improving early warning systems (with the use of GEE and vulnerability maps); promoting water conservation and harvesting techniques; investing in crop types and agricultural practices that are drought-resistant; increasing irrigation efficiency in vulnerable areas; imposing integrated water resources schemes based on impending shortages; and protecting vital water sources and ecosystems. The results give a solid basis for evidence for policymakers and development partners to set drought resilience-building activities as top priorities in the BRW.

6.2. Conclusion

Using a synergistic combination of approaches in four different studies (i.e. historical drought characterization in chapter two, spatial drought occurrences and distribution in chapter three, susceptibility modeling in chapter four and drought projection in chapter five), this PhD research conducted an integrated evaluation of the numerous characters of drought in the Bilate River Watershed (BRW), Central Rift Valley, Ethiopia. In order to provide a comprehensive body of knowledge to support management and adaptation, the overall objective was to characterize historical drought trends, evaluate current geographical events and vulnerability, and project future drought risk under climate change.

Using 39 years of station records (1981-2019), Chapter Two created the historical background by comparing several meteorological drought indices (SPI, SPEI, RDI, eRDI, and scPDSI). Strong correlations between 6- and 9-month SPI, SPEI, RDI, and eRDI were identified, and these metrics

were appropriate for describing notable previous droughts (e.g., 1984/85, 1999/2000, 2002/3, 2009), as well as for seeing an upward trend in drought conditions throughout the watershed. In order to overcome spatial data constraints, Chapter Three used satellite-remote sensing vegetation indices (VCI, TCI, and VHI) and Google Earth Engine for the years 2000–2022. This allowed for the mapping of high spatial clumping of drought impacts and confirmed that the southern/southwestern BRW was vulnerable to recent droughts (e.g., 2002, 2009, 2015, and 2022). Using the Analytic Hierarchy Process (AHP) and fifteen geographical indicators, Chapter Four created an integrated model of drought vulnerability and determined that the main drivers were temperature, evapotranspiration, rainfall, and soil moisture. The model provided a geographic risk framework that was validated with a reasonable level of accuracy (AUC=0.701), identifying the center and southern regions—in particular, the Wolayta and Hadiya zones—as hotspots with moderate-to-severe susceptibility. Last but not least, Chapter Five used SPEI to predict future drought features (2015–2100) for CMIP6 climate models under intermediate (SSP2-4.5) and high-emission (SSP5-8.5) scenarios. This prediction showed a sustained and robust increase in drought frequency, intensity, and duration over the 21st century, especially under SSP5-8.5, with a mid-century peak anticipated (2045-2054) and statistically significant abrupt transitions to drier periods mainly after the 2060s.

The study's overall findings indicate that the Bilate River Watershed faces a significant, geographically concentrated, and quickly rising risk of drought. It is anticipated that previous expansion of dryness will increase, promoting more frequent and severe hydrological, agricultural, and meteorological droughts, particularly in scenarios with significant greenhouse gas emissions. It is generally accepted that the south and middle regions are the most affected due to a combination of geographic, climatic, and maybe land-based factors. The necessity of proactive, spatially directed, climate-resilient drought readiness and adjustment measures to lessen negative effects on the region's water resources, agriculture, ecology, and society is highlighted by this combined assessment, which integrates historical research, spatial definition, susceptibility model, and futures analysis. The work gives significant scientific information for decision-making and makes a valuable contribution to our understanding of the dynamics of drought in the Ethiopian Rift Valley.

6.3. Future Research Directions

The low number (seven point of location) in its spatial extent of meteorological stations limited the spatial drought analysis in Chapter 2. Although the incorporation of satellite data in Chapter Three increased spatial coverage, the MODIS product resolution may still be insufficient to detect highly localized variability, and VHI only directly detects vegetation response rather than water availability. The AHP approach, which determines weights subjectively and whose validity depends on the quality and resolution level of the input geospatial data, was used to derive the sensitivity model in Chapter Four. Because there was insufficient extensive historical impact data, validation was also restricted to correlation with VHI and ROC analysis. The inherent uncertainties of GCM projections, the bias correction method, and the dependence on SPEI as the sole future drought indicator are addressed in Chapter 5.

These limitations inevitably suggest areas for further research. Incorporating radar-based soil moisture products and using higher-resolution satellite data (like Sentinel) could improve spatial monitoring (addressing Chapter 3 restrictions). AHP may be improved or replaced by looking at machine learning techniques for drought susceptibility modeling and forecasting (addressing the limits of Chapter 4). Future studies could link the impacts of meteorological drought (SPEI) on water resources by explicitly modeling hydrological drought from hydrological and streamflow models. In order to offer useful context for vulnerability assessments, it would be beneficial to quantify the socioeconomic effects of past and anticipated droughts and evaluate the local community's ability to adapt. Additionally, crucial is examining the viability and efficacy of particular adaptation strategies in the context of BRW.

6.4. Implications for Policy and Practice

The combined results have significant implications for drought management and adaptation planning in the Bilate River Watershed. The fact that the southern and central regions—the Wolayta and Hadiya zones—have been consistently identified as drought hotspots highlights the need of resource allocation and interventions that are regionally tailored. The insufficiency of reactionary actions to droughts is shown by confirmation of the increasing historical trend and ominous future projections, particularly the mid-century intensification and late-century shift towards dry conditions. Long-term, proactive planning that considers both moderate and high-emission climate change scenarios is required.

Both long-term hydrological droughts (as shown by SPEI-9/12 forecasts and vulnerability factors like drainage and soil moisture) and short-term agricultural droughts (as indicated by SPI/SPEI-3/6 and VHI variability) must be addressed by management practices. Measures such as enhancing early warning systems (via the use of GEE and susceptibility mapping), promoting water conservation and harvesting, investing in crop types and agricultural techniques that are resistant to drought, and boosting irrigation effectiveness in areas that are susceptible putting integrated water resource management plans into action with future scarcity in mind, and safeguarding important water sources and ecosystems are all necessary to address this. Policymakers and development partners can use the findings as a solid basis of evidence when deciding which measures to focus in order to increase drought resilience in the BRW.

6.5. Recommendations

The following recommendations are made to those concerned in drought management and development planning in the Bilate River Watershed based on the overall drought analysis carried out in this research:

- Use satellite remote sensing methods for near-real-time spatial drought monitoring (based on indices like VHI) and institutionalize its use, maybe by utilizing platforms such as GEE.
- To successfully target warnings, create and distribute timely and useful drought early warning information with included susceptibility information (Chapter 4) to various user groups (farmers, water managers, administrators).
- Create and implement IWRM plans that specifically address the increased frequency of droughts and water scarcity that are anticipated to occur in the future (Chapter 5).
- Adaptive water storage solutions, like managed aquifer recharge, augmented natural storage, and tiny reservoirs, should be adopted and studied in order to prepare for future hydrological challenges.
- Encourage the use of climate-smart agricultural techniques (such as agroforestry and conservation agriculture) and drought-tolerant crop varieties, especially in the regions with moderate-to-severe sensitivity identified (Chapter 4).
- Enhance irrigation water management and effectiveness in areas where irrigation is used to boost resilience during drought conditions.

- At the regional and local (zonal/woreda) levels, create or update plans for drought readiness and response, actively considering the future forecasts (Chapter 5 intensification) and the geographical patterns of vulnerability identified (Chapter 4 hotspots, such as Wolayta and Hadiya).
- Water, agricultural, environment, and health sectoral development strategies should include drought risk reduction and climate change adaptation.
- Using the envelope of possible future drought intensity, use the alternative climate change scenarios (SSP2-4.5, SSP5-8.5) to guide sound, long-term infrastructure and development planning.

Knowledge Contribution

This PhD research makes a valuable knowledge contribution to drought research:

- The methodology used in the study is an improvement from previous methods because, as explained in the second chapter, the drought indices were first assessed using correlation analysis and then further confirmed using Fleiss' kappa statistics. The indices chosen to be most associated were then used to characterize the historical drought. Conversely, several past studies have taken the stance of either comparing drought indices or primarily adopting a particular drought indicator to describe droughts.
- To the best of the researcher's knowledge, no previous study has specifically compared these five drought indices: scPDSI (self-calibrating Palmer Drought Severity Index), RDI (Reconnaissance Drought Index), eRDI (enhanced Reconnaissance Drought Index), SPI (Standard Precipitation Index), and SPEI (Standard Precipitation Evapotranspiration Index).
- This type of study has not been carried out before in Ethiopia's Rift Valley, which is one of the most vulnerable to drought. Consequently, the study has practical relevance for decision-makers and experts engaged in natural resource management and drought preparedness planning in the watershed.
- The data created for the validation of the susceptibility model in Chapter 3 and the data generated for the analysis of spatial statistics in Chapter 2 present novel approaches to research that have not been widely used in the past studies.

Appendix:

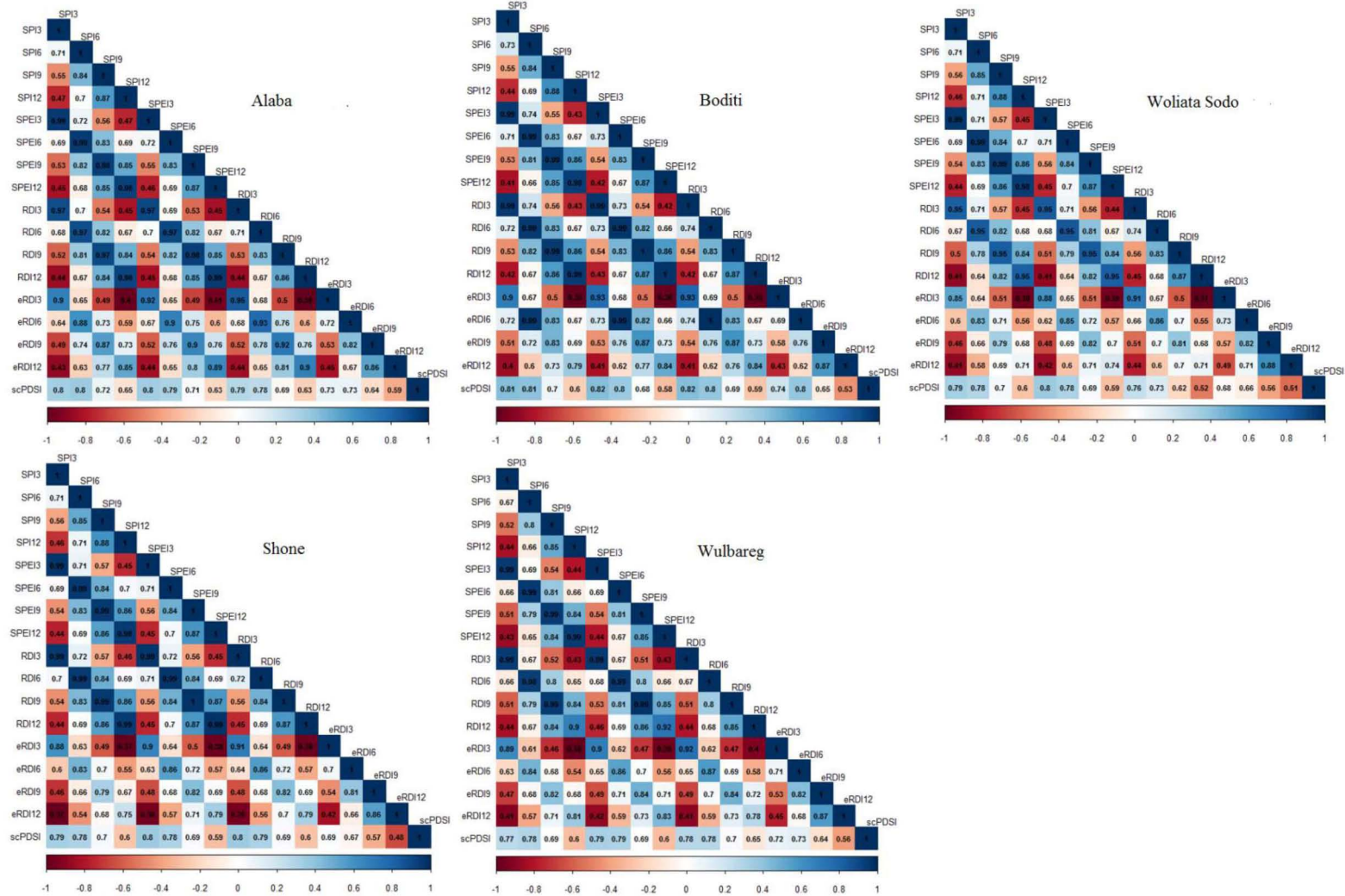


Figure 2.1: Pearson Correlation Matrix of drought indices at Alaba, Boditi, Wolayta sodo, Shone and Wulbaref Stations.

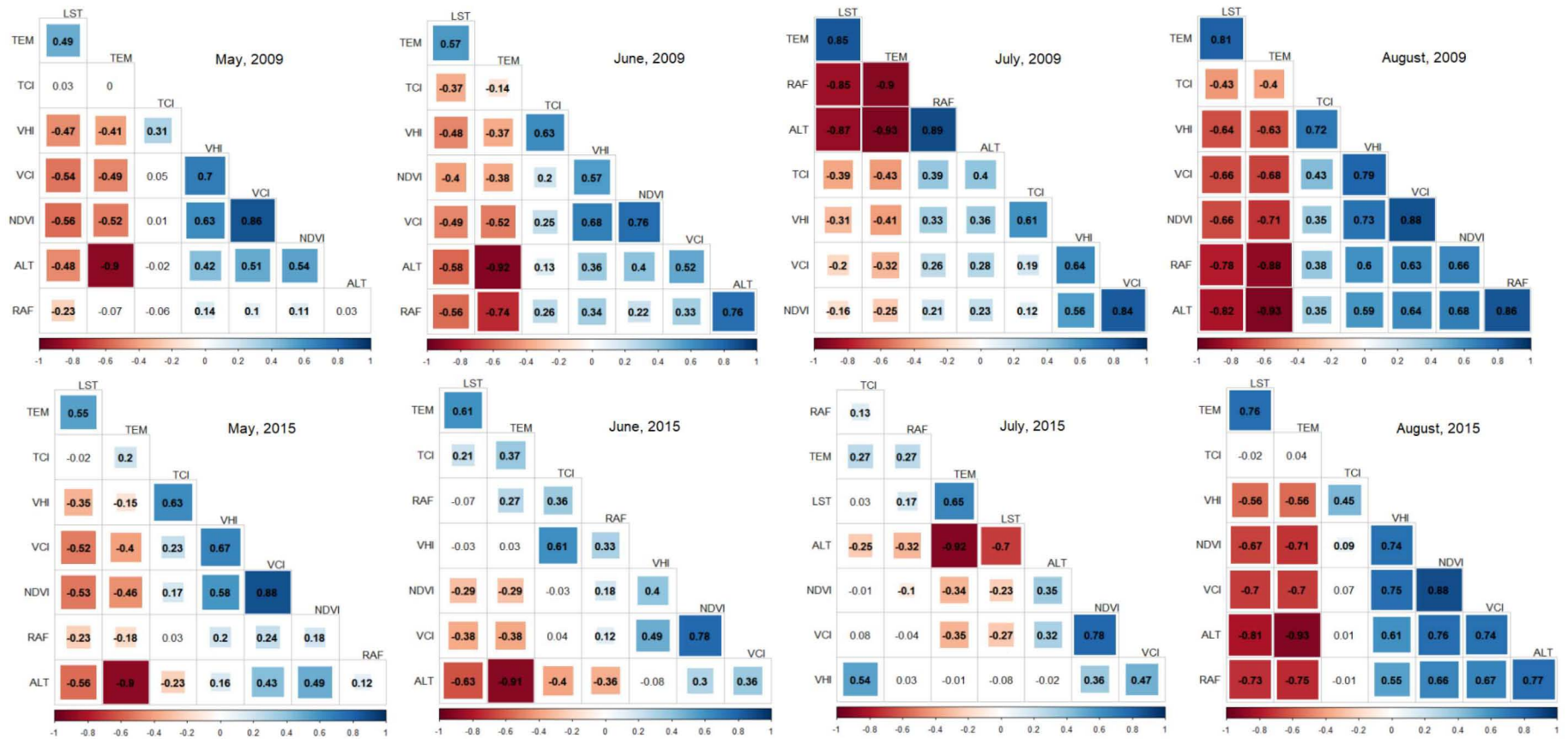


Figure 3.10: Correlation Matrix of May, June, July, and August of 2009 and 2015.