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Hydrological Drought Monitoring, Forecasting, and Projection System Development in Ethiopia

By

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HYDROLOGICAL DROUGHT MONITORING, FORECASTING AND PROJECTION SYSTEM DEVELOPMENT IN ETHIOPIA

By

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Dissertation Approval Sheet

The Thesis Committee of

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HYDROLOGICAL DROUGHT MONITORING, FORECASTING AND PROJECTION SYSTEM DEVELOPMENT IN ETHIOPIA

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Declaration

I, Kassa Abera Tareke, certify that the dissertation "Hydrological Drought Monitoring, Forecasting and Projection System Development in Ethiopia" is an accurate reflection of the work I have done since enrolling in the Ph.D. program at Addis Ababa University, Addis Ababa Institute of Technology (AAiT) and that it has not previously been a part of a thesis or dissertation submitted to this or any other institution for a degree, diploma, or other qualifications. I have reviewed the university's most recent research ethics policies, and I agree to be accountable for following the rules set forth by the institution. I have attempted to foresee any potential risks connected to this research that might emerge during its execution, have obtained the required ethical and/or safety permissions, and am conscious of my responsibilities and the rights of the participants. I acknowledge that this dissertation was conducted under the supervision of Prof. Dr. Admasu Gebeyehu Awoke.

Signature: ______________________

Date: ________________________

Dedication

I dedicated my dissertation to those who lost their life due to severe drought and unstable political war in Ethiopia!

Acknowledgment

First and foremost, I want to thank the Almighty God for protecting me from harm and He provides me with good health, knowledge, education, and all things in my life. Next, I want to express my gratitude and thanks to my supervisor Dr. Admasu Gebeyehu, my supervisor, who patiently guided and pointed me in the proper route. He has taught me a lot, and without his assistance, I would not have been able to finish this dissertation. I would also thank Wollo University, Kombolcha Institute of Technology for supporting me financially and by providing a personal computer to work my research safely. My thanks are also to Addis Ababa University, Addis Ababa Institute of Technology, School of Civil and Environmental Engineering which arranges this Ph.D. program and offers courses related to my research work timely. The Ministry of Water and Energy (MoWE) and Ethiopian Meteorology Institution (EMI) have a great role in my work which supports me by giving hydrological and meteorological data freely. So, I thank both institutions and their respective data collectors.

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List of Published papers

In this study, I have published four full article papers and one book chapter a total of five papers in a reputable international journal. All the articles are directly related to my dissertation work on objectives 1 – 3, and the book chapter is about the review part of my dissertation. The detail of my publication is discussed in the following table.

No	Title	Type	Journal	Publisher
1	Review of hydrological drought status in Ethiopia	Book chapter		IntechOpen
2	Hydrological drought analysis using streamflow drought index (SDI) in Ethiopia	Article	Advances in Meteorology	Hindawi
3	Hydrological and meteorological drought monitoring and trend analysis in Abbay river basin, Ethiopia	Article	Advances in Meteorology	Hindawi
4	Comparing surface water supply index and streamflow drought index for hydrological drought analysis in Ethiopia	Article	Heliyon	Elsevier
5	Hydrological drought forecasting and monitoring system development using artificial neural network (ANN) in Ethiopia	Article	Heliyon	Elsevier

Abstract

Due to its multifaceted effects and gradual beginning and end dissemination, the concept of drought is very debatable. However, experts divided drought into four categories: meteorological, agricultural, hydrological, and socioeconomic drought, which were characterized according to the lack of precipitation, soil moisture, surface, and subsurface water availability, and the imbalance between supply and demand, respectively. This study is primarily focused on hydrological drought monitoring and forecasting using two hydrological drought indices namely streamflow drought index (SDI) and surface water supply index (SWSI) across eight river basins in Ethiopia. Besides this spatiotemporal variability of meteorological drought in the Abbay river basin was analyzed using the standardized precipitation index (SPI) and reconnaissance drought index (RDI) to compare hydrological and meteorological drought correlation. Meteorological and streamflow data were collected from 50 rainfall stations and 35 streamflow stations from 1973 – 2014.

The result indicates several severe and extreme drought events occurred during the 1980s and 1990s compared to the 2000s and 2010s. The most identified severe drought years are 1975, 1981, 1984, 1986, 1991, 1994, and 2010 whereas 1983, 1984, 2001, 2003, and 2010 were extreme drought years. The spatial analysis shows that the Tekeze, Abbay, and Baro river basins have similar characteristics; Awash and Rift Valley river basins show relatively the same character, and Genale Dawa and Wabishebele river basins have a similar drought trend. However, the Omo Gibe River basin has a unique character in that the severe drought occurred in a different year than other river basins.

The statistical correlation of RDI and SPI, and SPI and SDI, RDI and SDI were found 0.95, 0.87, and 0.83 respectively, at an annual time scale. It implies that both hydrological and meteorological drought indices have an excellent correlation for long-term time scale and it also indicates the possibility of using SPI and RDI indices instead of SDI in areas having streamflow data scarcity. On the other hand, SDI and SWSI have a good relationship in all river basins except the Rift Valley basin. However, the overall result of hydrological drought analysis using SDI is better than SWSI compared to the previous historical drought events.

Climate change-induced hydroclimatic hazards have increased from decade to decade overall in the world. So, projecting drought conditions for the future plays a great role in hydrology. In this regard, in this study, streamflow was forecasted from 2026 to 2099 using an artificial neural network (ANN) model using downscaled precipitation data as input to the model. Recently, ANN has been a suitable forecasting technique in water resource engineering. The future input data was downscaled using the Regional Climate Model (RCM) and the downscaled data have bias corrected using the linear scaling bias correction technique. The ANN model was trained and tested using historically observed precipitation and streamflow data as input and output variables respectively. Then the bias-corrected precipitation data is used to forecast future streamflow. The statistical performance parameters such as the Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) were used to evaluate the performance of the ANN model and the result shows ANN has an acceptable value in humid areas than arid areas to forecast streamflow from precipitation data. Finally, the future hydrological drought condition of the country was investigated using SDI based on forecasted streamflow. The finding shows that the 2030s, 2040s, and 2060s are the expected critical and worth drought years in the country.

The result of this thesis presents the establishment of hydrological drought monitoring, forecasting, and projection skills. The articles presented in this thesis seek to offer novel perspectives on hydrological drought monitoring, forecasting, and projection, emphasizing existing difficulties and opportunities for the generation of valuable information that can help decision-makers and policymakers in the management of water resources. Overall, the historical and future drought trends of Ethiopia indicate the country is frequently hit by severe droughts. So, appropriate drought mitigation measurement is needed. However, the commonly adopted drought mitigation trend in Ethiopia is a reactive approach which is a short-term drought mitigation technique during the drought event that has occurred. However, this approach will never bring a sustainable solution for drought-victim societies in the country. Therefore, it is better to shift into a new paradigm, a proactive approach which is a long–term drought mitigation system. To do this, the national government should actively promote the construction of water conservation infrastructure like dams and reservoirs, afforestation (green legacy), and the development of a national drought policy.

Keywords: hydrological drought, meteorological drought, monitoring, forecasting, regional climate model

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Acronyms

AFR – 44	Africa Domain 44
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
BPMLP	Backpropagation Multi-Linear Perceptron
CMhyd	Climate Model Data for Hydrological Modeling
CMIP5	Fifth Phase Climate Model Intercomparison Project
CORDEX	Coordinated Regional Climate Downscaling Experiment
DCC	Data Change Correction
DEM	Digital Elevation Model
DEWS	Drought Early Warning System
DI	Drought Indices
DMAP	Drought Monitoring and Prediction
DMP	Distribution Mapping for Precipitation
DrinC	Drought Index Calculator
EMI	Ethiopian Meteorology Institute
ENSO	El Nino – Southern Oscillation
GCM	Global Climate Model
GERD	Grand Ethiopian Reconnaissance Dam
GHG	Greenhouse Gasses
GIS	Geographic Information System
HDI	Hydrological drought indices
IDMP	Integrated Drought Management Program
IDW	Inverse Distance Weighted

LS	Linear Scaling
MIROC5	Model for Interdisciplinary Research on Climate
MoWE	Ministry of Water and Energy
NMHS	National Meteorological and Hydrological Service
PET	Potential Evapotranspiration
PLIS	Precipitation Local Intensity Scaling
PT	Power Transformation
RACMO	Regional Atmosphere Climate Model
RCA4	Rossby Center regional Atmospheric model
RCM	Regional Climate Model
RCP	Representative Concentration Pathways
RDI	Reconnaissance Drought Index
SARIMA	Seasonal Autoregressive Integrated Moving Average model
SDI	Streamflow Drought Index
SDSM	Statistical Downscaling Model
SPI	Standardized Precipitation Index
SWSI	Surface Water Supply Index
WMO	World Meteorological Organization

1. INTRODUCTION

1.1 General background

A global natural hazard, drought affects social, environmental, and economic factors (District et al., 2013). Hydrological extreme events both high flow (flood) and low flow (drought) are the basic issues in the world (Edossa et al., 2014). Contrarily, compared to other catastrophic events, drought is one of the most frequent disasters that have a significant detrimental effect on water resource activities including irrigation, hydropower, and water supply (Venegas-cordero et al., 2021).

Almost all topographic and climatic zones are susceptible to drought, and the severity, duration, and other aspects of the condition vary greatly from one place to another (Zeleke et al., 2017). It is difficult to adapt the definition of drought as well as the impact associated with drought due to the interrelationship between different hydroclimatic variables such as ecology, geology, hydrologic, climate, and socioeconomic factors in a specific study area (Singh et al., 2019; Zeleke et al., 2017). The effect of drought can be continued for some period, it may take a year or above after termination due to its gradual propagation from moderate to severe stage (Zeleke et al., 2017). Because of this, drought has no common universal definition (Peng et al., 2019; Singh et al., 2019). However, droughts can be (1) meteorological, which is the scarcity of precipitation, (2) hydrological drought which is associated with the scarcity of streamflow, decrease in surface and subsurface water (Lake and reservoir volume) and groundwater level and, (3) agricultural drought related to reduction in available of soil moisture for crop production and (4) socio-economical drought refers to high demand on natural goods due to less supply and each drought is a cause of the other (Bąk and Kubiak-Wójcicka, 2014; Peng et al., 2019).

Meteorological and agricultural droughts are the main cause of the failure of crops while hydrological drought causes a shortage of water supply, a decrease in reservoir water level and groundwater level, and a decrease in irrigation and hydropower production (Van Loon, 2015; Barker et al., 2019; Tsige et al., 2019; Zeleke et al., 2017). A drought phenomenon lingers for a long period with extreme levels of meteorological, agricultural, and hydrological drought conditions results in socio-economical drought which is related to supply and demand imbalance (Edossa and Babel, 2011), in which the overall ecosystem of the drought region is disturbed, and there is loss of life (Boudad et al., 2018a). Due to climate change, the global vulnerability to floods and drought has been increasing (Easterling et al., 2007; Teshome and Zhang, 2019). Therefore, the recurrence and the persistence of drought require a scientific analysis to establish an estimate of probabilities that will contribute to the planning of strategies for the mobilization and management of water resources (Boudad et al., 2018a).

In Africa, assessment of the impact of drought on agricultural areas is extremely needed to reduce its negative adverse on society (Debarati Guha-Sapir et al, 2016). Many African countries strongly rely on rain-fed agriculture. Since rainfall is commonly the limiting factor for rain-fed agricultural systems, droughts can lead to severe socio-economic consequences like; crop failure, food shortages, and even humanitarian crises (Rosenzweig and Hillel., 2008). For instance, over the eleven decades between 1900 and 2013, episodes of drought in Africa resulted in more than 800,000 deaths and impacted around 262 million people (Debarati Guha-Sapir et al, 2016).

Despite having an abundance of surface and groundwater resources, Ethiopia has experienced droughts more frequently for several decades (Edossa et al., 2010; Tsige et al., 2019). Ethiopia has also experienced severe drought in recent decades (Bayissa et al., 2018; Mera, 2018a; Mulualem and Liou, 2020; Philip et al., 2018; Temam et al., 2019). From 1920 – 2016, 18 hydrological extremes occurred in Ethiopia. Sixty-nine percent was drought and the remaining 26% and 5% were floods and both drought and flood extremes, respectively (Teshome, 2019a). Researchers estimated that Ethiopia's drought recurrence interval is three to ten years (Mohammed et al., 2018). However, others stated that drought frequency in Ethiopia is every two to five years (Bayissa et al., 2018). Even though this recurrence time is quite short, no proactive drought mitigation measures have been established effectively. Measures are more localized and usually come in the form of food aid during a drought that has occurred somewhere in the country (Mohammed et al., 2018).

Most drought studies in Ethiopia were focused on meteorological drought and somehow agricultural drought (Bayissa et al., 2018; Bayissa et al., 2015; Belayneh et al., 2014; Edossa et al., 2010; Gebrehiwot et al., 2011; Mohammed, 2018; Tsige et al., 2019). Few research studies are conducted in Northern and Eastern and some parts of the Blue Nile in Ethiopia which are mainly focused on meteorological drought analysis (Gebrehiwot et al., 2011; Mohammed, 2018; Bayissa et al., 2015). But in addition to a lack of precipitation, the region is also experiencing a drought's effects on water resources (both surface and ground), especially in the most populous places like the Rift Valleys and the central Ethiopian highlands, where access to water supplies is scarce (Kenawy et al., 2016).

Hydrological drought has received minimal attention in previous research investigations, which have focused more on meteorological drought (Van Lanen et al., 2016). However, hydrological drought has drawn more attention in recent years due to its multidimensional impacts on the socio-economic and overall ecosystem (Vicente-Serrano et al., 2012). For example, recent studies found that hydrological droughts had a greater overall impact than other forms of droughts. Table 1 shows the most hydrological drought-vulnerable water-related sectors compared to other types of droughts. From this table, it is understood that further investigation of hydrological drought monitoring and impact assessment is important to develop a comprehensive drought mitigation measure.

Table 1 Impact category of different drought types on water-related sectors (Vicente-Serrano et al., 2012)

Affected Sectors	Drought Types			
	System	Meteorological drought	Agricultural drought	Hydrological drought
Agriculture	Rainfed	✓	✓	
	Irrigation		✓	✓
Ecosystem	Terrestrial	✓	✓	
	Aquatic			✓
Energy	Hydropower			✓
Industry	Cooling water			✓
Navigation				✓
Water Supply				✓
Recreation				✓

Now a day, in Ethiopia a lot of infrastructures are planned and constructed to use the available surface and groundwater resources in terms of water supply, irrigation, and hydropower. The source of water for those projects is mainly rivers, springs, lakes, and groundwater. Even though precipitation deficit is the primary cause of all types of droughts, hydrological drought is highly affecting surface and groundwater sources. However, hydrological drought studies in Ethiopia are limited to some parts of the nation such as the Wabishebele river basin (Awass., 2009), Awash river basin (Edossa et al., 2010), and some parts of the Blue Nile basin (Van Lanen, 2014). Finally, the researchers try to summarize the effect of hydrological drought events resulting from a particular area that occurred throughout the country. However, drought events are not consistent across all of Ethiopia. The variability of the temporal, spatial, and magnitude characteristics of drought events requires in-depth analysis to determine different approaches for mitigation (Tijdeman et al., 2022; Yirga, 2021).

Water resources, biological systems, and socio-economic development are all negatively impacted by hydrological drought, which is regarded as a sneaky threat because it grows gradually, is difficult to detect, spans a large area, and takes a long time (Goyal et al., 2017; Sutanto et al., 2020; Sutanto and Van Lanen, 2020). Compared to other types of droughts, they also have the most substantial effects in multiple sectors (Raphael M Wambua, 2019). Therefore, to develop permanent and effective drought mitigation measures, it is significant to analyze the historical propagation of hydrological drought and to better forecast drought occurrence.

In Ethiopia, there have been no national-level hydrological drought studies before and most studies focused on meteorological drought analysis. Therefore, the main goal of this study is to analyze historical hydrological drought across the nation using the streamflow drought index (SDI) and surface water supply index (SWSI), as well as to forecast streamflow using an artificial neural network (ANN) model to projected future hydrological drought condition in Ethiopia. Additionally, to assess the link between hydrological and meteorological drought events, the regional and temporal variability of meteorological drought in the Abbay river basin is computed using the standardized precipitation index (SDI) and reconnaissance drought index (RDI).

1.2 Statement of the problem

Globally, drought is one of the common natural hazards which has the characteristics of high frequency, long duration, and extensive influences (Wang et al., 2020). It is difficult to predict the exact onset and end of the drought and its severity (Barua, 2010). Due to this, drought analysis needs a detailed study in different regions. Most drought studies in Ethiopia focus on meteorological drought, which is related to the deficit of precipitation. However, hydrological drought is the cause of severe agricultural drought and socioeconomic drought. Unfortunately, in Ethiopia, extreme hydrological events, such as floods and drought are not emphasized until they occur. These events lead to excessive property damage and even the loss of human life resulting in an upset in the socioeconomic status of the region and even the nation. The hydrological drought analysis was studied in Upper Awash and Wabishebele basins by Belayneh et al., (2014) and Awass, (2009), respectively. Those studies were conducted in somehow relatively the same climate region in Arid and semi-arid eastern parts of Ethiopia and used meteorological drought indicators. Arid and semi-arid areas always experienced low flow (Loon, 2018) and therefore this may not represent the overall effect and intensity of drought throughout the country. Presently, drought early warning systems in Ethiopia are inadequate and do not provide adequate and appropriate early warning to the public (Abraha and Mannaerts, 2013; Tadesse et al., 2018). For example, the 2015/2016 drought affected most parts of the country (Warner and Mann, 2020), and the recent 2021/2022 drought affected some parts of the Oromia region and most parts of the Somali region (Bogale and Erena, 2022). As a result, unless monitoring and developing drought early warning system, severe drought continues to cause damage to infrastructure like reservoirs and interrupts the agricultural livelihoods of most of the population.

In Ethiopia, most farmers are engaged in rainfed agriculture and therefore, identification of the drought-prone areas in the country is the basis for planning for improving the socio-economic conditions of rural farming communities. Better methods for monitoring and forecasting drought will enable better planning, resulting in better management strategies, and lessen society's susceptibility to drought and its ensuing effects on the nation. Until recently, there has been no comprehensive nationwide effort to consolidate or centralize the hydrological drought effect at the national or regional level. This lack of planning and high vulnerability of many communities indicates the importance of developing accurate drought forecasting and drought early warning systems development for Ethiopia to minimize property losses, interruptions to livelihoods, and even loss of life. Recently, the Ethiopian Government has focused on water resource development such as; irrigation, water supply, and hydropower which all are highly dependent on surface water resources and affected by hydrological drought. Due to its high interdependence on processes including the effects of agriculture (irrigation), urban and rural water supply, and hydropower generation on the surface and subsurface water resources, investigation of hydrological drought is crucial. Therefore, this study aims to analyze, forecast, and monitor the hydrological drought in Ethiopia over eight major river basins to see its impact on surface water utilization

1.3 Research questions

To address the above-stated problems, the following research questions were discussed in this study.

1. How to characterize the historical hydrological drought using different drought indices?
2. In areas lacking streamflow data, can meteorological drought indicators be used instead of a hydrological drought index?
3. What is the application of Artificial neural networks in water resources; streamflow forecasting and hydrological drought projection?

1.4 Scope of the study

Within this study, it is impossible to study all aspects of drought types and their propagation from one type to another. Therefore, the researcher restricts his study mainly to hydrological drought monitoring, forecasting, and projection system development in Ethiopia with a special focus on eight major river basins and tries to relate the effect of drought on surface water resources and different water-related projects such as water supply, irrigation, and hydropower. Besides this, meteorological drought analysis was also conducted in one river basin (Abbay river basin) to see the relationship between hydro-meteorological drought indicators and to investigate the propagation of drought from meteorological to hydrological drought.

1.5 Significance of the study

The main significance of this study is to give information to the readers about the frequency, magnitude, and duration of hydrological drought in Ethiopian river basins and its severity effect on the socio-economic and overall development of the country. It is also used as a reference for different concerned sectors for the prediction of hydrological and meteorological droughts such as policymakers, climate change analysts, natural disaster preparedness and risk management organizations, future researchers, etc.

1.6 Objective

1.6.2 General objective

The main objective of this research is to monitor and forecast the historical and future hydrological drought conditions across selected major river basins in Ethiopia to assess its impact on surface water resources and to recommend effective mitigation measures in the future.

1.6.3 Specific objective

The following specific objectives have been established to fulfill the aforementioned broad objective:

- ✓ To monitor long-term hydrological drought trends in selected river basins in Ethiopia
- ✓ To compare hydro-meteorological drought indicators' performance in drought detection
- ✓ To project future hydrological drought based on simulated streamflow using an artificial neural network (ANN)

1.7 Motivation/ Rationale of the study

Global warming, climate change, population growth, and deforestation increase from decade to decade. Especially, population growth and deforestation aggravate climate change problems in developing countries such as Ethiopia. Drought is one of the natural hazards resulting from climate change and affects different sectors. Even though meteorological drought is the consequence of other droughts such as agricultural, hydrological, and socio-economic droughts; hydrological drought has a multidimensional impact. Because hydrological drought highly affects agriculture (irrigation), hydropower generation, and water supply. Ethiopia has high surface and groundwater potential. However, hydrological drought studies are still limited and drought disaster is a common problem that affects the living standard of society. Therefore, exploring the historical and future characteristics of hydrological drought is important to set measures on available surface water operation during severe and extreme drought conditions. In addition to this comparing and selecting good hydro-meteorological drought indicators plays a great role in future drought impact management. So, the main motivation of this study is due to the limited condition of hydrological drought studies in Ethiopia and the development of water-related infrastructures without the conceptualization of those drought impacts on the national economy.

1.8 Structure of the research

This research contains seven main chapters and some sub-topics in each chapter. All chapters introduced the general worldwide concept of drought and deep to the main objective of this study topic to hydrological drought status, trend, frequency, severity, propagation of meteorological to hydrological drought, and future expectations in different river basins over Ethiopia.

Chapter One: Introduction

The first chapter described the general background of the study from a global view of point to the specific study area. In this chapter; the motivation of the study, research questions, statement of the problem, scope and significance of the study, and the general and specific objectives have been discussed. A summary of hydrological drought impact in different sectors has been highlighted in a tabular form.

Chapter Two: Literature Review

Chapter two is a literature review related to the topic of this study, which includes the definition, characteristics, and types of droughts, as different approaches to monitoring and forecasting drought. The research gap related to hydrological drought analysis in Ethiopia is also assessed in this chapter.

Chapter Three: Hydrological Drought Analysis Using Streamflow Drought Index (SDI) in Ethiopia

In this chapter, the historical trend of hydrological drought conditions in Ethiopia is analyzed using the streamflow drought index (SDI). This chapter contains the abstract, introduction, method, and result with a clear discussion. This section is already published in a reputable journal as a full article.

Chapter Four: Comparing Surface Water Supply Index and Streamflow Drought Index for Hydrological Drought Analysis in Ethiopia

There are many hydrological drought indices throughout the world. But many of them are data-intensive and complex. In this chapter, two hydrological drought indices namely the Streamflow drought index (SDI) and Surface water supply index (SWSI) performance were compared based on the historical drought event. SDI uses only streamflow as input data whereas SWSI uses lake level, precipitation, and streamflow as input data. This topic is also published in a reputable journal.

Chapter Five: Hydrological and Meteorological Drought Monitoring and Trend Analysis in Abbay River Basin, Ethiopia

Even though the main concern of this research is on hydrological drought monitoring and forecasting, the relation of meteorological drought indices and hydrological drought indices was discussed particularly in the Abbay river basin using SPI, RDI, and SDI. This section is published in a reputable journal.

Chapter Six: Hydrological Drought Forecasting and Monitoring System Development Using Artificial Neural Network (ANN) in Ethiopia

The fifth chapter discusses in detail streamflow forecasting using an Artificial neural network and the projection of hydrological drought in the future based on the simulated streamflow. Observed streamflow and precipitation data were used to train the ANN model and downscaled precipitation data using the regional climate model is used as input data for future streamflow forecasting. This article was the final published in my dissertation work.

Chapter Seven: Conclusion and Recommendation

The final is chapter seven which is about conclusion and recommendation. This chapter summarizes the overall points of the study and its main result and recommends some points for further studies in the future.

Others: Appendix and References

Finally, the appendix and references are followed to elaborate and support the research with evidence by supplementary data and documents.

The references contain research articles, conference papers, books, and work papers that have good information related to drought, water resources, disaster preparedness, and risk management.

2. Review of hydrological drought analysis status in Ethiopia

Abstract

Drought is a complex natural disaster unlike flood, which covers a large area when it occurs. This review was conducted on hydrological drought analysis and monitoring status in Ethiopia by reviewing the master plan of eight major river basins and previous research related to drought. 24 article papers were reviewed and it is found that hydrological drought analysis studies cover only 8.33% of all of the river basins in Ethiopia; only Abbay and Wabishebele Basins have had hydrological drought analyses conducted. Researchers in the region have focused primarily on meteorological drought (37.5%) rather than hydrological and agricultural drought analysis. Although Ethiopia has long been dependent on rainfed agriculture for its economy and remains the primary livelihood of the population, the Ethiopian government has begun focusing on transitioning to an industrial economy, placing pressure on the water resource. The Ethiopian government has been constructing different water-related infrastructures (dam and reservoir) which are directly dependent on surface and subsurface water resources. In a region plagued by drought, drought analysis, and monitoring, drought early warning systems and effective mitigation measures are still limited and even lacking in some areas. Therefore, emphasis on hydrological drought analysis and development of suitable drought mitigation measurements is important to implement strategies for effective and sustainable water resource management by which water may remain available during the long dry seasons and the impacts of hydrological drought may be lessened.

Keywords: hydrological drought, drought mitigation, Ethiopian river basins

2.1 Introduction

Drought is a worldwide natural hazard and has a detrimental impact on society, the environment, and the economy (Mohammed et al., 2018). Extreme hydrological events both high (flood) and low (drought) flow are of particular concern globally. Of these hydrological extremes, drought is the most complex and widespread (Belayneh et al., 2014). It is one of the most common natural events that have devastating negative impacts on agriculture and water resources (Araya and Stroosnijder, 2011).

There is no universal definition for drought due to its complexity (Mera, 2018). Therefore, meteorologists define drought as a scarcity of precipitation (Keskin et al., 2011; Mohammed, 2018; Pashiardis and Michaelides, 2008; Shen et al., 2015; Svoboda and Fuchs, 2017; Zargar et al., 2004); hydrologists have defined hydrological drought as scarcity of surface and sub-surface water (Boudad et al., 2018b; Keskin et al., 2011; Khanna, 2010; Loon, 2015; Mohammed, 2018; Pashiardis and Michaelides, 2008; Shen et al., 2015; Svoboda and Fuchs, 2017; Trambauer et al., 2015; Yasa and, Mohammad Bisri, Moch Sholichin, 2018; Zargar et al., 2004); agriculturalists and agronomists define agricultural drought as related to soil moisture deficiency (Araya and Stroosnijder, 2011; Y. Bayissa et al., 2018; Tsige et al., 2019a), and sociologists and economists define the overall welfare crisis of the society caused by drought to be socio-economical drought (Ali, 2017; Mera, 2018; Teshome, 2019b; Viste et al., 2013; Zeleke, 2017). These types of drought have accumulating effects, thus meteorological drought results in losses, such as crop stress, predation by pests, and disease due to low moisture, to the agricultural systems while hydrological drought causes the shortage of water supply, decrease in reservoir water level and groundwater volume, lower irrigation and hydropower production (Loon, 2015). The accumulation of meteorological and hydrological drought results in socio-economical drought in which the overall ecosystem will be disturbed and human and animal lives will be negatively impacted and even lost (Boudad et al., 2018b).

Historically, Ethiopia has faced multiple seasonal drought events due to erratic rainfall and climate change (Philip et al., 2018). The most drought-prone areas in Ethiopia are in Northeast Ethiopia and the Upper Blue Nile Basin, including the Northern Tigray region, Some parts of Amhara regions such as South Wollo, North Wollo, South Gondar and Afar Region, most parts of Somalia Region, and Eastern parts of Oromia Region (Araya and Stroosnijder, 2011; Awass, 2009; Chemeda et al., 2010; Gebrehiwot et al., 2011; Gissila et al., 2004; Mohammed et al., 2018; Van Lanen HAJ, 2014). Drought in Ethiopia occurs at a recurrence interval of three - to ten years (Mohammed et al., 2018), and even though this frequent recurrence is well documented there still lacks any firmly established drought mitigation measures for these events. Only short-term response efforts are provided in the form of food aid when food supplies have decreased significantly due to extended drought.

Meteorological drought analysis has been studied frequently, yet hydrological and agricultural drought analysis and monitoring have not been studied adequately. It is thought that Ethiopia is a water tower in East Africa but water resource management in the region is not well developed. This aggravates natural hazards such as drought's impact on human life. Hydrological drought has a great influence on water supply irrigation and power production by reducing the availability of surface and subsurface water. There are few dams and reservoirs in the country and most of them are hydropower plants. However, there is a lack of water conservation to reduce drought impact when it occurs. Generally, drought monitoring and forecasting studies are untouched and need a thorough investigation to alleviate socioeconomic problems related to drought.

The objective of this review paper is to assess the status of hydrological drought studies in Ethiopia by reviewing different previously studied article papers related to drought. Totally 24 article papers were reviewed and the master plan of the eight-river basin was also reviewed. Of these, only two papers were related to hydrological drought and the remains were about meteorological and other drought-related topics. This implies that hydrological drought studies in Ethiopia require further analysis, monitoring, and forecasting investigation. Therefore, it is important to do this kind of review to show the gap in drought studies over the region for future researchers, stakeholders, and planners to develop a suitable early warning system.

2.2 Materials and Methods

2.2.1 Description of the study area

Ethiopia has an ample amount of water resources when compared to other African countries yet the development is still poor. There are 12 major River Basins in the country which generate an annual runoff of 124 BM^3 (table 2). From these, the Aysha and Ogaden river basins are dry and the Mereb and Denakle have insignificant streamflow over the year, the border basins from North to East direction (Figure 1). Eight river basins have a well-organized master plan, however, only the three river basins (Abbay, Awash, and Tekeze) are popularly studied for the development of irrigation, water supply, and hydropower projects. Different types of drought studies were also relatively studied in these river basins. In the Wabishebele river basin, one hydrological drought analysis was studied by Awas (2009). Abbay and Awash basins have good hydro-meteorological data and are highly invested when compared to other river basins. This review is focused on the assessment of hydrological drought analysis and the drought mitigation approach of previous research in Ethiopia related to drought.

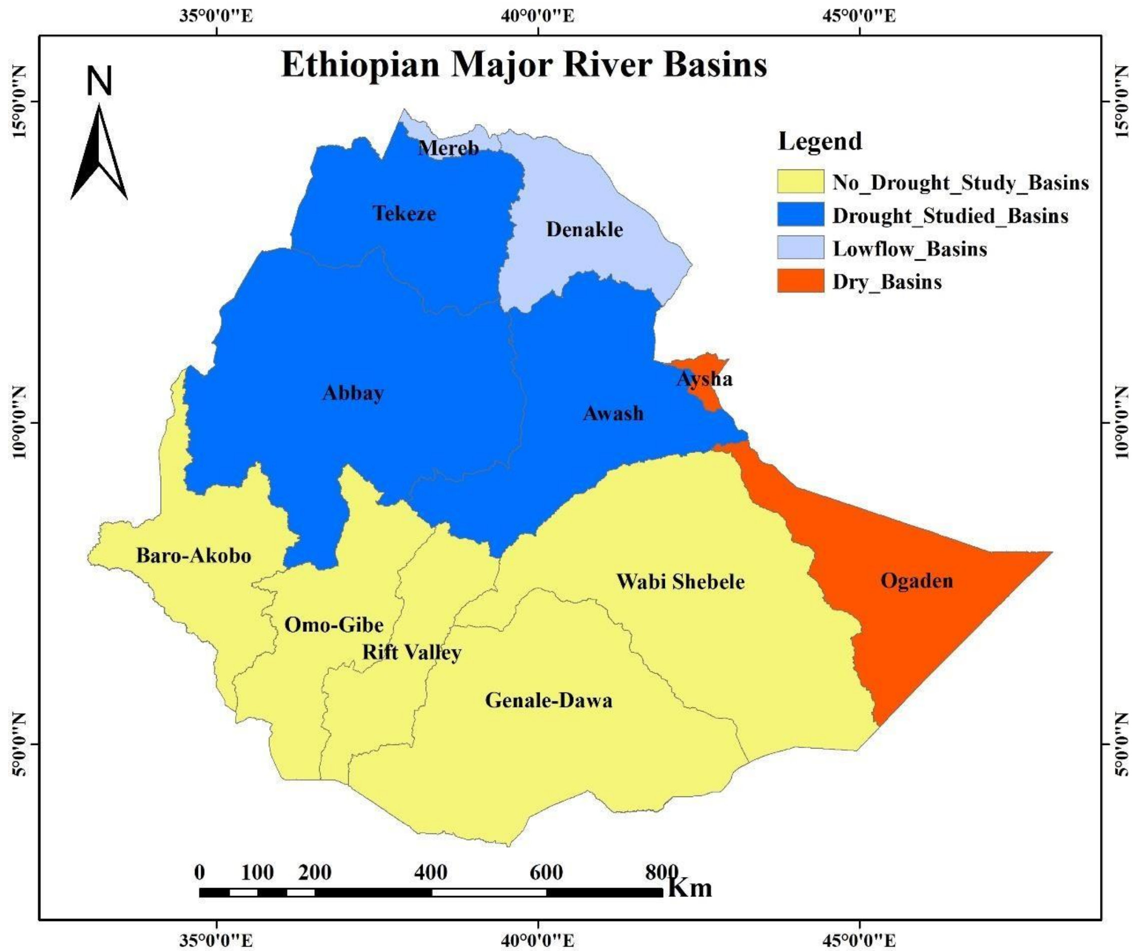


Figure 1 The 12 Ethiopian major river basins and drought-related studies information

Spatially, the Abbay river basin is the largest and it covers 43.1% of the surface runoff of the country. The general characteristics of each river basin in the country are given in Table 2. In Ethiopia, there is a high seasonal flow variation. As shown in Figure 2, Abbay and Omo Gibe river basins have high flow when compared to other river basins, and overall, the maximum flow is obtained during the summer season from June to August (JJA).

Table 2 Characteristics of Ethiopian Major River Basins

River Basin	Area (Km^2)	Annual Runoff (BM^3)	Terminus
Abbay	199912	52.6	Mediterranean
Awash	110000	4.6	Within the country
Baro	75912	23.6	Mediterranean
Genale Dawa	172259	5.8	Indian Ocean
Omo Gibe	79000	17.9	Lake Turkana
Tekeze	82350	7.6	Mediterranean
Rift Valley	52000	5.6	Chew Bahir
Wabishebele	202220	4.6	Indian Ocean
Mereb	5900	0.26	Sudanese Wetland
Denakle	64380	0.86	Within the country
Aysha	2223	0	
Ogaden	77120	0	
Total	**1123276**	**123.42**	

Source: River Basin Master Plan; Ministry of Water and Energy, Ethiopia

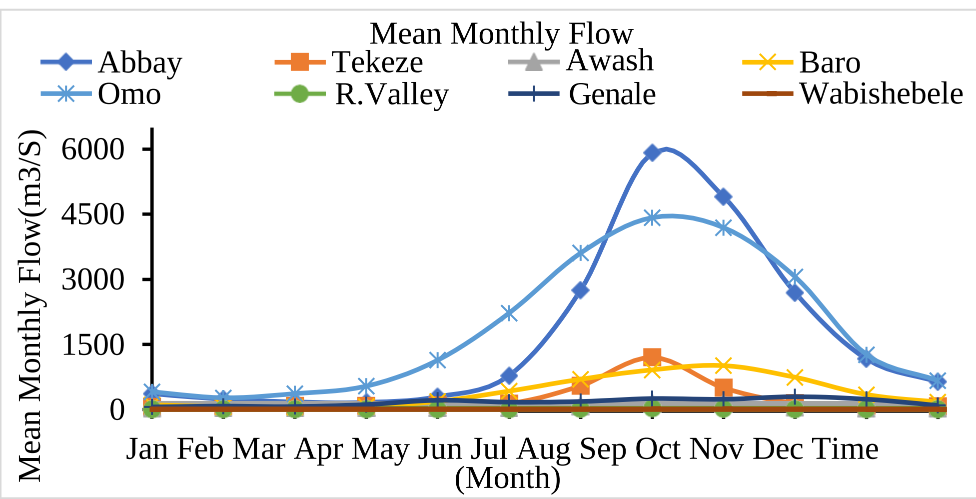


Figure 2 Mean monthly streamflow variation over Ethiopian River Basins

Even though, Ethiopia has 12 major river basins, most of which are transboundary rivers except the Awash river. The total surface water is estimated at 124 BM^3 and the groundwater potential is estimated near 30 BM^3 (Berhanu. B et al., 2014). 70% of the surface water originates from the central and western highlands on the western sides of the Great Rift Valley and flows to the west into the Nile River Basin system which covers 39% of the landmass and the remaining 30% of surface water originated from eastern highlands flow into east which covers 61% of the landmass.

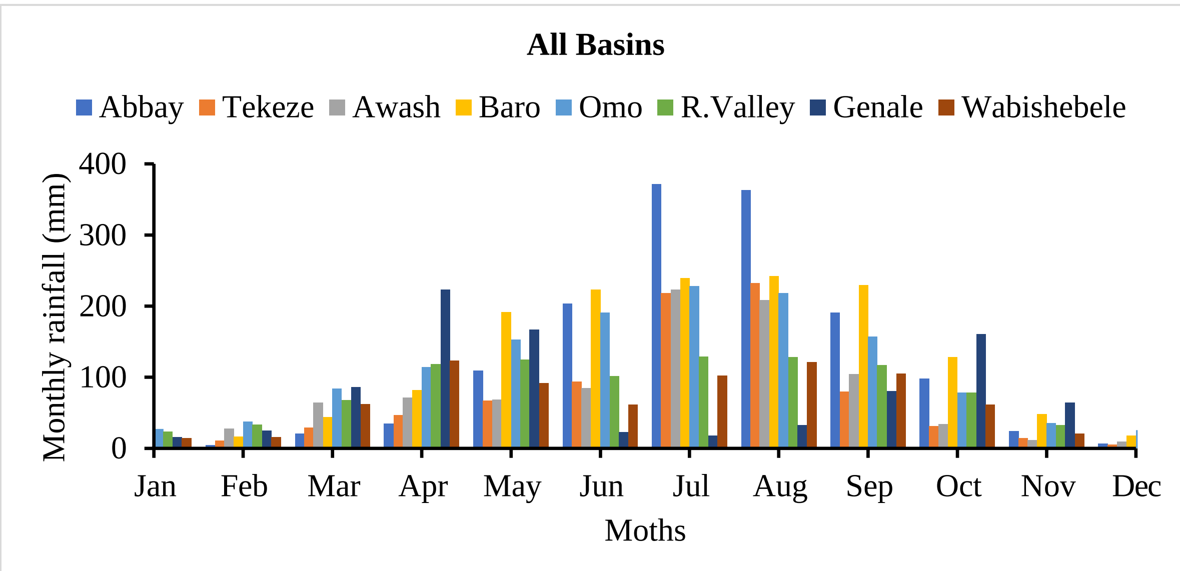


Figure 3 Mean monthly rainfall of eight river basins in Ethiopia for the selected station

2.2.2 Historical drought trend in Ethiopia

Ethiopia has experienced severe drought problems for the last decades. According to Mohammed et al., 2018, the most drought years in the east highlands of Ethiopia were 1984,1987, 1988, 1992, 1993, 1999, 2003, 2004, 2007, and 2008 (Mohammed et al., 2018). Bayissa et al(2018), also found that 1984/85 and 2003/04 were the extreme drought years in the Upper Blue Nile basin in Ethiopia (Yared A. Bayissa et al., 2015). Based on EM-DAT, 2014, the most severe drought years in Ethiopia from 1900 – 2013 were 1965, 1969, 1973, 1983, 1987, 1989, 1997, 1998, 1999, 2003, 2005, 2008, 2009, and 2012 with an average recurrence interval of 4 years (Ilyas Masih et al., 2014). This study shows that there were a minimum of two severe droughts in a decade. However, the development of effective drought mitigation measures and early warning systems are not implemented as a country to minimize the impact of drought on socioeconomic activities.

Generally, the year 1984 was a bad drought event in Ethiopia and it was globally known. Here, all the above-stated drought years were analyzed based on meteorological drought indicators especially the standardized precipitation index (SPI) and Palm drought severity index (PDSI) which does not give information on the status of hydrological drought conditions in terms of frequency, duration, and severity.

2.2.3 Data collection and analysis

To review the status of hydrological drought conditions in Ethiopia, important data were collected from the Ministry of Water and Energy (MoWE), department of Basin Development Authority. The river basin master plan was thoroughly reviewed and previous drought-related studies in Ethiopia were also assessed.

During this review, 24 articles and conference papers related to drought studies in Ethiopia were collected. From these 9 papers are meteorological drought studies, 7 papers are general drought impact studies and the remaining 8 were Agricultural, Hydrological, and socio-economic drought studies (Tables 3 and 4). Surprisingly, except for some general drought studies related to drought impact over the country, other drought studies were conducted in some specific parts of the country. Especially meteorological drought studies were highly focused on the Abbay river basin (Upper Blue Nile) and Awash river basin. Agricultural and socioeconomic drought studies slightly tried to see the overall drought conditions in Ethiopia. However, these are also not studied in depth.

Table 3 Summary of selected literature related to drought studies in Ethiopia for this review

No.	Author	Title	Drought Category
1	Philip et al., 2018	Attribution Analysis of the Ethiopian Drought of 2015	General
2	Belayneh et al., 2014	Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models	Meteorological
3	Yimer et al. 2017	Meteorological drought assessment in northeast highlands of Ethiopia	Meteorological

4	Araya and Leo Stroosnijder, 2011	Assessing drought risk and irrigation need in northern Ethiopia	General
5	Enyew et al., 2014	Assessment of the Impact of Climate Change on Hydrological Drought in Lake Tana Catchment, Blue Nile Basin, Ethiopia	Hydrological
6	Edosa et al., 2010	Drought Analysis in the Awash River Basin, Ethiopia	Hydro-meteorological
7	USAID Report, 2018	Economics of resilience to drought; Ethiopia analysis	Socio-economic
8	Philip et al.	The drought in Ethiopia, 2015	General
9	Jjemba et al.	Extreme drought in Ethiopia stretches drought management systems	Socio-economic
10	Gebrehiwot et al., 2011	Spatial and temporal assessment of drought in the Northern highlands of Ethiopia	Meteorological
11	Bayissa et al., 2018	Comparison of the Performance of Six Drought Indices in Characterizing Historical Drought for the Upper Blue Nile Basin, Ethiopia	Meteorological
12	Awass, 2009	Hydrological Drought Analysis Occurrence, Severity, Risks: The Case of Wabishebele River Basin, Ethiopia	Hydrological
13	EL Kenawy et al., 2016	Changes in the frequency and Severity of Meteorological drought over Ethiopia from 1960- 2013	Meteorological
14	Bayissa et al., 2015	Spatio-temporal assessment of meteorological drought under the influence of varying record length: the case of Upper Blue Nile Basin, Ethiopia	Meteorological
15	Zeleke et al. 2017	Trend and periodicity of drought over Ethiopia	Meteorological

16	Teshome and Zhang, 2019	Increase of Extreme Drought over Ethiopia under Climate Warming	General
17	Viste et al., 2012	Recent Drought and Precipitation Tendencies in Ethiopia	General
18	Getachew et al., 2020	Application of Artificial Neural Networks in Forecasting a Standardized Precipitation Evapotranspiration Index for the Upper Blue Nile Basin	Meteorological
19	Getachew, 2018	Drought and its impacts in Ethiopia	Socio-economic
20	Temam et al., 2019	Long-Term Drought Trends in Ethiopia with Implications for Dryland Agriculture	Agricultural
21	Dawit et al., 2019	Comparison of Meteorological and Agriculture-Related Drought Indicators across Ethiopia	Meteorological and Agricultural
22	Yared A. Bayissa et al., 2018	Developing a satellite-based combined drought indicator to monitor agricultural drought: a case study for Ethiopia	Agricultural
23	IDA GRANT-H0280, 2011	Emergency drought recovery project (EDRP) in Ethiopia	General
24	Sara Pantuliano and Mike Wekesa, 2008	Improving drought response in pastoral areas of Ethiopia	General

Table 4 Meteorological and hydrological drought studies status in some river basins

N0.	Basin	Article related to Meteorological Drought	Articles related to Hydrological drought
1	Abbay	3	1
2	Awash	2	
3	Omo-Gibe	1	
4	Rift Valley	1	
5	Tekeze	2	

6	Wabishebele	1

Agricultural and socio-economic drought studies were not focused on a particular river basin. 13 articles including agricultural, socio-economic, and general concepts and drought impacts in Ethiopia were covered in some parts of the country without specifying a particular river basin. Table 5 shows the percentage coverage of different types of drought studies in Ethiopia out of 24 papers.

Table 5 The percentage of different types of droughts studies in Ethiopia

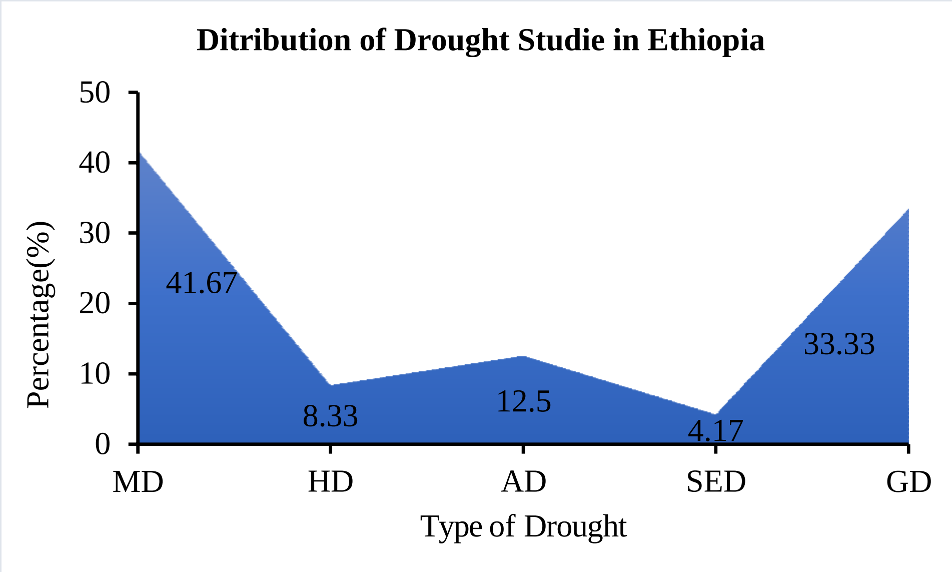
Type of Drought	Number of research papers	Percentage (%)
Meteorological Drought	9	37.5
Hydrological Drought	2	8.33
Agricultural Drought	3	12.5
Socio-Economic Drought	3	12.5
General related to drought Impact	7	29.16
Total articles reviewed	24	100

2.3 Result and Discussion

2.3.1 Hydrological drought status of the country

Ethiopia has been affected by drought many times over the last few centuries. However, drought studies and mitigation measurement investigations are still limited. Although there are few drought studies in the country, it is insufficient. Especially agricultural, hydrological, and socio-economic drought studies are untouched. As shown in Table 4, most drought studies in Ethiopia are focused on meteorological drought and other general drought-related impact assessments. Meteorological drought is highly varying within the short period scale in a month depending on the precipitation variability. Therefore, drought analysis from a short time scale may lead to an erroneous conclusion. However, a hydrological drought study requires a long-term time scale greater than six months of cumulative drought conditions in the study area. Mostly hydrological drought analysis is conducted annually based on and above which will give some concrete information about the drought situation of a particular study area. From this review, hydrological drought studies covered only 8.33%, which implies that it needs further study (one article in the Abbay sub-basin and one article from the Wabishebele basin). Almost 78% of the study was concentrated in the North Eastern and Upper Blue Nile Basin, Tekeze and Abbay, and Awash river basin which is meteorological drought (Table 4). Two researchers have studied hydrological drought in Abbay and Wabishebele Basins (table 3). However, the remaining 6 basins are still not studied. Now the government of Ethiopia is planning to transform from agricultural lead to industrial transformation. This will be achieved when the natural resource is properly managed and utilized. Water is the central part of all infrastructure development. However, the master plan of major river basins in Ethiopia focused only on the potential assessment of irrigation and hydropower and there is no drought trend analysis and future hydrological drought forecasting. Hydrological drought affects irrigation, water supply, hydropower, and other water-related sectors. So, it is important to study the historical hydrological drought characteristics such as frequency, magnitude, duration, severity, and future probability of the basin streamflow to satisfy all demands.

As far as reviewed from the basin master plan report and previous pieces of literature, there is no method adopted to analyze the hydrological drought in the region. But for sustainable water resource development, mitigation measurements of extreme hydrological events like floods and drought are impropriated. Otherwise, simply constructing any structure in the basin alone may not be a solution to improve poverty in the country.



Where: MD = Meteorological drought, HD = Hydrological drought, AD, Agricultural drought, SED = Socio-economical drought, and GD = general drought-related studies.

Figure 4 Percentage distribution of different types of drought studies in Ethiopia

2.3.2 Meteorological and Agricultural Drought

Of the reviewed papers, 37.5% covered meteorological drought analysis and monitoring studies, and agricultural drought studies covered 12.5% (Table 5). Ethiopia is highly dependent on rainfed agriculture; so, meteorological and agricultural drought analysis, monitoring, and early warning system development are crucial. But still, there is no well-adopted drought analysis technique for a nationwide or regional level. As a result, the development of drought early warning systems has lacked. At the same time, hydrological drought analysis and monitoring is also a key point for river basin development and water resource management. However, due to its large input data requirement, the hydrological drought study is not further investigated.

2.3.3 General drought-related studies

The socio-economic of Ethiopia is continuously affected by frequent drought disasters. It is difficult to cope with subsequent years after drought has occurred. 29.16% of the reviewed papers were related to drought impact, attribution, economics resilience to drought, extreme drought assessment, trend and periodicity of drought in Ethiopia (Mera, 2018; Teshome, 2019b; Viste et al., 2013; Zeleke, 2017). Except for some articles, most of the reviewed articles were conducted in some parts of the country and did not give good information about the effect of drought on the country.

2.4 Conclusion

During any river basin master planning, considering extreme hydrological events like floods and drought are important issues for sustainable water resource development. Otherwise, simply focusing on the investigation and assessment of the available natural resources in a specific river basin and utilization of the resource will never bring development. Particular attention is to be given to drought-affected areas and conjunctive use of ground and surface water is encouraged. Aridity is the general characteristic of an arid climate and represents a (relatively) permanent condition, while drought is temporary. In an arid climate, drought can still occur when local conditions are even drier than normal. However, 90% of the reviewed studies in Ethiopia were conducted in arid and semi-arid areas of the region. Generally, hydrological drought study lacked in the country. Therefore, in the future, it is important to focus on hydrological drought monitoring and forecasting to achieve the sustainable utilization of available surface and subsurface water resources in Ethiopia.

3. Hydrological drought analysis using streamflow drought index (SDI) in Ethiopia

Abstract

Drought is a natural disaster that has impacts on society, the environment, and the ecosystem. Ethiopia has faced many horrible severe drought events in the last few decades. Even though there are some drought-related studies in the country, most of the investigations were focused on meteorological drought analysis. This study was focused on hydrological drought analysis in Ethiopia using the streamflow drought index (SDI). The main objective was to identify drought-prone areas and severe drought event years. Streamflow data were collected from 34 stations to analyze SDI in seasonal (3-month) and annual (12-month) timescales. The analysis implies that seasonal time scale (3-month) hydrological drought has a high frequency of occurrence but short duration, whereas annual (12-month) analysis has a low frequency with a large magnitude. The overall result shows that 1984/85, 1986/87, 2002/03, and 2010/11 were the most severe and extreme drought years in most river basins. The 1980s were found severe and extreme drought years in which most hydrological drought events occurred in the country. The spatial analysis shows that the Tekeze, Abbay, and Baro river basins have similar characteristics; the Awash and Rift Valley river basins show relatively the same character, and the Genale Dawa and Wabishebele river basins have similar characteristics. However, the Omo Gibe River basin has a unique character in that the severe drought occurred in a different year than other river basins.

Keywords: hydrological drought, Streamflow drought index, Ethiopia

3.1 Introduction

Drought is a worldwide natural hazard and has a severe impact on the social, environmental, and economic aspects (District et al., 2013). Hydrological extreme events both flood (high flow) and drought (low flow) are the most concerning issues in the world (Edossa et al., 2014). However, drought is one of the most common natural disasters that have a great negative impact on agriculture and water resources projects in a wide range (Arash Asadi, 2013). However, researchers are more focused on flood disasters than drought.

Drought is a complex phenomenon and due to its notorious nature, there is no universal definition for it (Svensson et al., 2017). Albeit it has no universal definition, droughts can be (1) meteorological, which is a scarcity of precipitation (Alegre et al., 2020; Giri et al., 2021; Nasir et al., 2021a), (2) hydrological drought, which is the scarcity of streamflow water, reduction of reservoir and Lake water level (Alemu et al., 2021; Botai et al., 2021; Kolachian and Saghafian, 2021), (3) agricultural drought related to deficit of soil moisture (Keyantash and Dracup, 2004; Tsige et al., 2019a) and (4) socio-economical drought which is the imbalance between supply and demand (Juana, 2015; Kruse and Seidl, 2014) and each drought is a cause of the other (Bąk and Kubiak-Wójcicka, 2014). Meteorological and agricultural droughts mainly cause the failure of crops, while hydrological drought is a deficiency of water supply, a decrease in reservoir water level and groundwater level, and a decrease in irrigation and hydropower production (Loon, 2015). The aggregated impact of meteorological, agricultural, and hydrological drought and the contradiction between water supply and demand results in socio-economical drought (Y. Bayissa et al., 2018; Liu et al., 2020), in which the overall ecosystem of the drought region is disturbed, and there is a loss of life (Boudad et al., 2018a). The overall propagation of each drought development is summarized in Figure 1.

The scientific analysis of the recurrence and persistence of drought seeks to establish an estimate of probabilities that will contribute to the planning of strategies for the mobilization and management of water resources (Boudad et al., 2018a). Due to climate change, the global vulnerability to floods and drought has been increasing (Hasan et al., 2019). The assessment of droughts affecting agricultural areas in Africa is highly relevant. Many African countries strongly rely on rain-fed agriculture. Since rainfall is commonly the limiting factor for rain-fed agricultural systems, droughts can lead to severe socio-economic consequences like; crop failure, food shortages, and even humanitarian crises. For example, drought events have caused more than 800,000 deaths and affected about 262 million people in Africa from 1900 to 2013.

Ethiopia has also experienced severe drought in the past centuries. Researchers have thought that severe drought occurred once in three to ten years recurrence interval (Mohammed et al., 2018). Even though this recurrence time is quite short, no permanent drought mitigation measures have been established effectively. Measures are more localized and usually come in the form of food aid during the drought period.

Large-scale drought analysis studies have been recently conducted globally or continental level for present and future climate change (Lanen et al., 2013). But in the case of Ethiopia, drought studies were focused on catchment level and they do not give good information about the drought condition of the country. Few drought studies were conducted in the Northern and eastern parts of Ethiopia, which are mainly focused on meteorological drought analysis (Gebrehiwot et al., 2011). Finally, the researchers try summarizing the effect of drought events throughout the country. However, drought events are inconsistent across all of Ethiopia. The variability of the temporal, spatial, and magnitude characteristics of drought events requires in-depth analysis to determine different approaches for mitigation. The government of Ethiopia developed and planned different water resource infrastructure development to reduce poverty. Yet, hydrological drought analysis is not well studied. Therefore, to develop permanent and effective drought mitigation measures, it is important to analyze the historical hydrological drought over the nation. So, the main objective of this study is to analyze and characterize historical hydrological drought in Ethiopia using the Streamflow Drought Index (SDI) for a better understanding of its impact on water resource infrastructure development.

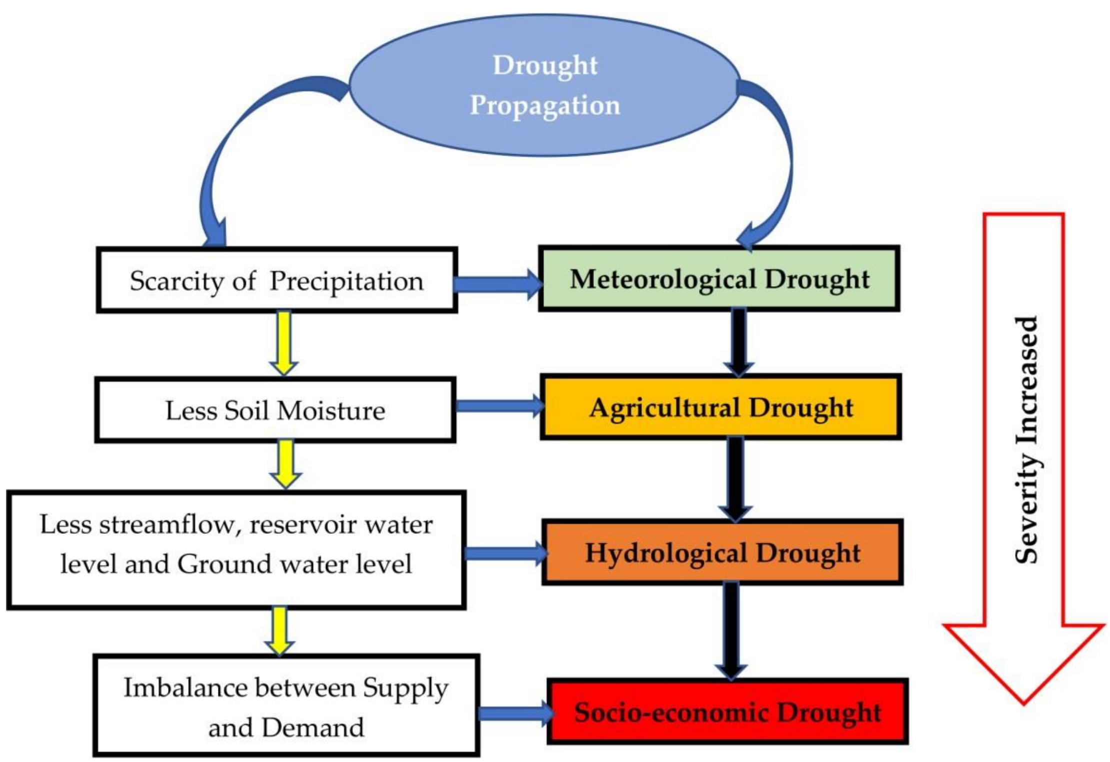


Figure 5 Relationship and propagation of different types of droughts

3.2 Methods

3.2.1 Description of the study area

Ethiopia is located in the eastern horn of Africa, which is located at 3^0 N and 15^0 N latitude and 33^0 E and 48^0 E Longitude. The area of the country is about 1.13 million km^2 and this study covers 87.3% of the country. Because, of 12 major river basins, 4 are not included in this study due to lack of data. (Figure 6). The population of the country rapidly increases from decade to decade causing, deforestation and expansion of urban areas. As a result, variability in climate conditions also increased. There are twelve major river basins yet the development of water resources is still low. Of the existing 12 major river basins, three (3) are dry and one river basin has low flow and low recorded data as presented in Figure 6 northeast part. Due to this reason, this study was focused only on eight (8) major river basins. The drought phenomenon is a common natural hazard throughout the country, especially since the severity is high in the northern and eastern parts. The country receives high rainfall during the summer (June, July, and August). The mean annual rainfall and temperature range from 510 – 1300 mm and 16^0c – 27^0c respectively.

The topography of Ethiopia and the respective major river basins are described by the Digital Elevation Model (DEM), it was collected from the Ministry of Water, Irrigation and Electricity, GIS division with a spatial resolution of 30 m × 30 m. The river network and basin boundary are automatically extracted from the DEM itself by performing the ArcGIS software and the spatial location of 34 streamflow gauge stations and some major reservoirs are indicated in Figure 6.

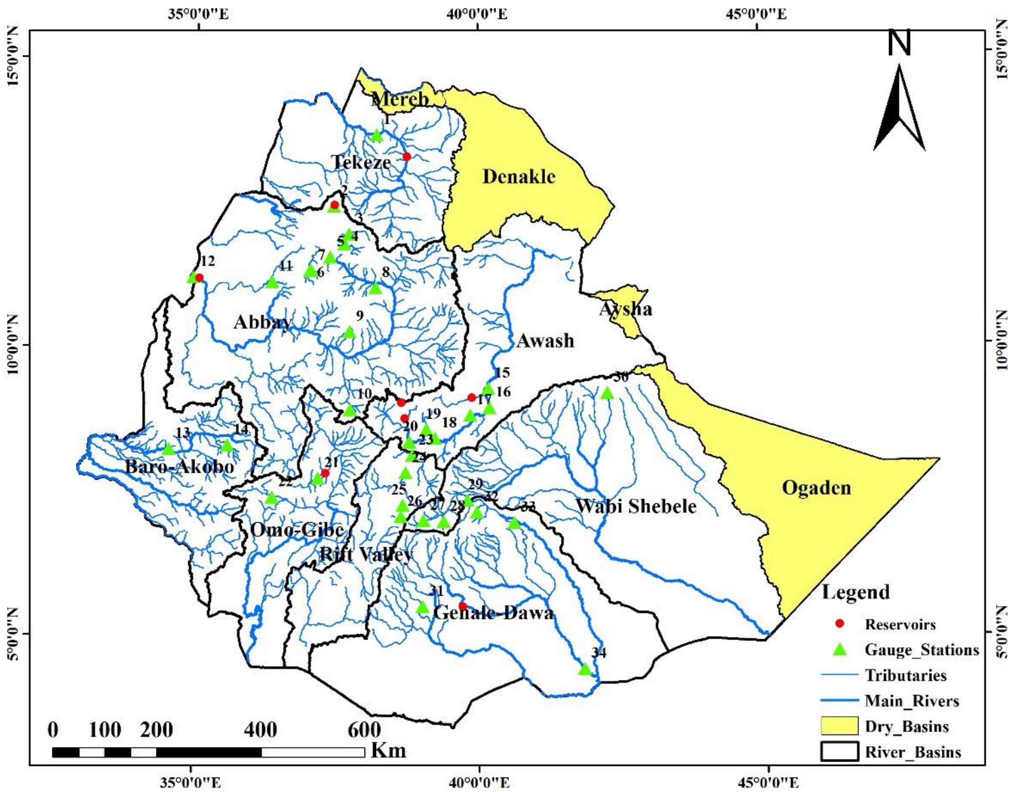


Figure 6 Location of selected streamflow stations in each river basin

3.2.2 Data collection and preparation

Streamflow data were collected from the Ministry of Water, Irrigation, and Electricity (MoWIE). The stations were selected based on data quality, recorded length, and area coverage. The data were collected from 34 streamflow stations with a length of 35 – 41 years, except for the Tekeze basin, which has only 21 years of record length (Table 6). The streamflow stations in the Tekeze basin have more missing data and it is difficult to analyze drought trends with minimum data availability. Therefore, for this basin, only one streamflow station is considered, which has 21 years of recorded data from 1994 to 2014. However, the other seven basins fulfill the minimum data length required (30 years) for drought analysis. Table 6 summarizes the spatial location of the gauge station and their corresponding data record length.

Table 6 Streamflow stations location and a corresponding record year in each river basin

No	Station Name	Basin	Latitude (^{0})	Longitude (^{0})	Area (Km^2)	Recorded Year
1	Embamadre	Tekeze	13.73	38.20	45694	1994 - 2014
2	Megech	Abbay	12.48	37.45	462	1980 - 2014
3	Rib	Abbay	12.00	37.72	1592	1972 - 2012
4	Gummera	Abbay	11.83	37.63	1394	1973 - 2014
5	Bahir Dar	Abbay	11.60	37.38	15319	1973 - 2014
6	Gilgel Abbay	Abbay	11.37	37.03	1664	1972 - 2012
7	Koga	Abbay	11.37	37.05	244	1972 - 2012
8	Kessie	Abbay	11.07	38.18	65784	1973 - 2014
9	Chemoga	Abbay	10.30	37.73	364	1973 - 2009
10	Gilgel Beles	Abbay	11.17	36.37	675	1973 - 2014
11	Guder	Abbay	8.95	37.75	524	1973 - 2009
12	Abbay Border	Abbay	11.23	34.98	17254	1973 - 2014
13	Gambela	Baro	8.25	34.58	23461	1973 - 2014
14	Sorie	Baro	8.32	35.60	1622	1973 - 2014
15	Melkawerer	Awash	9.32	40.17	31183	1973 - 2010
16	Awash7 Killo	Awash	8.98	40.18	19110.75	1973 - 2013
17	Metehara	Awash	8.85	39.85	16416.8	1982 - 2014
18	Wonj	Awash	8.45	39.23	11690	1973 - 2014
19	Mojo	Awash	8.60	39.08	1264.4	1973 - 2014
20	Hombel	Awash	8.38	38.78	7656	1973 - 2014
21	Assendabo	Omo Gibe	7.75	37.18	2966	1980 - 2018
22	Gojeb	Omo Gibe	7.42	36.38	3577	1980 - 2018
23	Meki	Rift Valley	8.15	38.83	2433	1973 - 2014
24	Kekersitu	Rift Valley	7.85	38.72	7488	1980 - 2014
25	Dedeba	Rift Valley	7.28	38.67	156	1980 - 2014
26	Wosha	Rift Valley	7.08	38.63	20	1980 - 2014
27	Wabi Bridge	Wabishebele	7.02	39.03	1035	1976 - 2014

28	Leliso	Wabishebele	7.00	39.38	135	1976 - 2014
29	Weiyb	Wabishebele	7.37	39.80	7719	1983 - 2014
30	Erer	Wabishebele	9.23	42.25	469	1983 - 2014
31	Chenemasa	Genale Dawa	5.52	39.02	10574	1983 - 2014
32	Shaya	Genale Dawa	7.17	39.97	4338	1981 - 2014
33	Weib	Genale Dawa	6.98	40.62	3576.9	1984 - 2014
34	Halewe	Genale Dawa	4.43	41.83	54093	1984 - 2014

The annual flow in each basin varies from season to season. Abbay, Baro Akob and Omo Gibe River basins (northwest, western, and southern parts) have a high flow than other basins, with 52.6, 23.6, and 17.9 BM^3 annual runoff respectively whereas Tekeze Genale Dawa, Rift Valley, Awash, and Wabishebele (northern, central and eastern parts) has a relatively moderate flow, 7.6, 5.8, 5.6, 4.6 and 4.6 BM^3 annual runoff respectively (see table 2).

3.3 Hydrological drought indicators selection

There is no single drought indicator for all types of drought in a specific region (Barua, 2010). Because all available drought indicators have their limitation during development and application (Nairizi, 2017). Therefore, drought indicator selection requires a thorough investigation related to the type of drought and the respective drought indicator based on the availability of data, ease of communication, result implication, strength and limitations of the indices, and the objective of the investigation (Barua, 2010). Among many drought indices, the most common are discussed below in Table 7.

Table 7 Summary of drought indicator's strength and weakness

No	Indicator	Strength	Weakness
1	Decile	Easy for analysis and used for all types of droughts at a different time scale	Uses only precipitation and does not consider temperature and other hydrological variables

2	Palmer Drought Severity Index (PDSI)	Widely used, good for agricultural drought	The need for serially complete data causes problems
3	Palmer Hydrology Drought Index (PHDI)	Its water balance approach allows the total water system to be considered	Frequencies will vary by region and time of year
4	Standardized Precipitation Index (SPI)	Easy to calculate, applicable in all climate regimes	The temperature effect is not considered
5	Standardized Precipitation Evapotranspiration Index (SPEI)	Account for the impact of temperature on a drought situation, the output applies to all climate regimes	The requirement for a serially complete dataset for both temperature and precipitation limits its use due to insufficient data
6	Reconnaissance Drought Index (RDI)	Easy to use, precipitation and temperature as input, consider the water balance of the region	Comparing RDI for different climate regions may be subject to error
7	Streamflow Drought Index (SDI)	The program is widely available and easy to use. Missing data are allowed,	A single input (Streamflow) does not consider management decision
8	Surface Water Supply Index (SWSI)	considering the full water resources of a basin provides a good indication of overall hydrological health of a particular basin or region	As data sources change or additional data are included, the entire index must undergo recalculation

Source: *Handbook of Drought Indicators and Indices; Integrate Drought Management Program (IDMP); World Meteorological Organization WMO – No. 1173 (2016)*

From the water resources development and management perspective, it is important to define the reference flow levels and indicators of drought severity (what drought duration and/or flow deficit constitutes mild or severe drought). Several indices measure how much streamflow for a given period has deviated from historically established norms. Most water supply planners find it useful to consult one or more indices before making a decision (Cancelliere et al., 2003; Wu et al., 2018).

Hydrological drought can be defined in terms of the differences between the water supply and water demand time series. The supply time series is characterized by a river flow and the demand time series - by the demand of a particular user (e.g., irrigation) or by the total demand for all users. When demand exceeds supply, water shortages occur, which represent the start of a such as storage is also a useful indicator of water shortages, due to data availability on a daily or weekly basis. Simultaneously, these data are strongly influenced by the reservoir operation rules (Lucy J. Barker et al., 2019).

The hydrological drought indices (HDI) depend on the purpose of hydrologic monitoring and prediction, such as reservoir operation and water allocation for hydroelectric generation, irrigation, and domestic or industry water supply. Most hydrological drought indices are largely based on stream flows. Streamflow deficit regarding normal conditions is not always the true representative, particularly in the river systems with diversion of virgin flows. Therefore, hydrological drought is characterized by more factors than just low flows. The preparation of streamflow data for drought management or any purpose is hampered by the lack of adequate data due to shorter record lengths and artificial influences (such as abstraction) and even the longer recorded stations have high missing values in developing countries such as Ethiopia.

Drought indices and definitions based solely on flow or reservoir storage are normally designed for reservoir operation and are seldom (if at all) used as triggers for drought relief, or drought monitoring over vast territories. Although none of the major indices is inherently superior to the rest in all circumstances, some indices are better suited than others for certain uses (Davis and Stampone, 2014).

In Ethiopia, there is a high scarcity of data for streamflow analysis of both flood and drought. Most reservoirs in the country have no gauge staff and groundwater level is not well known in all basins, which makes it difficult to use more data-intensive drought indicators for hydrological drought analysis. Therefore, in such circumstances, SDI is the best alternative for hydrological drought analysis due to its lower input requirement and simplicity for analysis and interpretation (Nalbantis, 2008). Streamflow is the most crucial variable in the quantity of water that expresses the availability of surface water resources. Therefore, in terms of normal conditions, a hydrological drought occurrence is linked to the streamflow deficit (Hasan et al., 2019; Lanen et al., 2013). Therefore, due to the following reasons, SDI is selected for this study: i) the areal extent of a drought event is very useful for meteorological drought, but it is not of interest for hydrological droughts since water managers are interested in streamflow only as a small number of points in space (Basin outlets, Reservoir inlets, and outlets); ii) streamflow at these points provides an integrated measure of spatially distributed runoff; iii) furthermore, the river basin can be proposed as the unit for applying measures for water resource protection and management; iv) in Ethiopia, there is a scarcity of data availability especially Lake level, reservoir level, soil moisture, and groundwater level. Relatively, precipitation and streamflow data are available from the 1970s to date.

3.3.1 Streamflow Drought Index

The Streamflow Drought Index (SDI) was developed (Tsakiris, 2009), which is used to characterize the streamflow drought conditions. Its calculation is similar to SPI and therefore has the same characteristics of simplicity and efficiency. The SDI is based on monthly observed streamflow volumes at different time scales and thus offers the advantage of controlling streamflow drought or the supply of water in the short, medium, and long term. The calculation is given by the following Eq. (1):

$$Vi, j = \sum_{j=1}^{k} Qi, j \quad i = 1, 2 \ldots\ldots, j = 1, 2, \ldots 12 \text{ and } k = 1, 2, 3, 4 \qquad (1)$$

Where: $V_{i,j}$ is the cumulative streamflow volume for the i-th streamflow year and the k-th reference period, K is a seasonal value (four-season, Ethiopia case)

$Q_{i,j}$ is monthly streamflow volume at i^{th} streamflow year and j^{th} month within that year

Based on the cumulative streamflow volumes $V_{i,k}$, the Streamflow Drought Index (SDI) is

defined for each reference period k of the i-th streamflow year as follows Eq. (2):

$$SDI = \frac{Vi,k - Vkm}{Sk} \qquad (2)$$

Where: i = 1, 2; …, and k = 1, 2, 3, 4

In which Vkm and sk are respectively the mean and the standard deviation of cumulative streamflow volumes of the reference period k as these are estimated over a long period. The range of wetness and dryness of SDI ranges between -2 and +2. The extremely dry and wet values are below -2 and above +2, respectively. According to Nalbantis and Tsakiris, 2009, hydrological drought classification using SDI is shown below in Table 8.

Table 8 Drought classification according to the SDI values (Nalbantis and Tsakiris, 2009

SDI value	Category
> = 2	Extremely wet
1.5 - 1.99	Severely wet
1 - 1.49	Moderately wet
0.5 - 0.99	Slightly wet
-0.49 - +0.49	Normal
-0.5 - -0.99	Mild drought
-1 - -1.49	Moderately drought
-1.5 - -1.99	severely drought
< = -2	Extremely drought

3.3.2 Hydrological drought characterization

The drought index plays a great role in evaluating the consequences of drought impact and deciding various drought characterization, such as duration (D), Severity (S), magnitude (M), and relative frequency (RF) (Eskandaripour, 2022; Soo et al., 2012). Drought duration is the time taken between consecutive drought events (onset and end of drought). The duration is from the start of the negative SDI value and turns to a positive SDI value. Drought severity is the summation of negative SDI values from onset to end of drought event as defined by Eq. (3). The magnitude of drought is the ratio between drought severity and drought duration which is defined by Eq. (4).

$$Si = -\sum_{i=1}^{D} SDIi \quad (3)$$

$$M = \frac{S}{D} \quad (4)$$

The relative drought frequency is the ratio between the number of droughts (n) with negative SDI in drought duration and the total number of drought years in the analysis (N) (Yisehak et al., 2021) and RF is defined as Eq. (5):

$$RF = \frac{n}{N} * 100 \qquad (5)$$

3.4 Results and discussion

3.4.1 Hydrological drought analysis using drought indices

Indices are important to give quantitative information about drought events in terms of duration, intensity, frequency, and recurrence interval for readers and scientists. Such information is extremely important for planning and water resource management (Buttafuoco and Caloiero, 2014). There are many hydrological drought indices such as SDI, SWSI, PHDI, ADI, etc. But except for SDI, all indices are more data-intensive (Christian et al., 2020; Nalbantis, 2008). Therefore, in this study, the historical hydrological drought trend in Ethiopia was analyzed using SDI. SDI is a point or site drought indicator that gives information about the river's temporal and special variation. The analysis was computed using the DrinC model (Drought Indicator Calculator), which was developed to determine SPI, RDI, and SDI using monthly input data (Tigkas et al., 2015, 2013).

3.4.2 Hydrological drought analysis using SDI

The daily streamflow data were prepared monthly and normalized to zero mean and unit standard deviation to illuminate the flow variation of stations in time and space. Then, SDI was estimated using equation (2) for short and long–term scales (SDI3 and SDI12), the seasonal base for the three-month duration (SDI3), and the annual base for the twelve-month duration (SDI12). In Ethiopia, the summer covers from June to August (JJA), during this season nearly all river basins receive high rainfall, and streamflow volume increases. Hydrological drought develops gradually due to the scarcity of precipitation in the region when there is no rainfall for some consecutive months or a year. Therefore, this study focuses on the summer season (SDI3) and annually-based (SDI12) hydrological drought analysis. Because, the remaining three seasons, Autumn (SON), Winter (DJF), and Spring (MAM) follow the summer season drought condition and it can be summarized by the annual drought conditions. The analysis result indicates that the 3-month time scale (SDI3) analysis frequency of drought occurrence was high compared to the long-term time scale, the 12-month (SDI12). This finding agreed with previous studies such as (Alegre et al., 2020; Boudad et al., 2020; Christian et al., 2020; Shahidi, 2017; Wambua et al., 2015). But for the long-term time scale, drought duration is maximum and the SDI value is minimum as shown in Figure 4. In this study, the temporal and spatial variation of streamflow drought in Ethiopia was analyzed using SDI. Therefore, the most severe and extreme drought years over different river basins were identified. As shown in Table 9, the Rift Valley river basin was highly affected by 13 severe and 4 extreme droughts followed by the Abbay river basin for the last four decades. These drought years were selected from the common severe and extreme drought years of most stations of each river basin.

Table 9: Hydrological drought years in different river basins in Ethiopia from 1973-2014

River Basin	Severe drought years	Extreme drought year
Abbay	1979, 1981, 1983, 1984, 1986, 1994, 2010	1983/1984, 1984/1985
Awash	1979, 1996, 1997, 2001	1986/1987, 1987/1988, 2002/2003
Baro	1982, 1984, 1985, 2002	2002/2003, 2004/2005
Genale Dawa	1996, 2002, 2003, 2010	
Omo Gibe	1980, 1981, 1986	
Rift Valley	1980, 1983, 1984, 1985, 1987, 1990, 1999, 2001, 2002, 2004,2010,2011, 2012	1984, 1985, 2003, 2012
Tekeze	1996	
Wabishebele	2001, 2002, 2004, 2005, 2007	2002

In the Abbay river basin, 11 streamflow stations were considered for hydrological drought analysis using SDI. Since SDI is a point or site drought indicator, the discussion here considers all gauging stations within the basin and the result of each station is shown in Figure 7. The correlation of each station implies that the Abbay Border station correlates well with Kessie, Ribb, Megech, Gummera, and Bahir Dar (0.85, 0.61, 0.61, 0.6, and 0.44) respectively. This 42 years drought analysis shows that the lower and central parts of the basin have similar drought occurrence seasons (Abbay border, Chemoga, Kessie, Guder, Gilgel Abbay, and Gilgel Beles), and the upper part of the basin is affected by drought differently (Megech, Bahir Dar, Ribb, and Koga). Commonly, the most severe streamflow drought year of all gauging stations in the Abbay basin was obtained in 1979, 1980, 1981,1982,1983, 1986, 1987, and 2010. This implies that for seven consecutive years (1980 – 1987), most parts of the basin were affected by severe drought (Figure

7). Besides these drought events, the period from 2001 to 2004 was dominated by moderate and severe drought conditions in most stations. But Chemoga station was specifically affected by extreme drought in both seasonal (SDI3) and annual (SDI12) timescale during 2001 (Figure 7). In this basin, an extreme drought occurred in 1983/1984, 1984/1985 in the upper, middle, and lower parts of the basin. The result is supported by (Y. Bayissa et al., 2018; Yared A. Bayissa et al., 2015), however, these studies were focused on the upper parts of the basin only but the lower and middle parts of the basin yet studied before.

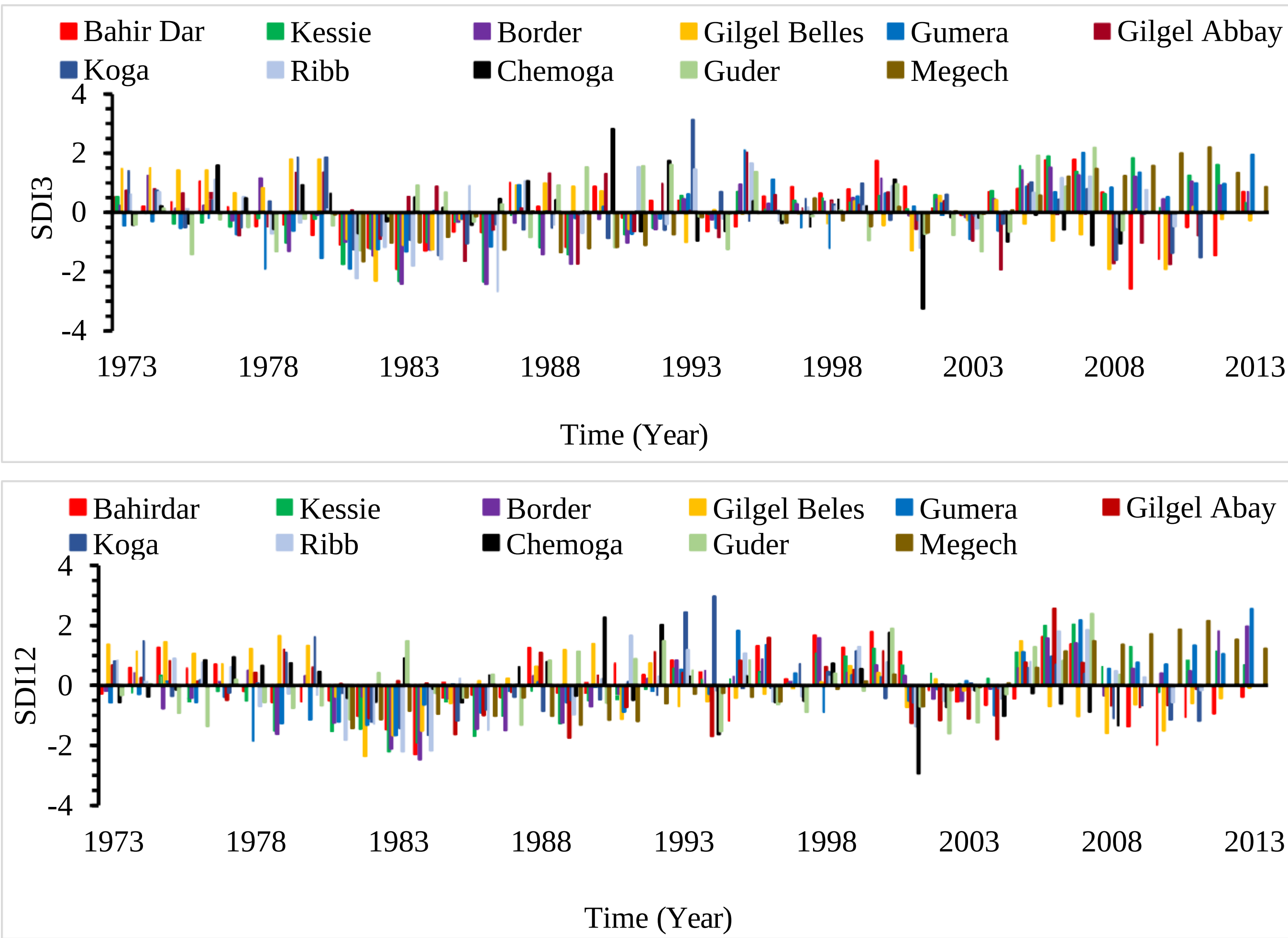


Figure 7 Temporal variation of hydrological drought in seasonal (SDI3) and annual (SDI12) for the Abbay river basin

The Awash River basin is country-locked and it is extensively used for different purposes such as water supply, irrigation, and hydropower generation compared to other river basins in the country. However, according to (A. Belayneh et al., 2014), the basin is frequently affected by severe drought in the last few decades. In this study, six streamflow stations were considered to analyze hydrological drought over the whole basin and the result indicated that the most severe drought years were found in 1979, 1996, 1997, and 2001, whereas extreme drought occurred in 1986, 1987, and 2002 as shown in Figure 8. In addition to (A. Belayneh et al., 2014), the result is supported by other previous studies, such as (Edossa et al., 2010). According to this researcher, 2002, 1965, and 1984 were the worst drought years 99%, 97%, and 95% of the total basin area was affected by severe drought during the listed years, respectively. But during this analysis 1984/85 is a moderate drought year and its magnitude is less relative to the Abbay river basin, but other drought years agreed with the previous studies.

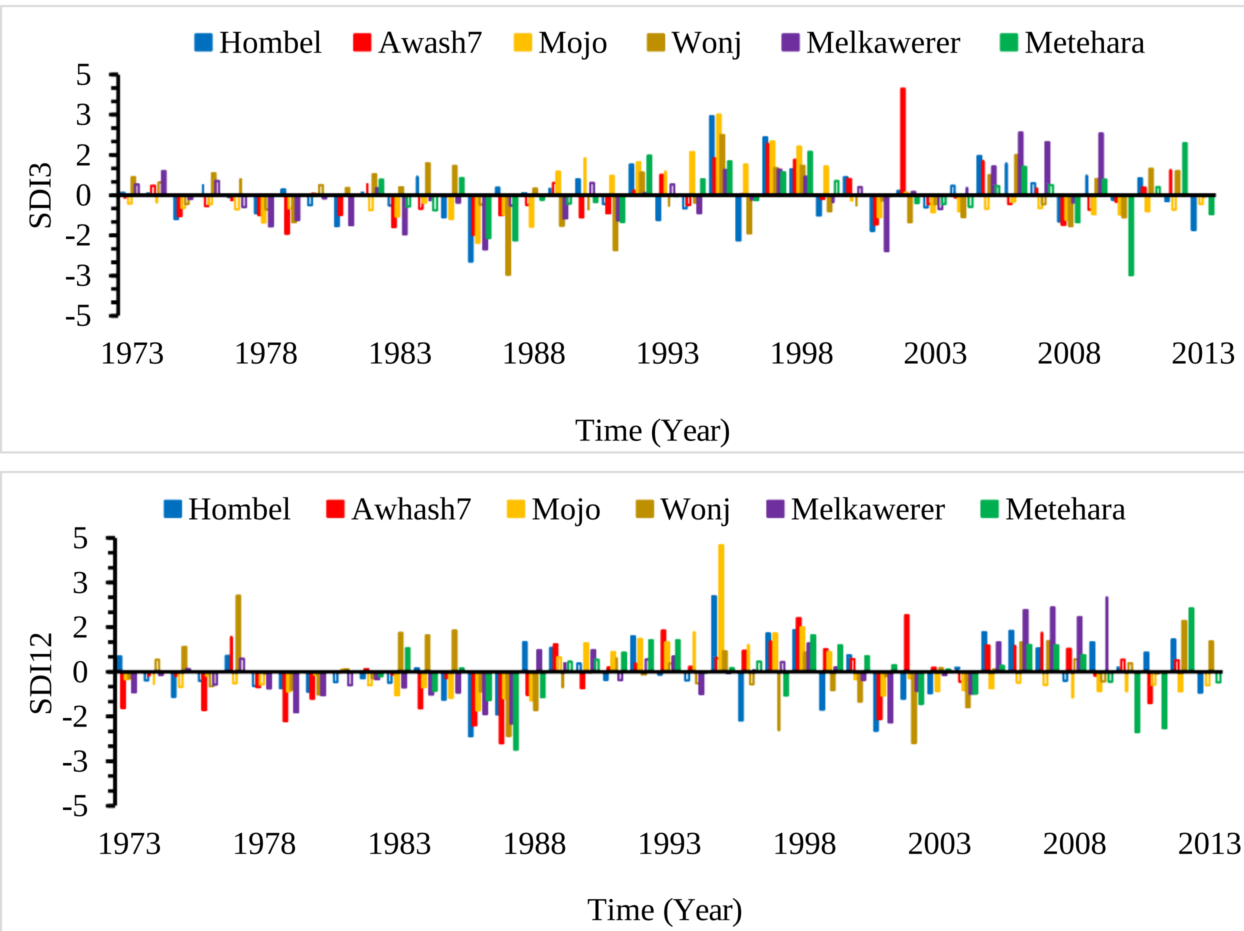
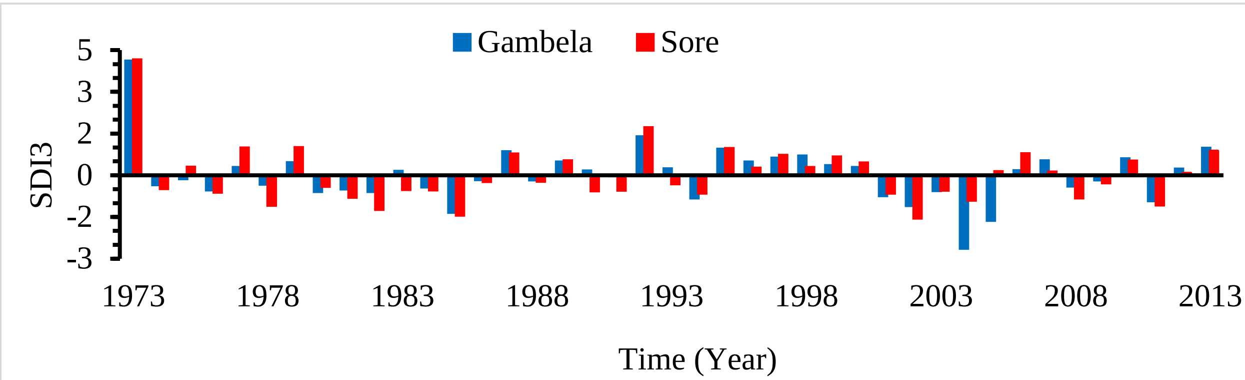


Figure 8 Temporal variation of hydrological drought in seasonal (SDI3) and Annual (SDI12) for Awash River Basin

Two streamflow stations (Gambela and Sore) were considered in the case of the Baro Akobo River basin drought analysis. This basin receives rainfall in two seasons, spring (MAM) and summer

(JJA). So, the frequency of severe and extreme drought occurrence is less compared to other river basins in the country. In the Baro Akobo river basin, a drought analysis study is not conducted before this study. Results of this study show that the Baro Akobo basin was under moderate to severe drought conditions in the periods from 1980 – 1986 and 2001 – 2005 (seasonal and annual timescale analysis) and the most severe drought years of this basin occurred during 1982/1983, 1984/1985 and extreme drought years were 2002/2003 and 2004/2005 respectively as shown in Figure 9.



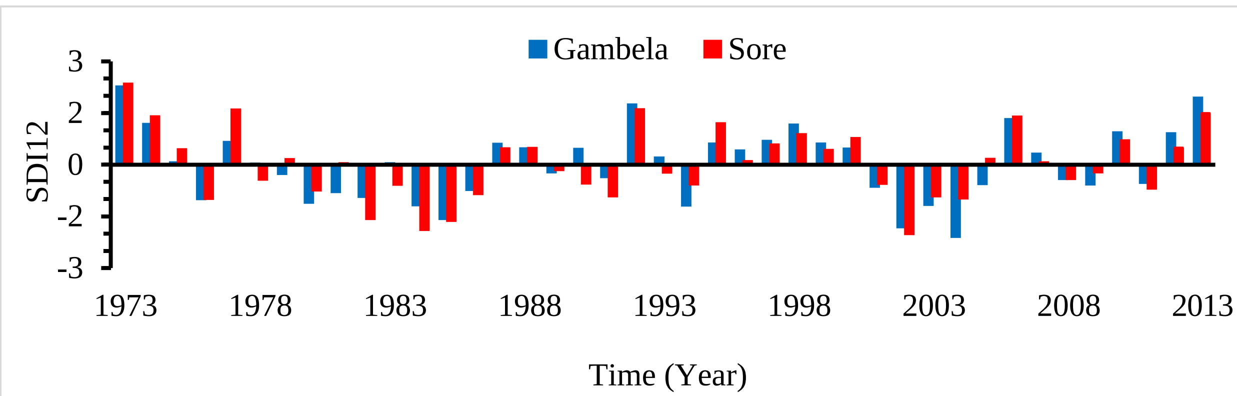
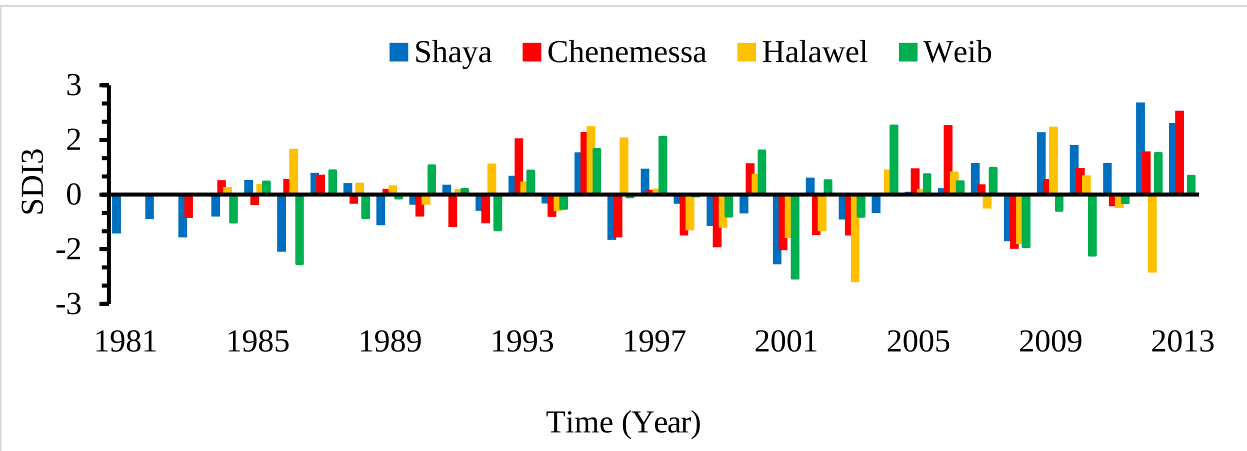


Figure 9 Temporal variation of hydrological drought in seasonal (SDI3) and annual (SDI12) for Baro River Basin

Genale Dawa river basin is one of the drought-prone areas and receives less annual rainfall (Kassahun and Mohamed, 2018). For the last few decades, drought analysis studies have not been conducted in this basin, particularly hydrological drought analysis. Four streamflow stations were considered to identify the historical hydrological drought conditions of the basin during the period from 1981 to 2014 (34 – years). As shown in Figure 10, SDI3 has a higher frequency and magnitude than the annual timescale (SDI12) in this basin. From 1981 to 1988, the basin was under mild to moderate drought conditions, whereas 1996 and 1999 were moderate drought years, and from 2001 to 2004 the basin was under moderate to severe drought. Previous meteorological studies concluded that the eastern and southeastern part of the country is frequently affected by drought in which this basin is located (Haile, 2019; Ilyas Masih et al., 2014; Mera, 2018; Temam et al., 2019; Teshome, 2019b; Zeleke, 2017). However, meteorological drought results cannot be a good indicator of hydrological drought. Because the source of surface water for the Genale and Wabishebele river basins is from the central part of the country, the flow travels a long distance in the arid area. Besides, the hydrological drought of this basin has been low if the central part of the country received good rainfall during the summer. The selected streamflow stations are from the upper part of the basin near the source. Therefore, in this study, the result generally shows that the basin is highly experienced with moderate to severe drought from the period of 1981 – 2012.



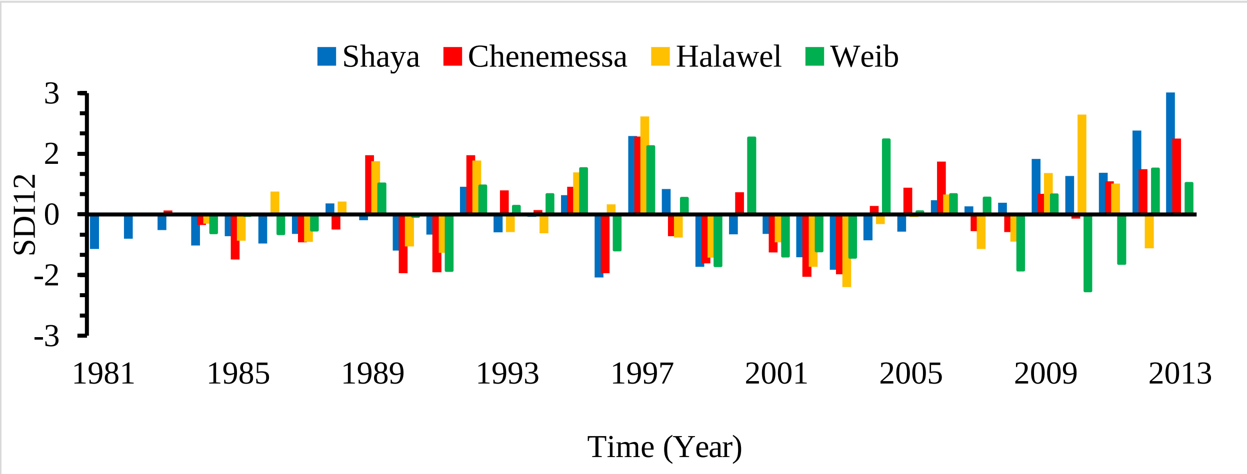
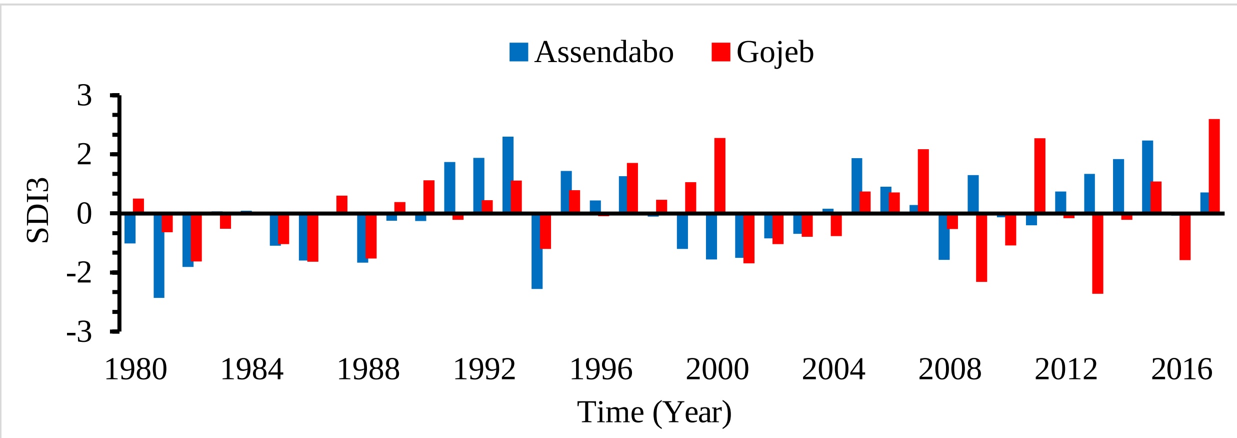


Figure 10 Temporal variation of hydrological drought in seasonal (SDI3) and annual (SDI12) for Genale Dawa River Basin

Omo Gibe and Baro Akobo river basins are the wettest basins compared to other basins in the country. These basins received rainfall in two seasons (Spring and Summer). Assendabo and Gojeb streamflow stations were selected for Omo Gibe River basin hydrological drought analysis during the period from 1980 to 2017 (38 -years). Results indicated that 1980 – 1981 and 2001 were severe drought years for Asseendabo station whereas 1986, 2002, and 2016 were for Gojeb station. Generally, this basin was under severe – moderate – mild drought conditions from 1980 – 1989 and 2001 – 2004, respectively, to the order of the years. Figure 11 indicated that 1980 – 1987 and 2001 to 2004 were the most drought event year in the basin. But its severity is less than compared to Abbay river basins in the same drought event such as 1980 to 1987.



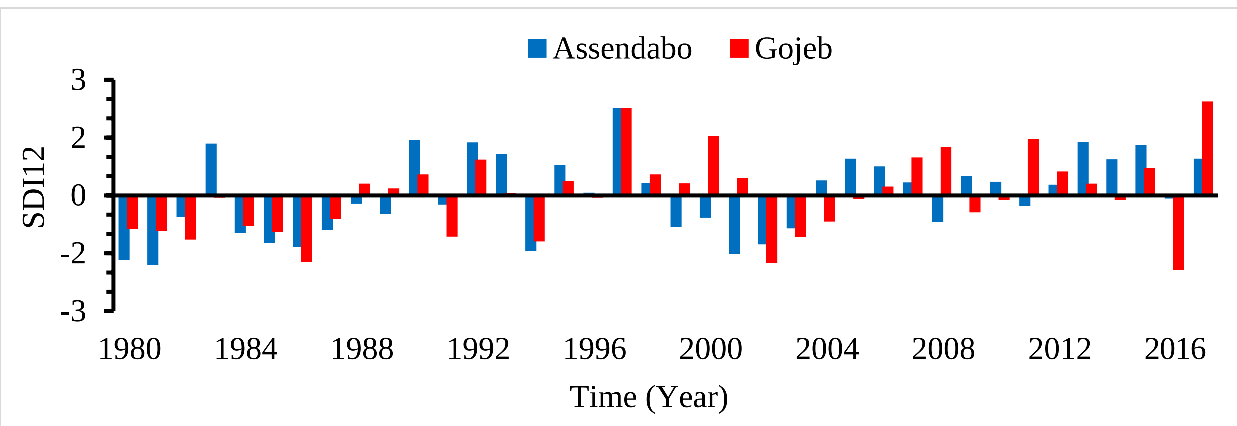


Figure 11 Temporal variation of hydrological drought in seasonal (SDI3) and annual (SDI12) for Omo Gibe River Basin

Relatively Rift Valley river basins have been frequently affected by severe drought compared to other basins in the last three decades (Figure 12). This result is agreed with (Yisehak et al., 2020) in which the basin has been hit by moderate to severe droughts more than 13 events in the last three decades. Particularly in this basin, the severity of drought increases from decade to decade. Figure 12 indicates that both seasonal and annual timescale analysis imply the occurrence of severe and extreme droughts over the three continuous decades (the 1980s, 1990s, and 2000s) increased. Especially, after 2010 the severity of drought at Wosha station increased. Because Wosha station is the most downstream station of the four considered stations in the basin for this study and is nearer to arid and semi-arid river basins such as Genale Dawa and Wabishebele. Two stations from the Genale Dawa river basin (Weib and Halewe) and two stations from the Wabishebele river basin (Wabi@bridge and Weiyb) have also indicated the same drought condition after 2010 as Wosha (See Figure 10 and Figure 14).

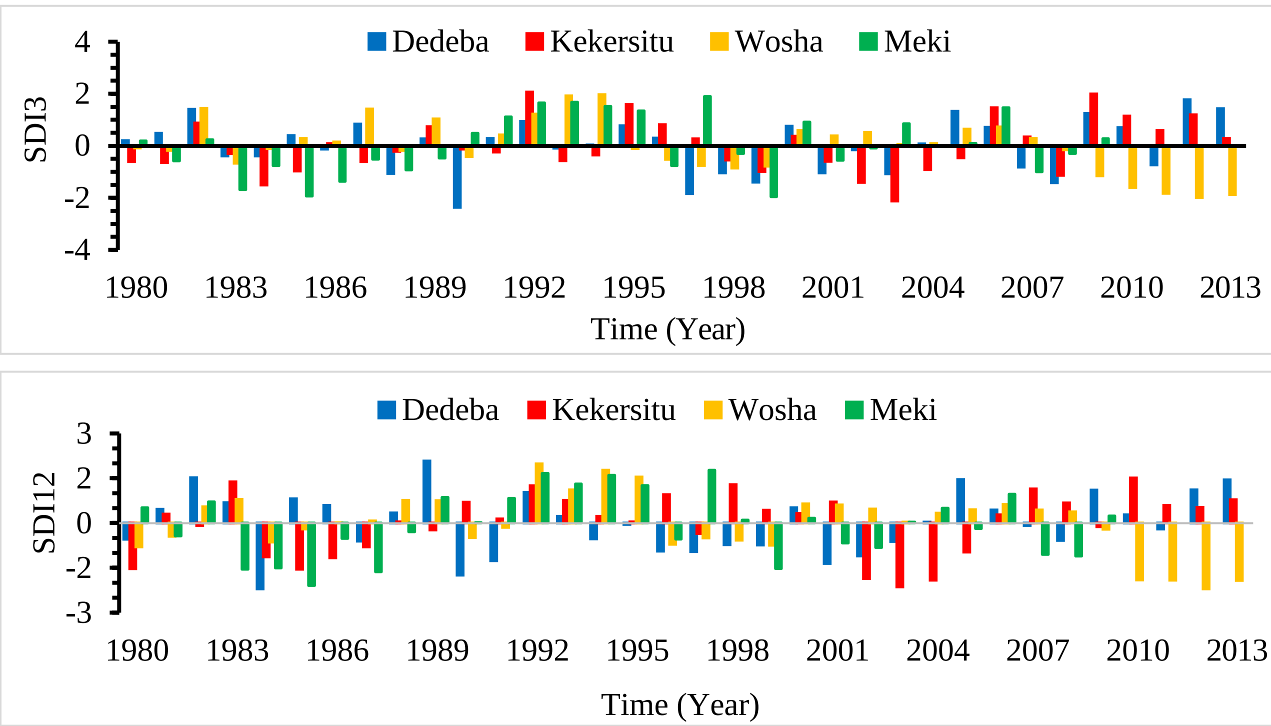


Figure 12 Temporal variation of hydrological drought in seasonal (SDI3) and annual (SDI12) for Rift Valley River Basin

Drought analysis for the Tekeze basin was considered from 1994 to 2014 (21 years). Most flow stations located above Tekeze dam have no good data for drought analysis purposes. So, the Embamadre station, which is located below the dam was considered for this study. After the completion of the Tekeze dam, the downstream flow has been regulated starting from 2008 (Fentaw et al., 2018). Therefore, for the last decade, the streamflow has increased due to the conservation of flow by the Tekeze reservoir. As a result, the occurrence of severe as well as extreme drought is dramatically decreased. Figure 13 shows that the annual timescale has a severe drought in 1996 whereas the seasonal timescale implies a severe drought occurred in 2008 and 2009. But from 2001 to 2014, the result indicates wet years. Different studies reveal that the northern part of Ethiopia is frequently affected by drought (El Kenawy et al., 2016; Ilyas Masih et al., 2014; Mera, 2018; Mohammed, 2018; Teshome, 2019b; Zeleke, 2017). Therefore, this station is not a good representation of Tekeze Basin hydrological drought analysis and it needs further investigation.

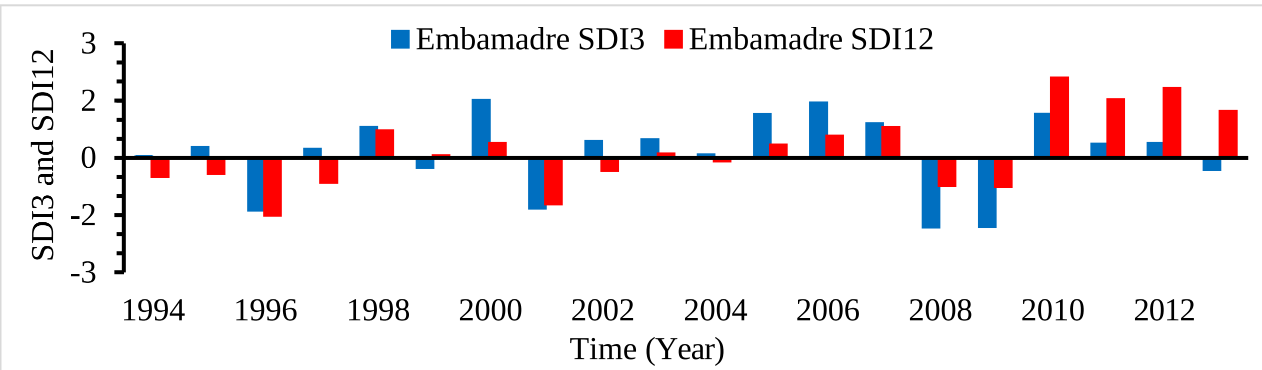
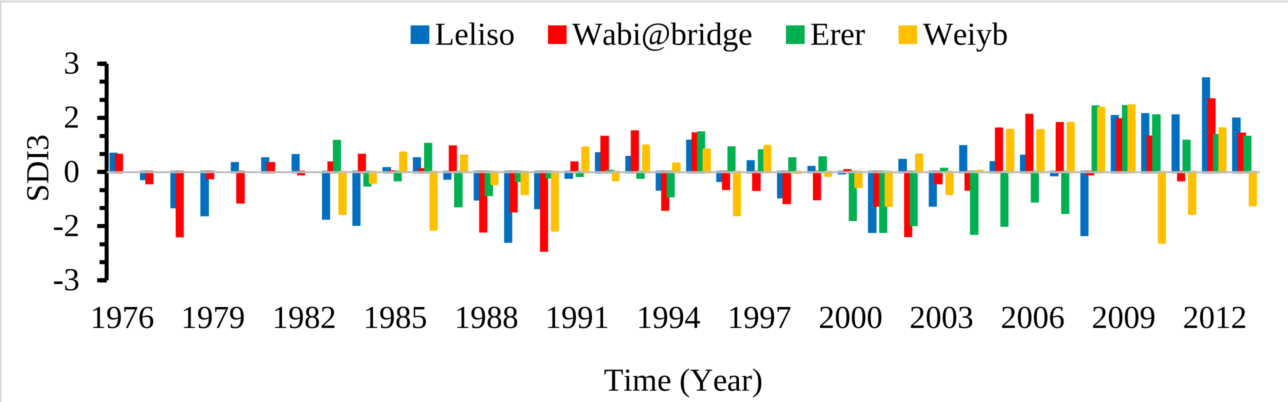


Figure 13 Temporal variation of hydrological drought in seasonal (SDI3) and annual (SDI12) for Tekeze River Basin

The Wabishebele river basin is one of the water-scarce basins in the country. While having the largest area coverage, its annual runoff and water availability are one of the lowest among the major river basins. One decade before, a drought study was conducted by Awass, 2009, in this river basin. His result shows that the most severe drought years of the basin were 1984/85, 1991/92, and 1998. However, in this study, the most severe and extreme drought events were in 1986, 1988, 1989, 1990, 1991, 2001, 2002, 2004, 2005, and 2011. Figure 14 indicated that the magnitude of SDI3 was maximum compared to SDI12 for the above-listed drought years.



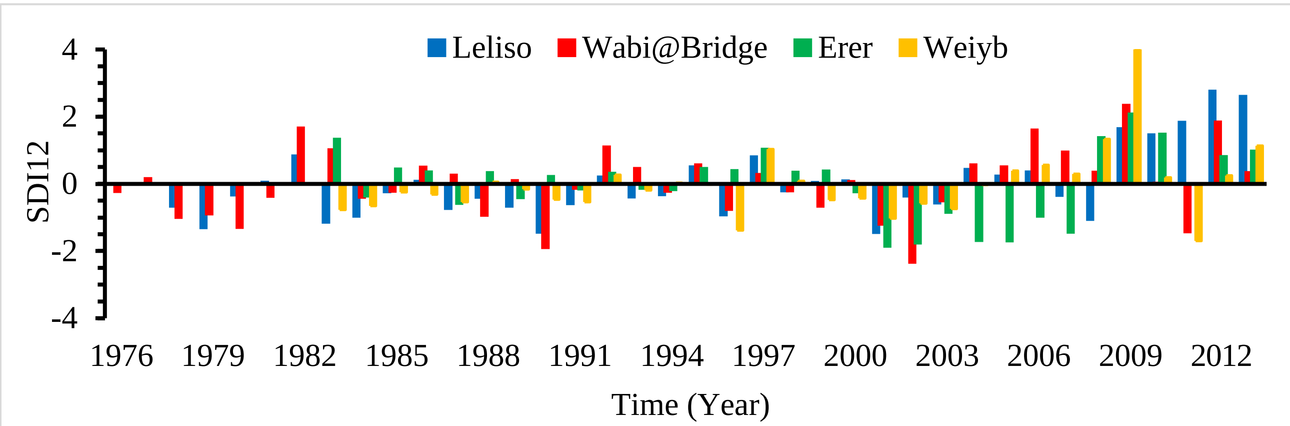


Figure 14 Temporal variation hydrological drought in seasonal (SDI3) and annual (SDI12) for Wabishebele River Basin

In arid and semi-arid areas, the variation of streamflow is not significant. Because low flow is the common characteristic of these areas. Therefore, moderate drought is more dominant than severe and extreme drought conditions for the Genale Dawa and Wabishebele river basins, respectively (Figures 11 and 14).

In all river basins, the occurrence of extreme drought has decreased since 1990. For the case of Abbay, Awash, and Baro river basins, the analysis was considered for the long term (1974 - 2014) which results in different drought conditions, especially since the 1980s was the major drought event decade at the national level.

3.4.3 Hydrological drought characteristics

The hydrological drought characteristics of the 12-month (SDI12) timescale are shown in Table 10 and Annex 1. The result implies that the difference in duration (D), severity(S), magnitude (M), and relative frequency (RF) have high variation at different gauge stations within a basin (See

Annex 1) but the average value of each drought characteristics has relatively the same value for all river basins (see Table 10). The maximum drought duration, severity, magnitude, and relative frequency is observed in the Abbay river basin from 1980 to 1998 (19 years) at Megech station with 55.88% relative frequency. The hydrological drought condition of the Rift Valley river basin is agreed with Yisehak et.al., (2020), he was investigating drought characteristics at the Kulfo river and the result is almost the same as this finding (Yisehak et al., 2020).

Table 10 Recapitulation of hydrological drought characteristics in eight river basins of Ethiopia

	D (year)			**S**			**M**			**RF (%)**		
Basin	Max	Min	Aver	Max	Min	Aver	Max	Min	Aver	Max	Min	Aver
Abbay	19	1	3.2	15.6	0.16	2.48	2.12	0.09	0.72	55.88	2.44	8.25
Awash	14	1	3.03	8.54	0.15	2.33	1.64	0.15	0.79	34.15	2.44	7.55
Baro	5	1	2.17	6.48	0.21	1.87	1.30	0.21	0.74	12.2	2.44	5.28
Genale Dawa	7	1	2.54	5.52	0.43	1.87	1.56	0.22	0.83	21.21	3.03	8.25
Omo Gibe	8	1	2.69	6.77	0.2	2.35	1.89	0.2	0.89	21.05	2.63	7.09
Rift Valley	6	1	2.33	8.16	0.2	2.29	2.2	0.2	0.89	20	2.94	7.08
Tekeze	3	2	2.33	2.4	1.47	1.80	0.8	0.74	0.77	15.00	10.00	11.67
Wabishebele	8	1	2.43	10.52	0.22	1.82	1.7	0.16	0.70	25.81	2.63	7.03

3.4.4 Spatiotemporal variability analysis

The main important point in drought analysis and monitoring development is identifying the spatial extent of a drought over the river basin (Yisehak et al., 2021). The drought-prone area identification was accomplished using ArcGIS software by applying a spatial analysis interpolation tool called inverse distance weighted (IDW). The result of SDI for the selected severe drought years was used as input for IDW in ArcGIS. The four severe and extreme drought years were selected to identify drought-prone areas over the region. Relatively the common severe drought years for most river basins of the country were found in 1984/85, 1986/87, 2002/3, and 2010/11. The spatial variability of those identified drought years is shown below in Figure 15. In 1984, the north and northwest part of the country was affected by severe droughts (Tekeze, Abbay, and Baro), and some parts of the south and northeast part were at moderate drought conditions (Rift Valley and Awash) (Figure 15 a). In 1986, the central and South parts (Awash and Baro) of the country were affected by severe drought, (Figure 15 b). Severe drought was extended in the western part (Baro) and eastern part (Genale Dawa and Wabishebele) in 2002 (Figure 15 c). However, in 2010, the drought was high in the Abbay basin and occurred in the Genale Dawa and Rift Valley basins (Figure 15 d).

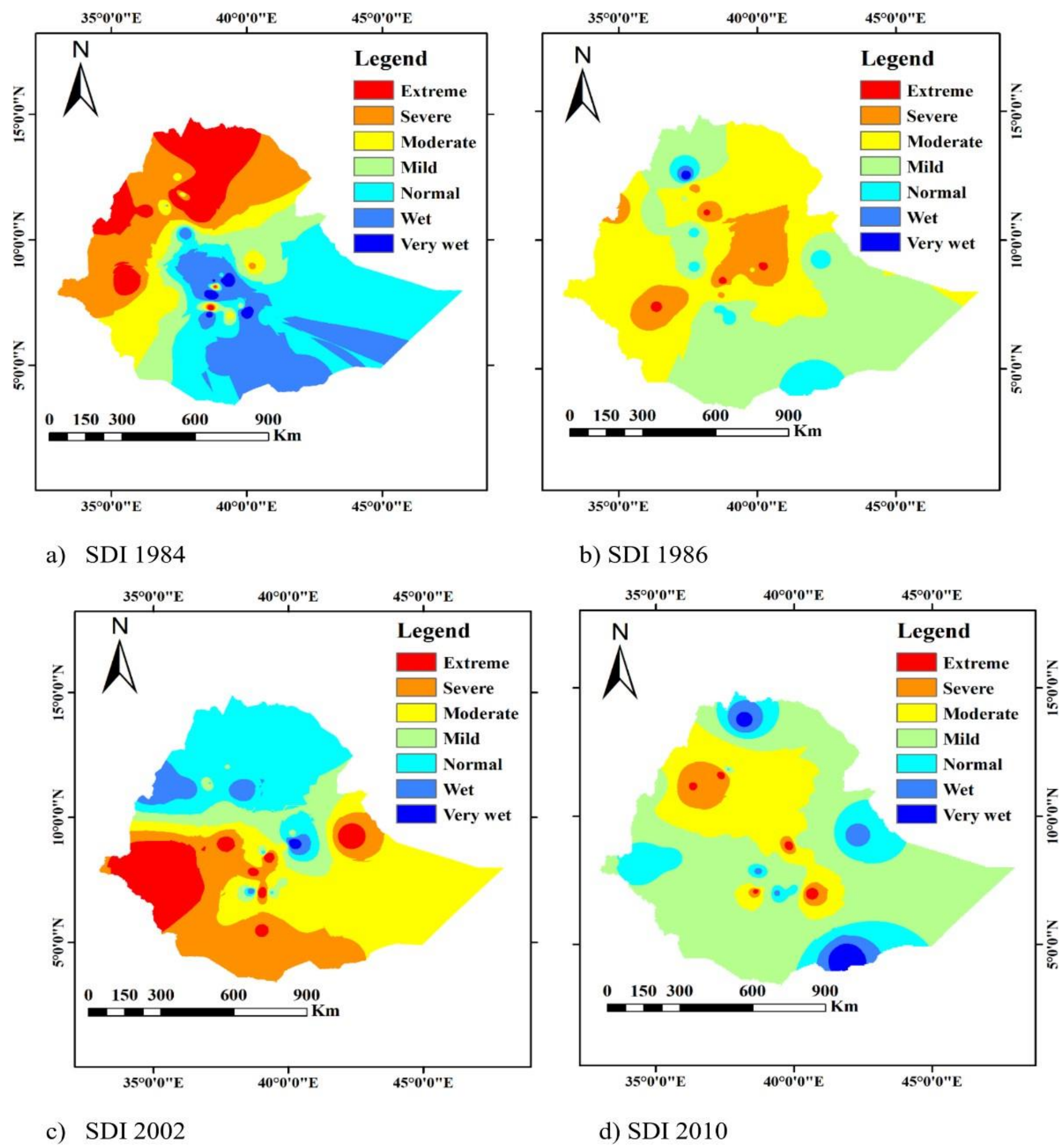


Figure 15 Spatial variation of streamflow drought in Ethiopia in four severe drought years

3.5 Discussion

This study assessed the historical hydrological drought conditions in Ethiopia from 1973 to 2014. The analysis was computed using the streamflow drought index (SDI) on a 3 – 3-month and 12–month timescale for 34 streamflow stations in all basins. The results indicate that the occurrence of severe and extreme drought events declined from decade to decade, especially in the last two decades 2000s and 2010s compared to earlier decades (1970s, 1980s, and 1990s). However, less severe and extreme drought events occurred from 2001 to 2004 in some river basins, particularly, Baro, Rift Valley, Genale Dawa, and Wabishebele river basins. Even though there is a limitation of hydrological drought analysis at a national level, some previous meteorological drought studies supported this finding such as (El Kenawy et al., 2016).

This study also suggests that all river basins in Ethiopia experienced some degree of drought both at seasonal (3-month) and annual (12-month) timescale. The most severe and extreme drought events occurred in the period from 1981 to 1987 and 2002 to 2004. This result is also assured by (Y. Bayissa et al., 2018). The proportional area affected by mild and moderate drought showed a statically increasing trend over the 42 years. The areas subjected to droughts of high intensity (i.e., severe and extreme) also exhibited a statistically significant decrease with the peak of the decline from the 1990s and 2000s. These findings imply that the decrease in drought frequency in the recent decade is associated more with a decrease in the frequency of intense drought episodes. The overall analysis also indicates anon – synchronous occurrence of drought episodes over the country, whereas some severe drought episodes were witnessed in specific periods, while no droughts correspond to these episodes across other regions of the study area.

The spatial variability of hydrological drought occurrence has a wide range from basin to basin. These different drought occurrence patterns are related to diverse geographical areas and are associated with different temporal variations. It is observed that there is a strong relationship between streamflow and drought potential basins in the regions (Hasan et al., 2019), where the most significant pattern of the drought was specifically found over the arid areas, while less significant patterns were observed over the most humid regions.

The 1980s was the driest year in all river basins. At a country level, four severe to extreme drought years were identified, 1984/1985, 1986/1987, 2002/2003, and 2010/2011 from 1973 to 2014 (see Figure 15). However, only 1984/1985 was national as well as global attention. However, other severe drought years hindered the economic growth of the country in the last three decades.

3.6 Conclusion

In Ethiopia, many sectors such as agriculture, water supply, and hydropower are highly affected by hydrological drought in most human activities depend on these sectors. However, hydrological drought is not well-studied in the country. Particularly, Baro Akobo, Omo Gibe, Genale Dawa, and Rift Valley River basins are not been studied before. Abbay, Awash, Tekeze, and Wabishebele river basins are partially studied, more focused on meteorological drought than other droughts. Therefore, this study analyzed hydrological drought in Ethiopia using SDI to identify the most severe and extreme drought years and Drought-prone areas. Accordingly, 1979, 1981,1983 1987, 1996, 1997, and 2001 were the most severe drought years, whereas 1984, 1986, 2002, and 2010 were relatively extreme drought years in all river basins in Ethiopia from 1973 to 2014. However, globally, only the 1984 severe drought event was popularly recognized and other drought years were not focused but affected food security, water supply, and hydropower production systems over the country. Abbay, Awash, and Rift Valley River basins were frequently affected by severe streamflow drought, but for the case of Baro Akobo and Omo Gibe River basins, the frequency of severe drought was less. Genale Dawa and Wabishebele river basins were located in arid and semi-arid areas in which drought condition is dominated by their aridity nature and the occurrence of severe and extreme drought events was rare. However, mild and moderate drought events frequently occur in these basins. Generally, severe and extreme drought frequency relatively decreased for all river basins in the 1990s and 2000s compared to the 1970s and 1980s. The source of streamflow for all river basins is from highlands and mountainous areas. Therefore, most of the streamflow stations considered for this study were from the upstream and middle parts of the basins. Therefore, the drought conditions for these stations can represent the downstream parts of the basins. Generally, the Abbay and Awash River basins are the most populated basins and cover large investment areas in which the investigation of hydrological drought and development of drought early warning systems is important. Therefore, this study gives good information about hydrological drought conditions for all river basins for decision-makers for good mitigation measurement development.

4. Comparing surface water supply index and streamflow drought index for hydrological drought analysis in Ethiopia

Abstract

Recently, floods and drought have become common natural hydroclimatic hazards in several countries. Consequently, the identification of an appropriate drought index is now a challenging task for researchers. There is no single best drought index; rather a comparison of indices will give a relative option. The objective of this study was to compare two hydrological drought indices; the modified surface water supply index (M1SWSI) and streamflow drought index (SDI) over eight river basins, in Ethiopia. The M1SWSI and SDI value was computed from 1973 to 2014 using 34 streamflow stations, 42 rainfall gauge stations, and 3 lake-level data. The two indexes' results showed that the 1980s were the most severe drought years for all river basins. However, in the case of the Genale Dawa and Wabishebele basins, the drought severity increased from 2000 to 2014. Hydrological drought analysis using SDI has more drought occurrence frequency than M1SWSI. In all river basins from 1973 to 2014, there were a total of 18 severe drought events when using M1SWSI, but there were a total of 39 severe and 12 extreme drought events when using SDI. This implied that M1SWSI reduced the occurrence probability of severe drought by 53.85% and extreme drought by 100%. It is known that Ethiopia has been stricken by extreme droughts in the last few decades. But M1SWSI doesn't detect those invidious drought events. In this study, SDI is found to be a better hydrological drought index. Therefore, policy and strategic planners, master plan developers, and decision-makers can use SDI to analyze historical and future hydrological drought trends to develop effective drought mitigation measures.

Keywords: Hydrological drought, modified surface water supply index, streamflow drought index

4.1 Introduction

Floods and droughts are natural hydroclimatic hazards affecting several countries in the world. Globally, flood studies have more concern than drought due to their fast impact and short duration (Budhakooncharoen, 2003). Flood and drought disasters become a bottleneck for the economic development of many countries. However, drought is the most complex and widespread hydrological extreme than flood (Prabnakorn, 2020). Drought has a devastating negative impact on water supply, irrigation, hydropower, and all kinds of water resource projects (Araya and

Stroosnijder, 2011). As a consequence, recent drought analysis and forecasting studies become more interesting to develop effective drought mitigation measures (Hamdy, 2008).

The definition of drought is more subjective due to its complex nature and scholars defined it from a different perspective (Mera, 2018). However, drought can commonly be classified into four types (a) meteorological drought associated with scarcity of precipitation for long periods below normal situations(Alegre et al., 2020; Boudad et al., 2018b; Mohammed and Yimam, 2021), (b) hydrological drought related to the low water level in surface and subsurface water resources such as a lake, reservoir, streamflow and groundwater (Boudad et al., 2018b; Kwon and Kim, 2006; Lanen et al., 2013; X. Liu et al., 2016; Y. Liu et al., 2016; Muli Wambua, 2018; Sur et al., 2019), (c) agricultural drought related to lack of soil moisture to attain the minimum crop water required in the soil and distracts agricultural productivity (Winkler et al., 2017) and (d) the fourth one is socio-economic drought which is the overall welfare crisis of the society caused by severe drought (Bhuiyan, 2000; Mera, 2018; Teshome, 2019b; Venton, 2018) Meteorological drought highly affects the agricultural systems by aggravating food insecurity, especially in developing countries due to crop failures before harvesting season while hydrological and agricultural drought causes low production of industries because of shortage of water supply to irrigation, municipals, and industries, hydropower generation (Loon, 2015). The cumulative effects of meteorological and hydrological droughts lead to socioeconomic drought, which disturbs the entire ecosystem and badly affects and even causes the lives of humans and animals (Boudad et al., 2018b). In addition to this extreme hydrological events have a high influence on water quality and it needs a wide concern (Wu et al., 2022).

Studies revealed that Ethiopia has faced several severe and extreme drought events in the last few decades as a result of erratic rainfall and climate change (Philip et al., 2018). Northern Tigray region, some parts of Amhara region such as South Wollo, North Wollo, South Gondar, and Afar region, most parts of Somalia region, and eastern parts of Oromia region (Borena Zone) have frequently been affected by severe drought in Ethiopia (Edossa et al., 2010; I Masih et al., 2014; Philip et al., 2018; Zeleke et al., 2017). According to (Mohammed et al., 2018), drought in Ethiopia occurs at a recurrence interval of three to ten years. Even though this frequent recurrence is well recognized there is still a lack of any firmly established drought mitigation measure for these disasters. In Ethiopia, drought response efforts are provided in the form of food aid when food supplies have decreased significantly due to extended drought for a short-term recovery.

Relatively, meteorological drought analysis is more focused than other types of droughts in Ethiopia. There are few drought indices comparison studies across Ethiopia specifically Upper Blue Nile in the Abbay river basin, respectively (Y. Bayissa et al., 2018; Tsige et al., 2019b). Bayissa (2018) tried to compare six drought indices in Upper Blue Nile; three meteorological indices, two agricultural indices, and one hydrological index. The number of input data and the purpose of the index developed affect the selection of the appropriate drought index for a specific study area. Tsige et al. (2019) (Tsige et al., 2019b) also compared two indices (meteorological and agricultural indices) in which the finding was relatively good compared to Bayissa's findings. However, both scholars were focused on meteorological drought indices rather than hydrological drought indices. Hydrological drought analysis is not well studied in Ethiopia at a national level which has a great influence on national economic development.

Hydrological drought is related to surface and subsurface water shortage in terms of volume from the long-term normal conditions. Hydrological drought always lags behind meteorological drought and its propagation process from meteorological to hydrological drought is important to develop an effective drought early warning system(Wu et al., 2021a). For long-time drought events, meteorological and agricultural droughts have been propagated to hydrological drought which caused streamflow, reservoir and lake level, and groundwater level reduction. As a result, water supply, irrigation, and hydropower generation have been directly affected. Because the development of hydrological drought is directly related to the transformation of precipitation into effective streamflow generation(Wu et al., 2021b). Ethiopia has many perennial rivers and lakes, but still, those resources are not well utilized. While hydrological and agricultural drought analysis and monitoring have not been thoroughly explored, meteorological drought analysis has been regularly studied in various parts of the country(Tareke and Awoke, 2022).

Many drought indices are region-sensitive and developed in different countries(Tigkas et al., 2015). Most of the indicators are developed for meteorological and agricultural drought analysis. However, there are also drought indicators used for hydrological drought analysis such as the palmer hydrological drought index (PHDI) (Agwata, 2021), streamflow drought index (SDI) (Akkurt Eroğluer and Apaydin, 2020), and surface water supply index (SWSI) (Kwon and Kim, 2006). SDI is simple and requires a single input data (streamflow) and is suitable for drought study at the site (Tareke and Awoke, 2022) whereas, SWSI was developed at Colorado University by Shafer and Dezman (1982) and is used for regional or basin-level hydrological drought analysis by considering the available surface water from different sources (Kwon and Kim, 2006). It requires all forms of surface water sources such as streamflow, precipitation, reservoir level, and groundwater level. Hydrological drought analysis gives good information for policymakers and sectors related to water. Because drought related to transboundary rivers has crucial importance for special treatment during drought events it is important to develop a good water resource management strategy before and after drought has occurred. Many Ethiopian rivers are transboundary rivers and need effective assessment and management. Therefore, this study was aimed to analyze hydrological drought conditions in Ethiopia by comparing two hydrological drought indicators (SWSI and SDI). The severity condition of drought obtained by these indicators was also compared using Pearson's correlation coefficients.

4.2 Methods and materials

4.2.1 Study area

The total area of Ethiopia and its geographical location in the northern and eastern directions is clearly described in chapter three (3.2). Figure 16 shows the major river basins in Ethiopia and the spatial location of hydrometeorological stations including streamflow and rainfall gauge stations and Lake Tana, Hawassa, and Ziway locations. The streamflow drought index uses only streamflow data as input to monitor hydrological drought. But, in the hydrological cycle, there are several hydrological variables on the surface of the earth. Therefore, to incorporate the contribution of different forms of water on the surface for water availability during drought, the Surface water supply index (SWSI) was applied in this research. Finally, the result obtained from SWSI was compared with the SDI result to see the frequency, duration, and magnitude of hydrological drought in the last four decades.

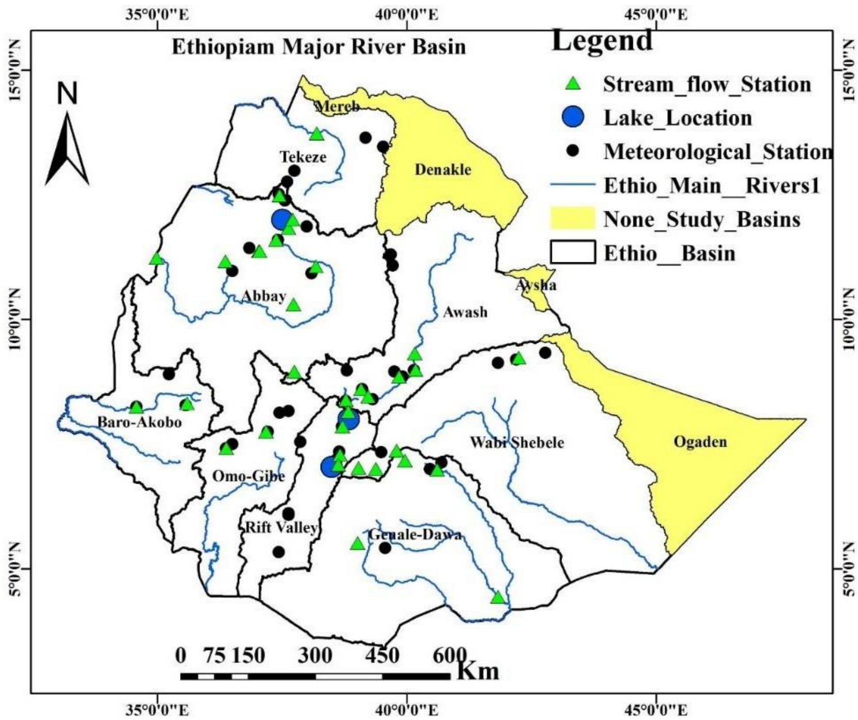


Figure 16 Location of selected hydrometeorological stations in different river basins, in Ethiopia

Ethiopia is the tropical Zone laying between the equator and the tropics of Cancer. It has three different climate zones according to elevation. These are: Kolla (Tropical Zone) below 1830 m in elevation and the annual average temperature and rainfall are 27^{o}c and 510 mm respectively. The second is Woina Dega (Subtropical Zone), which is composed of highland regions between 1830 and 2440 meters in elevation and has an average annual temperature of nearly 22^{0}C and 510 to 1530 mm of rainfall. The third is Dega (Cool zone), which is located above 2440 m in elevation and has an annual rainfall range of 1270–1280 mm with an average yearly temperature of about 16^{0}C. The country has four major seasons: Summer ‘Kiremet’ (June – August; JJA); autumn ‘Tibe’ (September – November; SON); winter ‘Bega’ (December – February; DJF) and spring ‘Belg’ (March-May; MAM). However, the coldest month is not always in ‘Bega’ and the hottest month is not always in ‘Kiremet’. Ethiopia lies near the equator where maximum heat from the sun is received. The length of days and nights is almost the same in most regions.

Precipitation is the main source of streamflow generation for river basins in Ethiopia. For the eight studied basins, most of them have received high rainfall during the summer season (JJA). But for the case of Genale Dawa and Wabishebele, they receive high rainfall during the spring season

(MAM) and low rainfall during summer (JJA), and the variation of streamflow level also corresponds to the precipitation time variance.

The spatial distribution of rainfall over the country highly varies; Abbay, Baro Akobo and Omo Gibe River basins receive high rainfall whereas the remaining five river basins receive medium to low rainfall., semi-arid and arid basins such as Genale Dawa, Wabishebele, and Ogaden receives below 1000 mm annually. Tekeze, Awash, and Rift Valley have an annual rainfall range between 770 to 1100 mm.

4.3 Methods

4.3.1 Data preparation

Precipitation data were collected from the Ethiopian Meteorology Institute whereas streamflow and lake level data were collected from the Ministry of Water and Energy (MoWE). Based on data record length, quality, and availability; 42, 34, and 3 precipitation gauge stations, streamflow, and lake level stations were collected respectively over eight major river basins in the country. But for all those stations, the data record length is not the same. In particular, streamflow data length varies from basin to basin. However, the dominant record range was decided from 1973 to 2014. Missing data for precipitation was completed using the areal ratio method and for streamflow, XLSTAT was used. XLSTAT is a statistical analysis tool integrated with Microsoft excel used to fill in missing data, analyze hydrological tests such as consistency and homogeneity, and visualize and plot hydroclimatic data (Vidal et al., 2020).

Hydrometeorological data can be affected by natural hazards or by human intervention. For example, the gauge station may collapse, break, or miss reading, and data collectors may collect wrong data. Due to those and other reasons, the information generated from these poor-quality data is affecting the decisions of researchers, stakeholders, and planners. Therefore, before any data is used as model input, data quality analysis is mandatory. In any water resource management activities, the hydroclimatic data should be as much as possible stationary, homogeneous, consistent, stable variance and mean (Branisavljevi et al., 2009; Zhao et al., 2018). So, in this study, consistency and homogeneity tests were checked using double mass curves and non-dimensional ratio methods, respectively for all selected meteorological stations (Kocsis, 2020; Sillmann, 2014).

The analysis of consistency and homogeneity shows, that for the case of Awash and Omo Gibe River basins, two stations were found inconsistent and nonhomogeneous (Melkawerer and Bonga). However, the remaining 40-gauge stations within the respective river basins showed good homogeneity and consistency results. Therefore, the Melkawerer station from the Awash river basin and the Bonga station from the Omo Gibe River basin were not considered for further drought analysis in this study.

4.3.2 Original Surface Water Supply Index

Shafer and Dezman (1982), (Doesken and Mckee, 1991) in Colorado, developed SWSI to supplement the Palmer Drought Severity Index by taking streamflow, reservoir storage, and snowpack into account. The steps to calculate the SWSI for a specific basin are as follows: monthly data are gathered and added for all the reservoir inflow, streamflow monitoring stations, and precipitation stations throughout the basin. A long-term mean is used to normalize each component's sum. Each element is given a weight based on how frequently it contributes to the surface water in that basin (Kwon and Kim, 2006). The large portion of available water resources in Ethiopia is surface water (streamflow) which meteorological drought indexes such as SPI, RDI, and PDSI do not explicitly include.

The main inputs for SWSI are streamflow, precipitation, reservoir storage, and groundwater level (optional). However, reservoir storage is directly related to the inflow stream condition of the basin and groundwater level is important for groundwater drought analysis. Therefore, for this research streamflow, precipitation, and lake level instead of reservoir storage were used as input for SWSI analysis. The equation is given below in Equation (6):

$$SWSI = \frac{\mathrm{aPNstrm+bPNprec+cPNlal-50}}{12} \tag{6}$$

Where: SWSI = Surface Water Supply Index, PNstrm, PNprec, and PNlal are a percentage of non-exceedance (%) of monthly streamflow, precipitation, and lake level respectively, and a, b, and c = weight for each hydrologic component in which; a + b + c = 1. Subtracting 50 centers the SWSI values around zero, and dividing by 12 compresses the range of values between -4.2 to +4.2. The non-exceedance probabilities are taken from probability distributions fitted to each hydrologic component.

4.3.3 Modified Surface Water Supply Index (M1SWSI)

This method was modified by [45] using forecasted streamflow and reservoir storage volume. But it does not explicitly analyze different hydrological components and this masks important information about the behavior of each hydrological component. The equation is given by Equation (7):

$$SWSI = \frac{(P-50)}{12} \tag{7}$$

Where: P = the non-exceedance probability (%) of a long–term mean

The surface water supply index (SWSI) is one of the hydrological drought indicators which gives a wider range of drought characterization than SDI. It is applicable for basin-level drought analysis and it was developed based on PDSI algorism(Muli Wambua, 2018; Raphael M. Wambua, 2019). For this work without altering the algorism, the equation is modified to make it easy to compare with the SDI value. SWSI was developed to incorporate multiple hydrologic/meteorological components into a single objectively derived index value for each river basin (Garen and Ph, 2011).

However, still, SWSI is still more subjective, and compared with PSDI which is meteorological drought indices, the hydrological components considered need explicit analysis. So, it is important to modify the equation to make it comparable with a hydrological index such as SDI by reducing the compressed range from -4.2 to +4.2 into -2.1 to +2.1. This reduction of the range is done without altering the algorithm of the model and simply reduces the range by increasing the denominator. Now it can be comparable with the SDI value for a given basin and the equation is given by Equation (8):

$$M1SWSI = \frac{aPNstrm + bPNprec + cPNlal - 50}{24} \tag{8}$$

Where: M1SWSI is modified SWSI, and all other terms are described in Equation (1).

The value of weighted factors a, b, and c were more subjective in the original SWSI development even though eliminated by the revised one (Kwon and Kim, 2010). But it is important to make it objective and give a sense of the art of science. Therefore, the value of these weighted factors is formulated below in Equation (9).

$$Pa = Pb = Pc = \frac{Xi}{X\max} \tag{9}$$

Where: P_a P_b and P_c are the proportional values of monthly or annual streamflow, precipitation, and lake level respectively whereas Xi and Xmax are the observed monthly or annual value and maximum values, respectively for all components. Now the weighted factors can be determined as follows in Equation (10).

$$a = \frac{Pa}{Pt}, b = \frac{Pb}{Pt}, c = \frac{Pc}{Pt} \tag{10}$$

Where: Pa, Pb, and Pc are as described earlier in equation (4) and Pt is the total proportionality of each component (Pt = Pa + Pb +Pc); a b and c are weighted factors of each surface water component (streamflow, precipitation, and lake level) respectively.

The probability of non-exceedance for each component was determined using Equation (11) as shown below developed by Weibull (Adeboye and Alatise, 2007).

$$PN = 1 - \frac{m}{n+1} \tag{11}$$

Where: PN is the non-exceedance probability of each component, m is the rank and n is the total number of data considered in the time series.

Table 11 shows the drought criteria originally classified by Shafer and Dezman in 1982 and the modified classification is downscaled by half from the original.

Table 11 Original SWSI (Shafer and Dezman, 1982) and Modified M1SWSI values

Original SWSI Range	M1SWSI range	Description
≥ +4	≥ +2	Abundant supply
3.99 to 1.99	1.99 to 0.99	Wet
2 to – 0.99	1 to -0.49	Normal
-1 to -1.99	-0.5 to -0.99	Incipient drought
-2 to -2.99	-1 to -1.49	Moderate drought
-3 to -3.99	-1.5 to -1.99	Severe drought

≤ -4	≤ -2	Extreme drought

Note: M1SWSI is a modified surface water supply index

4.3.4 Streamflow Drought Index Analysis

The Streamflow Drought Index (SDI) was developed by Nalbantis and Tsakiris (2009) (Tsakiris, 2009), which is used to characterize the hydrological drought situation of a study area. Since its calculation is similar to SPI's, it has the same efficiency and simplicity. The SDI gives the advantage of controlling hydrological drought or the availability of water in the short, medium, and long term because it is based on monthly observed streamflow amounts at various time scales. The SDI is defined as follows for each reference period k of the i^{th} hydrological year based on the cumulative streamflow volumes Vi,k:

$$SDI = \frac{Vi,k - Vkm}{Sk} \quad (12)$$

Where: i = 1, 2; …, and k = 1, 2, 3, 4

Since these are calculated over a long period, Vkm and Sk are the mean and standard deviation of the cumulative streamflow volumes of the reference period k, respectively. The SDI runs from -2 to +2 in terms of wetness and dryness. Below -2 and above +2, respectively, are the values that are exceedingly dry and wet. The SDI criteria for identifying the worst and most intense drought occurrences are shown in Table 12.

Table 12 Drought classification according to the SDI values (Nalbantis and Tsakiris, 2009)

SDI value	Category
≥ 2	Extremely wet
1.5 - 1.99	Severely wet
1 - 1.49	Moderately wet
0.5 - 0.99	Slightly wet
-0.49 - +0.49	Normal
-0.5 - -0.99	Mild drought
-1 - -1.49	Moderately drought
-1.5 - -1.99	Severely drought

≤ -2	Extremely drought

SWSI was developed based on the PDSI algorithm. However, PDSI is more important for meteorological and agricultural drought analysis than hydrological drought (Wan et al., 2017). Therefore, comparing SWSI with PDSI is subjective and it needs some modification of the range of SWSI results and weighted factors. After compressing the value of SWSI from -4.1 to +4.1 into -2.1 and +2.1; it is possible to compare the result with SDI for a given river basin. Based on this, the correlation of the two hydrological drought indices was computed.

4.4 Results and Discussion

4.4.1 Analysis of Hydrological Drought Using SWSI

Even though SWSI analysis requires more input data, this analysis was computed using three input data for the Abbay and Rift Valley River basins (streamflow, precipitation, and lake level), whereas, for the remaining six river basins, two input data were used (streamflow and precipitation) due to data scarcity of lake level. All the input data were summed separately and their non-exceedance probability was computed using Equation (11). The value of component weights (a, b, c) for each basin is different and it was estimated for seasonal and annual values (Table 3). There are four seasons in Ethiopia, Autumn (Tibe or *Meher*), Winter (*Bega*), Spring (*Tsedey or Belg*), and Summer (*Kiremt*). The value of component weights was computed for all seasons but the rainiest seasons in Spring and Summer were selected for discussion. The weightings a, b, and c in Table 3 indicated the component potential impact on surface water available in the basin. As observed from Table 3, the most surface water source for all basins in Ethiopia is precipitation. In the Abbay and Rift Valley River basins, the lake level was considered and it shows that the seasonal variation of lake level is insignificant when compared to the variation of streamflow and precipitation (Table 3). The one fact is that the value of component weight for each basin is not always constant as stated in Table 13, rather it will change as the number of gauging stations increases or decreases. However, the variation is not that significant.

Table 13 M1SWSI Seasonal and annual component weights summary

Basin	Season	Weights		
		a (1)	b (2)	c (3)
Abbay	Spring	0.21	0.32	0.47
	Summer	0.29	0.40	0.31
	Annual	0.29	0.40	0.31
Awash	Spring	0.47	0.53	-
	Summer	0.38	0.62	-
	Annual	0.42	0.58	-
Baro	Spring	0.31	0.69	-
	Summer	0.33	0.67	-
	Annual	0.45	0.55	-
Genale Dawa	Spring	0.38	0.62	-
	Summer	0.66	0.34	-
	Annual	0.44	0.56	-
Omo Gibe	Spring	0.36	0.64	-
	Summer	0.49	0.51	-
	Annual	0.45	0.55	-
Rift Valley	Spring	0.22	0.45	0.32
	Summer	0.19	0.44	0.37
	Annual	0.27	0.38	0.35
Tekeze	Spring	0.19	0.81	-
	Summer	0.45	0.55	-
	Annual	0.39	0.61	-
Wabishebele	Spring	0.12	0.88	-
	Summer	0.44	0.56	-
	Annual	0.27	0.73	-

Where 1, 2, and 3 indicate: (1) Streamflow (2) Precipitation (3) Lake level, and (-) implies no data

In all river basins, the 1980s were the driest years, according to the hydrological drought analysis produced by M1SWSI and SDI (Tables 4 and 5). However, the severe drought has regularly affected the Abbay and Awash River basins (Table 4). M1SWSI gives the drought information over a large area; as a result, it compresses the magnitude of hydrological drought impact in a specific area. Previous studies revealed that Ethiopia is recurrently affected by severe and extreme drought events. But here, the result of M1SWSI indicated that there was no extreme drought event in the last three decades (Table 14). As shown in Table 14, the magnitude of M1SWSI is almost near the moderate drought range category except for Awash in 2001, Baro in 1985, and Genale Dawa in 2003. Genale Dawa, Wabishebele, and Rift Valley river basins are located in lower parts of Ethiopia and highly exposed to prolonged drought in the last decades (Kidane Giorgis, 2018; Wolteji et al., 2022). However, the hydrological drought analysis using M1SWSI minimized the frequency and magnitude of severe drought events in those areas. This indicates that hydrological drought analysis using multiple hydroclimate data may hide the information and it will directly affect the water resource management system.

Table 14 Summary of Severe drought years and magnitude in each river basin in Ethiopia using M1SWSI

River Basin	Severe drought years	Magnitude
Abbay	1982, 1983	-1.52, -1.58
Awash	1979, 1986, 1987, 2001	-1.56, -1.56, -1.72, -1.91
Baro	1985, 2002	-1.73, -1.71
Genale Dawa	2003	-1.73
Omo Gibe	1981, 1994, 2016	-1.59, -1.56, -1.73
Rift Valley	1985	-1.64
Tekeze	1996, 2008	-1.6, -1.67
Wabishebele	2011	-1.57

4.4.2 Analysis of Hydrological Drought Using SDI

To eradicate the flow variation of stations across time and space, the daily streamflow data were compiled monthly and standardized to zero mean and unit standard deviation. Then, SDI was calculated by applying Equation (12) to the seasonal base for the three-month length (SDI3) and the yearly base for the twelve-month duration (SDI12). The result implies that the 3-month time scale analysis has a higher frequency of drought than the long-term time scale, 12 months. But for the long-term time scale, drought duration is maximum and the severity is increased. The result is supported by previous studies related to hydrological and meteorological drought analysis(Alegre et al., 2020; Boudad et al., 2018b; Raphael M. Wambua, 2019). The most intense and severe drought years across many river basins were recognized in this study. Table 15 reveals that during the past three decades, there have been 11 severe and 4 catastrophic droughts that have had an impact on the Rift Valley River Basin. Besides, the Wabishebele and Abbay river basins experienced severe drought in the 1980s and 2000s, respectively. The result of hydrological drought analysis using SDI agrees with previous meteorological drought study findings in Ethiopia (Bayissa, 2018; FeyisaSebokaTura, 2017; Nasir et al., 2021a; Tadesse et al., 2022). However, the result from M1SWSI contrasts with SDI results.

Table 15 Severe and extreme hydrological drought years and magnitude in Ethiopian River Basins using SDI

River Basin	Severe drought years	Magnitude	Extreme drought years	Magnitude
Abbay	1978, 1983, 1984, 1986, 1994, 2010	-1.84, -1.66, -1.91, -1.69, -1.69, -1.98	1983, 1984	-2.21, -2.29
Awash	1986, 1987, 2001		1986, 1987, 2002	-2.16, -2.4, -2.38
Baro	1982, 1984, 1985, 2002	-1.57, -1.88, -1.62, -1.81	2002, 2004	-2.01, -2.09
Genale Dawa	1996, 2002, 2003, 2010	-1.52, -1.51, -1.76, -1.9	-	-
Omo Gibe	1980, 1981, 1986	-1.64, -1.77, -1.69	-	-
Rift Valley	1980, 1983, 1984, 1985, 1987, 1990, 1999, 2002, 2004, 2010, 2012	-1.52, -1.54, -1.5, -1.55, -1.64, -1.74, -1.52, -1.86, -1.91, -1.91, -1.92	1984, 1985, 2003, 2011	-2.2, -2.1, -2.14, -2.21
Tekeze	1996	-1.51	-	-
Wabishebele	1990, 2001, 2002, 2004, 2005, 2011	-1.9, -1.86, -1.76, -1.69, -1.7, -1.7	2002	-2.34

4.4.3 Comparing SDI and M1SWSI

SDI value indicated that the Rift Valley river basin is recurrently affected by severe and extreme drought events (Table 5). However, the M1SWSI result indicates Rift Valley river basin is less affected by drought compared to other basins (Table 4). A previous study indicates the Rift Valley river basin is frequently affected by drought (Teshale and Olsedo, 2021). The result of this study agreed with recent findings. However, the M1SWSI result deviated from the historical trend not only Rift Valley river basin but also in others. As shown in Table 16, except Rift Valley River basin, SDI and M1SWSI have a good correlation in all river basins. The reason for the Rift Valley River basin is that the streamflow value is very minimal and directly joined to a lake which increases the lake level regularly. Therefore, the available surface water in the basin is dominated by lakes and precipitation rather than streamflow. As a result, the cumulative drought analysis technique using M1SWSI gives wet season frequently and the overall result of the index can be dominated by the available lake water.

Table 16 SDI and M1SWSI Correlations

Basin	Correlation	Basin	Correlation
Abbay	0.70	Omo Gibe	0.64
Awash	0.51	Rift Valley	0.19
Baro	0.72	Tekeze	0.68
Genale Dawa	0.53	Wabishebele	0.62

Table 17 shows that the occurrence of severe and extreme drought frequency is higher for SDI than for M1SWSI. This is because SDI gives a site or point drought condition of a single river from the basin but SWSI results are based on the cumulative contribution of different surface water sources such as streamflow, precipitation, and lake level. It is also understood that the probability of occurrence of extreme drought using M1SWSI was insignificant (Table 17). Except for the Awash and Tekeze river basins, the frequency of severe drought in all basins has reduced when drought is analyzed by SWSI. The average occurrence of severe and extreme drought using SWSI was reduced by 53.85% and 100% respectively when compared with SDI. This implies that SWSI will hide the impact of local drought and affect the drought management program by reducing the severity of drought over the region. Therefore, for water resource planning and infrastructure development in a river, SDI gives more information about the historical frequency of drought conditions than M1SWSI.

Table 17 Number of droughts that occurred in Ethiopia from 1973 – 2014 using SDI and M1SWSI

Basin	Number of Severe Drought Occurred			Number of Extreme Drought Occurred		
	SDI	SWSI	% of reduction	SDI	SWSI	% of reduction
Abbay	6	4	33.33	2	0	100
Awash	***3***	***4***	***25***	3	0	100
Baro	4	2	50	2	0	100
Genale Dawa	4	1	75	0	0	100
Omo Gibe	3	3	0	0	0	100
Rift Valley	13	1	92.3	4	0	100
Tekeze	***1***	***2***	***50***	0	0	100
Wabishebele	5	1	80	1	0	100

The annual time series of SDI and M1SWSI for all river basins in Ethiopia is shown below in Figures 6 to 13. All Figures from 17 to 24 imply that the probability of severe and extreme drought occurrence was high for SDI than M1SWSI. Because M1SWSI has been obtained from a combination of many hydroclimate variables and the result is more dominated by wet events than dry events. This is due to the combination of different hydrological components for a single basin drought analysis. However, the two indexes have good correlations for all river basins except the Rift Valley River basin.

In the case of the Abbay river basin, the hydrological drought frequency was high for SDI from 1973 to 2000. But from 2000 to 2014, the frequency of drought was obtained high by M1SWSI (Figure 17). The result revealed by some researchers such as (Y. A. Bayissa et al., 2018) indicates that the basin was under severe drought from 1980 to 1990.

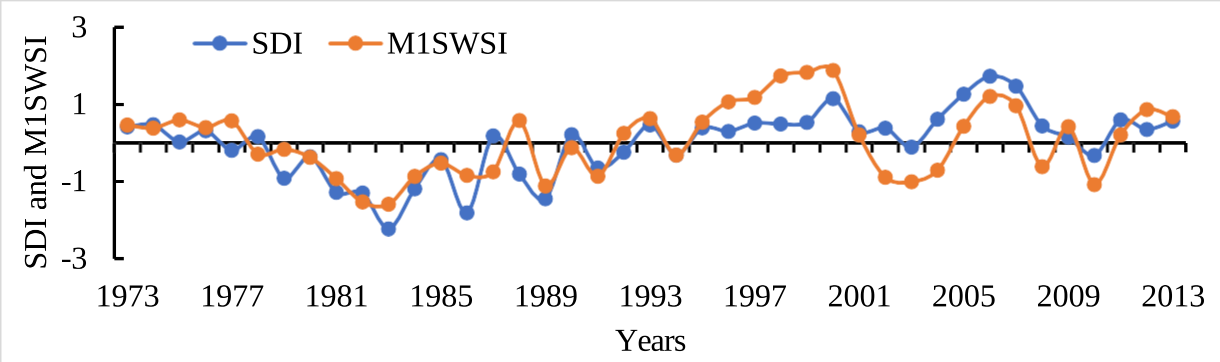


Figure 17 Comparison between SDI and M1SWSI in the Abbay river basin

SDI and M1SWSI in Awash River have less correlation compared to the Abbay and Baro river basins (Table 16). Similarly, SDI has a high frequency from 1973 to 2000 but it becomes wetter from 2001 to 2014 compared to M1SWSI. The more severe probability of the basin is obtained by SDI than M1SWSI (Figure 18). (A Belayneh et al., 2014; Edossa et al., 2010) also stated that the Awash river has been frequently affected by drought during the last five decades.

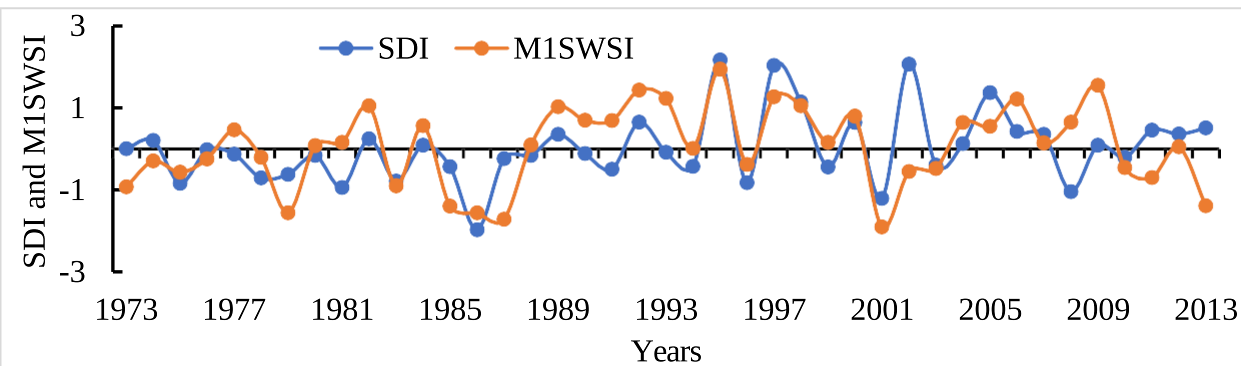


Figure 18 Comparison between SDI and M1SWSI in the Awash River basin

A drought study has not been conducted in the Baro river basin before. The analysis of this study shows the two hydrological drought indices (SDI and M1SWSI) have a good correlation for the Baro river basin (Table 16). Baro river is the wettest river basin compared to all basins and the occurrence of drought frequency is less. However, the basin was severely affected by drought between 1985 and 2002 (Figure 19).

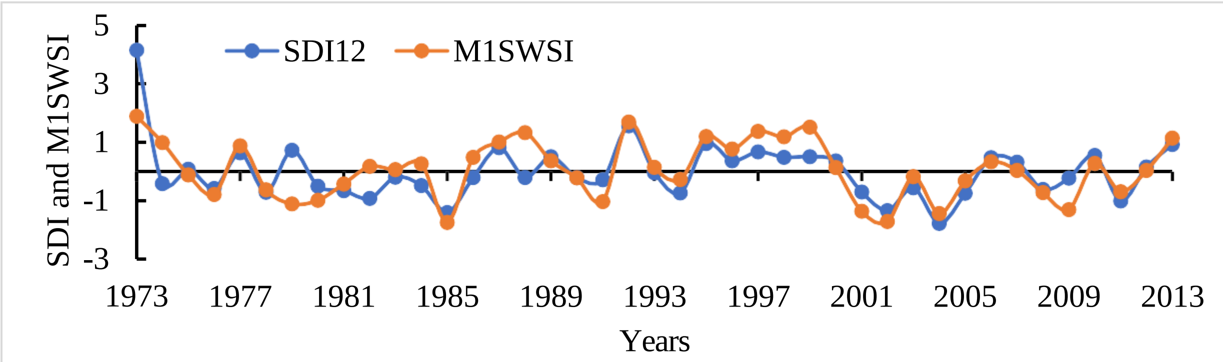


Figure 19 Comparison between SDI and M1SWSI in the Baro river basin

In Genale Dawa, the two indices have high variation and from 1984 to 2007 moderate to severe droughts were more frequent for M1SWSI than SDI. This is because the Genale Dawa river basin is located in arid and semiarid areas in which the contribution of rainfall for surface water is minimal. But the source of streamflow is from the highlands of the central parts of the country and depends mainly on a good climate zone. As a result, SDI is relatively wetter than M1SWSI during the analysis time (Figure 20). The severe drought event occurred in the basin period in 2003 for both SDI and M1SWSI. Seven moderate drought events occurred in the Genale Dawa river basin from 1984 to 2012. 43% of the drought occurred during 1990, 1996, and 2007 (M1SWSI), 43% were in 1998, 1999, and 2001 (by SDI and M1SWSI), and 14% were during 2008 (SDI). This result is the same as previous drought studies in the basin (Mera, 2018).

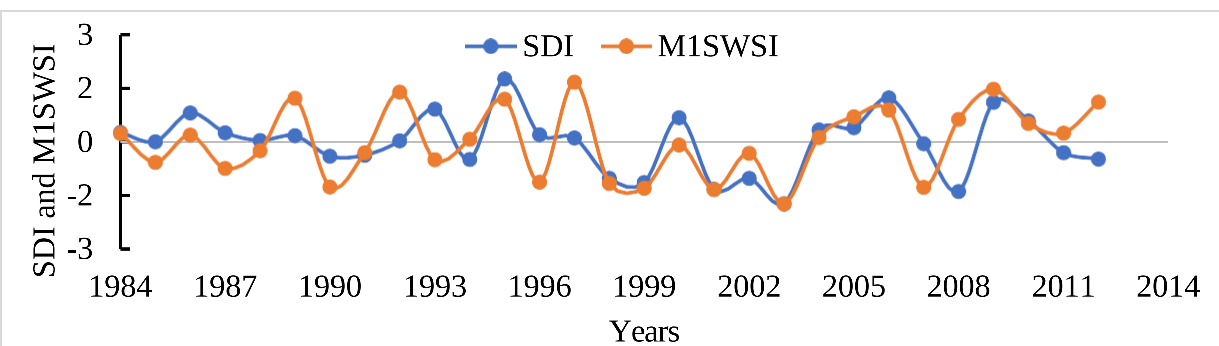


Figure 20 Comparison between SDI and M1SWSI in the Genale Dawa river basin

Omo Gibe River basin is located in a good climate zone, which receives high rainfall in two seasons (Spring and summer). As a result, the analysis of drought by different indices (SDI and M1SWSI) relatively gives the same result. Figure 21 shows that from 1980 to 1993, SDI results in moderate to severe drought whereas from 1994 to 2016 the moderate and severe drought events were dominated by M1SWSI.

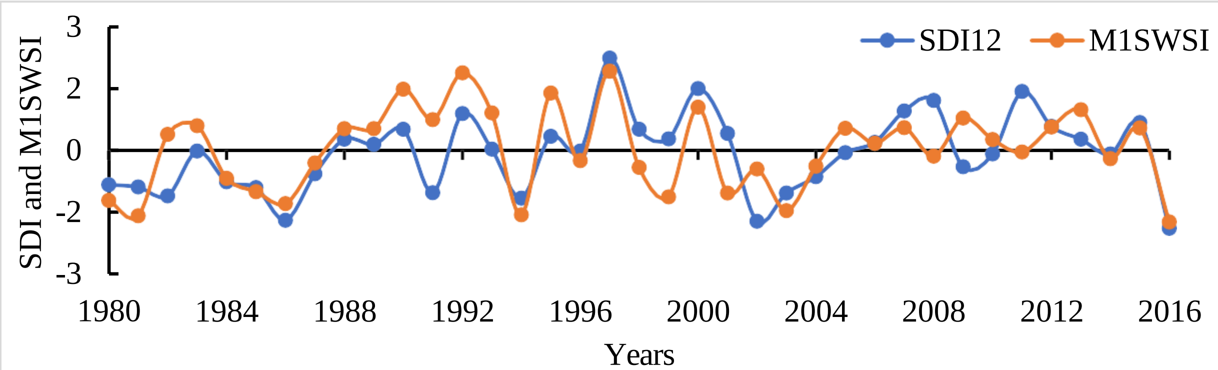


Figure 21 Comparison between SDI and M1SWSI in the Omo Gibe River basin

The Rift Valley River basin is highly dominated by lakes and receives minimum rainfall. Many streamflow joins into different small lakes and the rivers flow is restricted from flowing a distance. The basin is located in a depression area and the precipitation variation is insignificant (Belete et al., 2016). The fluctuation of lake level in this river basin is constant as stated by (Mohammed, 2021). The drought analysis for this basin considered three input parameters such as streamflow, precipitation, and lake level. The result shows that M1SWSI is influenced by lake level which results in the basin being in normal to wetter conditions (Figure 22). But SDI result implied that the area is highly affected by frequent drought and the correlation between SDI and M1SWSI is poor (Table 16). This implies that SDI is more suitable for hydrological drought analysis in this basin than M1SWSI. Because other studies also show that (Mohammed, 2021; Yisehak et al., 2020) the area is frequently affected by severe drought but M1SWSI minimized the impact of drought in the area due to the combination of different surface water sources.

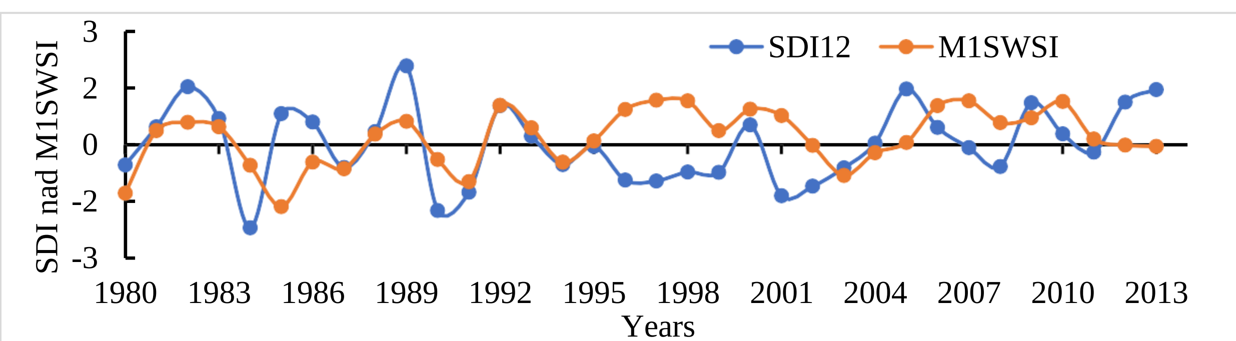


Figure 22 Comparison between SDI and M1SWSI in the Rift Valley River basin

SDI and M1SWSI in the Tekeze river basin have a good correlation (Table 16). As shown in Figure 23, the drought time series of the two indices have a similar fashion. But relatively, M1SWSI results in more drought frequency compared to SDI. Due to the construction of the Tekeze dam, the variation of streamflow in the Tekeze river is balanced (Fentaw et al., 2018). SDI value is dependent on streamflow data; therefore, the result also depends on the fluctuation of flow. However, historical drought studies imply that the area is frequently affected by severe drought (Gebrehiwot et al., 2011; Gebrehiwot and Veen, 2013). But in this study, the annual SDI12 value of the Tekeze river basin is in the reverses of previous studies. Therefore, the future drought condition of the Tekeze basin needs a detailed study using different additional streamflow stations located in the tributaries of the Tekeze river.

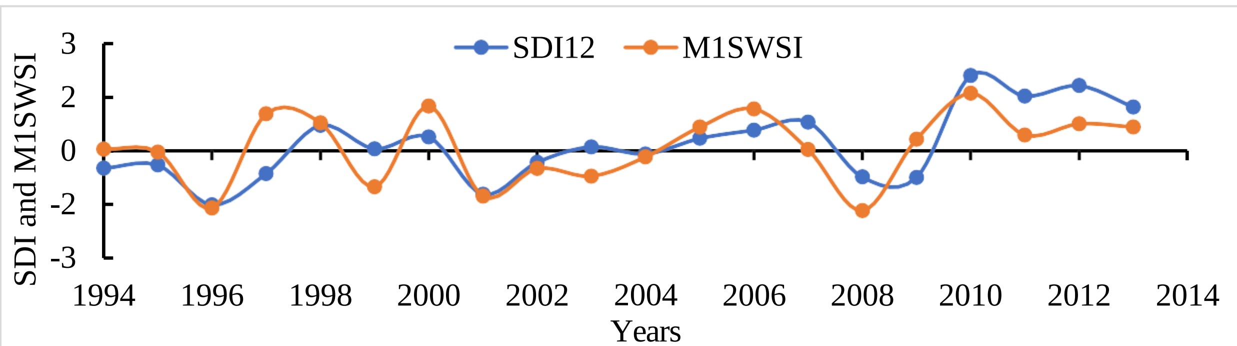


Figure 23 Comparison between SDI and M1SWSI in the Tekeze river basin

Wabishebele River basin is one of the arid basins and is commonly affected by severe drought compared to other river basins (Awass., 2009). 1990 and 2011 are the most severe drought years whereas 2002 was the extreme drought year in this river basin. From those drought events, only 2011 was the same for SDI and M1SWSI and the remaining drought events were obtained by SDI (Figure 24).

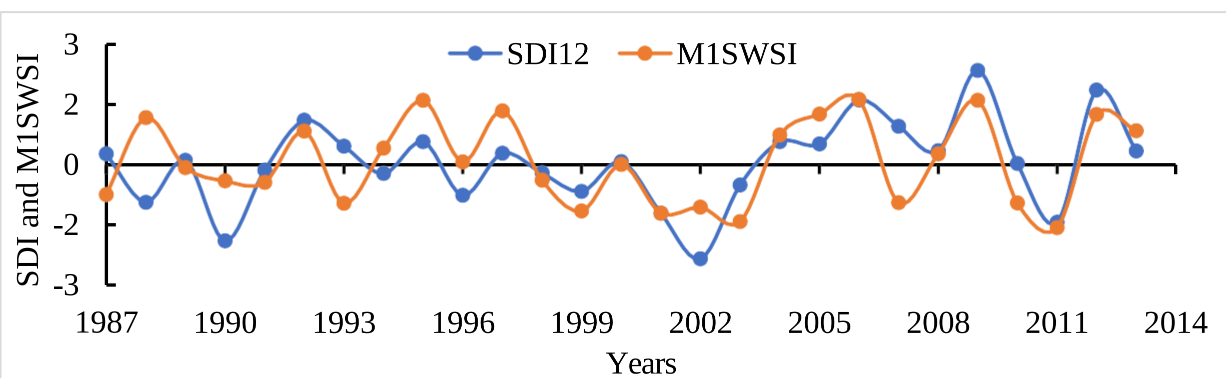


Figure 24 Comparison between SDI and M1SWSI in the Wabishebele river basin

4.5 Conclusion

This study has compared two hydrological drought indices (SDI and M1SWSI) and the result showed that the 1980s were the most prolonged hydrological drought event years in Ethiopia. SDI resulted in more frequent severe and extreme drought events occurring over the country than the M1SWSI. M1SWSI uses multi-hydrological components cumulatively as input which results in a small magnitude of drought severity and its occurrence frequency was decreased due to the aggregation of components. The number of severe drought events obtained using M1SWSI in all basins was less than 53.85% of the SDI result. Because some hydrological components were dominating the scarce data which will affect the overall analysis. The result of SDI values agreed with previous historical drought events. Therefore, SDI is the best hydrological drought index compared to M1SWSI for all basins in Ethiopia and this index gives good information for a single river as well as basin-level drought conditions. So, water resource managers and infrastructure development sectors can use this index for decision-making for the best utilization of the available water resources within the basin. Water supply, irrigation, and hydropower projects are more dependent on streamflow and need hydrological drought monitoring system development. Therefore, decision-makers, policy, and strategic planners, and master plan developers can use SDI for historical and future hydrological drought analysis to develop effective drought mitigation measures in Ethiopia.

5. Hydrological and meteorological drought monitoring and trend analysis in Abbay River Basin, Ethiopia

Abstract

The definition of drought is very controversial due to its multi-dimensional impact and slow propagation in onset and end. Predicting the accurate occurrence of drought remains a challenging task for researchers. The study focused on hydrological and meteorological drought monitoring and trend analysis in the Abbay river basin, using the streamflow drought index (SDI), standardized precipitation index (SPI), and reconnaissance drought index (RDI), respectively, to fill this research gap. The study also looked into the interrelationships between the two drought indicators. The SDI, SPI, and RDI were calculated using long-term streamflow, precipitation, and temperature data collected from 1973 to 2014. The data were collected from eight streamflow stations and fifteen meteorological gauge stations. DrinC software (Drought Indicator Calculator) was used to calculate the SDI, SPI, and RDI values. The result from meteorological drought using SPI12 and RDI12 shows that 1975, 1981, 1984, 1986, 1991, 1994, and 2010 were extreme drought years whereas 1983, 1984, 2001, and 2010 were the most extreme hydrological drought years based on the SDI12 result. Except for Bahir Dar and Gondar, a severe drought occurs at least once a decade in all stations considered in this study. In general, the SPI, RDI, and SDI results indicated that the study area was exposed to the most prolonged severe and extreme drought from 1981 to 1991. The findings of this study also demonstrated that the occurrence of hydro-meteorological droughts in the Abbay river basin has a positive correlation at long time scales of 6 and 12 months. The trend analysis using the Mann – Kendall Test implied that there was a significant meteorological drought trend in two stations (Debre Berhan and Fiche) at SPI 12 and RDI12 time scale but for the remaining thirteen stations there is no trend in all time scales. The hydrological drought trend also resulted in three streamflow stations (Kessie, Gummera, and Border), has a positive trend for SDI3 and SDI12. This implies that water resource management is still a vital tool for the sustainable development of the Abbay river basin in the future.

Keywords: Drought, Mann-Kendall test, Sustainable development, Trend analysis

5.1 Introduction

Drought is a series of problems everywhere in the world and it aggravates food insecurity, and shortage of water supply, and reduces irrigation and hydropower production for a prolonged period (Lanen et al., 2013). Contrasting to other natural hazards, such as floods, hurricanes, and tornados; droughts developed slowly in their onset and impacts. Therefore, the definition of drought is very controversial due to its multi-dimensional impact. However, based on the duration of the lack of different forms of water (precipitation, moisture, streamflow, etc.) and the development of drought impact, drought can be categorized into four. These are (i) meteorological drought, related to deficiency of precipitation, (ii) agricultural drought, which is a lack of soil moisture, (iii) hydrological drought, which is associated with a deficiency in surface and sub-surface water and (iv) socio-economical drought, supply and demand imbalance (Bogdan Bąk, 2015; Group et al., 2005; Kwon and Kim, 2010; Lanen et al., 2013; X. Liu et al., 2016; Loon, 2018). Shortage of precipitation is the primary cause of meteorological drought and gradually propagates to agricultural and hydrological drought related to loss of soil moisture and decrease in surface and groundwater availability, respectively (Alegre et al., 2020; Keskin and Taylan, 2011; Nasir et al., 2021b; Sarailidis, 2019). The overall aggregated drought impact develops into a socio-economic drought, in which the demand for water via different groups increases and may cause conflicts among the community (Bogdan Bąk, 2015; Juana, 2015).

Most African countries are dependent on rainfeed agriculture and highly vulnerable to climate change-induced hazards like floods and droughts (Mwadzingeni and Mugandani, 2022). In the last six decades, Africa has been frequently affected by severe, intense, and widespread drought (I Masih et al., 2014; Yugi et al., 2022). In Africa, continentally the most unique extreme droughts were recorded during 1972/73, 1983/84, and 1991/92. Recent studies show that the African continent is expected to face widespread severe and extreme droughts in the forthcoming. (I Masih et al., 2014).

Ethiopia has an ample amount of water resources and serves as a source of surface water for other downstream countries like Sudan and Egypt. However, studies revealed that Ethiopia is under water stress due to a recurrence of drought (Bayissa et al., 2021a). The recurrence of catastrophe floods and droughts in Ethiopia leads to more economic loss (Teshome, 2019a). Therefore, this drought phenomenon has increased the water stress in the eastern part of the country due to low surface water potential and unlimited demand for irrigation practices such as the Awash river basin. Even though the water stress problem is more common in these areas, water supply practice is concentrated in the western part due to the availability of excess surface and subsurface water potential such as the Abbay river basin. To improve the imbalance in supply and demand as well as to mitigate drought impact, the construction of dams and reservoirs plays a great role (Melo et al., 2016).

Drought is still not well studied in Ethiopia both at the National and basin level. Relatively meteorological drought analysis is studied in different basins of the country due to the easy accessibility of observed and satellite-recorded precipitation data (Yared A Bayissa et al., 2015a; Blue et al., n.d.; Lemma et al., 2022; Mohammed, 2018; Mohammed et al., 2017). However, the hydrological drought is still needing investigation to balance the available water potential for supply and demand. (Bayissa et al., 2021b), was investigated to characterize both meteorological and hydrological droughts in the Abbay river basin using a standardized precipitation index (SPI) and standardized runoff-discharge index (SRI). However, the researcher used a single streamflow data at the Abbay border (Ethiopian -Sudan border), the outlet points of the Abbay river basin for hydrological drought analysis in the entire river basin. Since the standardized runoff-discharge index gives a point value and it is difficult to see the spatial variability of the drought over the basin using a single streamflow station. Therefore, investigation of drought condition by considering additional streamflow station which at least represent some sub – basins of Abbay river basin will give good information about spatiotemporal variability of drought over the entire basin.

The goal of this research is (i) to analyze the historical hydrometeorological droughts using SPI, RDI, and SDI, respectively, (ii) to determine long–term drought trends through the Mann – Kendall test, and (iii) to investigate the relationship between hydrological and meteorological droughts over the study period in Abbay river basin. Historically, droughts have frequently occurred in the Abbay river basin in the past four decades (Bayissa et al., 2021b). As a result, there is an obvious need for improved and integrated drought mitigation strategies developed in the Abbay river basin to minimize the adverse impact of future droughts. Therefore, this study has good information for researchers, planners, stakeholders, and Abbay basin authorities for future drought preparedness based on the historical drought trend findings.

5.2 Methods and materials

5.2.1 Study area description

Abbay river basin is the second largest river basin in the area next to the Wabishebele river basin. This river basin has an annual runoff of 54.5 BM^3 and covers an area of approximately 176, 000 km^2 (Yared A. Bayissa et al., 2015a). Spatially Abbay basin is located at 7^0 40' N and 12^0 51' N latitude and 34^0 06' E and 40^0 00' E longitude (Bayissa et al., 2021b) (See Figure 25). In the Abbay river basin, there are sixteen sub-basins from the major tributaries. This basin has crucial importance to Sudan and Egypt. Because it contributes 62% of the Nile River flow without considering the Baro Akobo and Tekeze rivers basins (Mengistu et al., 2020). Topographically, the basin elevation ranges from 350 m near to Ethiopia - Sudan border and 4230 m above sea level in the central part of the basin lowest to highest, respectively (Mengistu et al., 2020; Roth et al., 2018).

Depending on the topographical variation, the basin has high climate variation. The mean annual rainfall ranges between 780 mm and 2250 mm; in some parts of the basin such as Beshilo, Guder, Muger, and Weleka, the annual rainfall is less than 1000 mm. The minimum and maximum average temperatures of the basin are 15^0c and 28^oc, respectively (Khairy, 2021; Mengistu et al., 2020; Roth et al., 2018; Yimere and Assefa, 2021). However, in the highland parts of the basin temperature is sometimes lower to -1^oC, and the maximum temperature for the northwestern part increases to 38^oC, respectively (Yimere and Assefa, 2021).

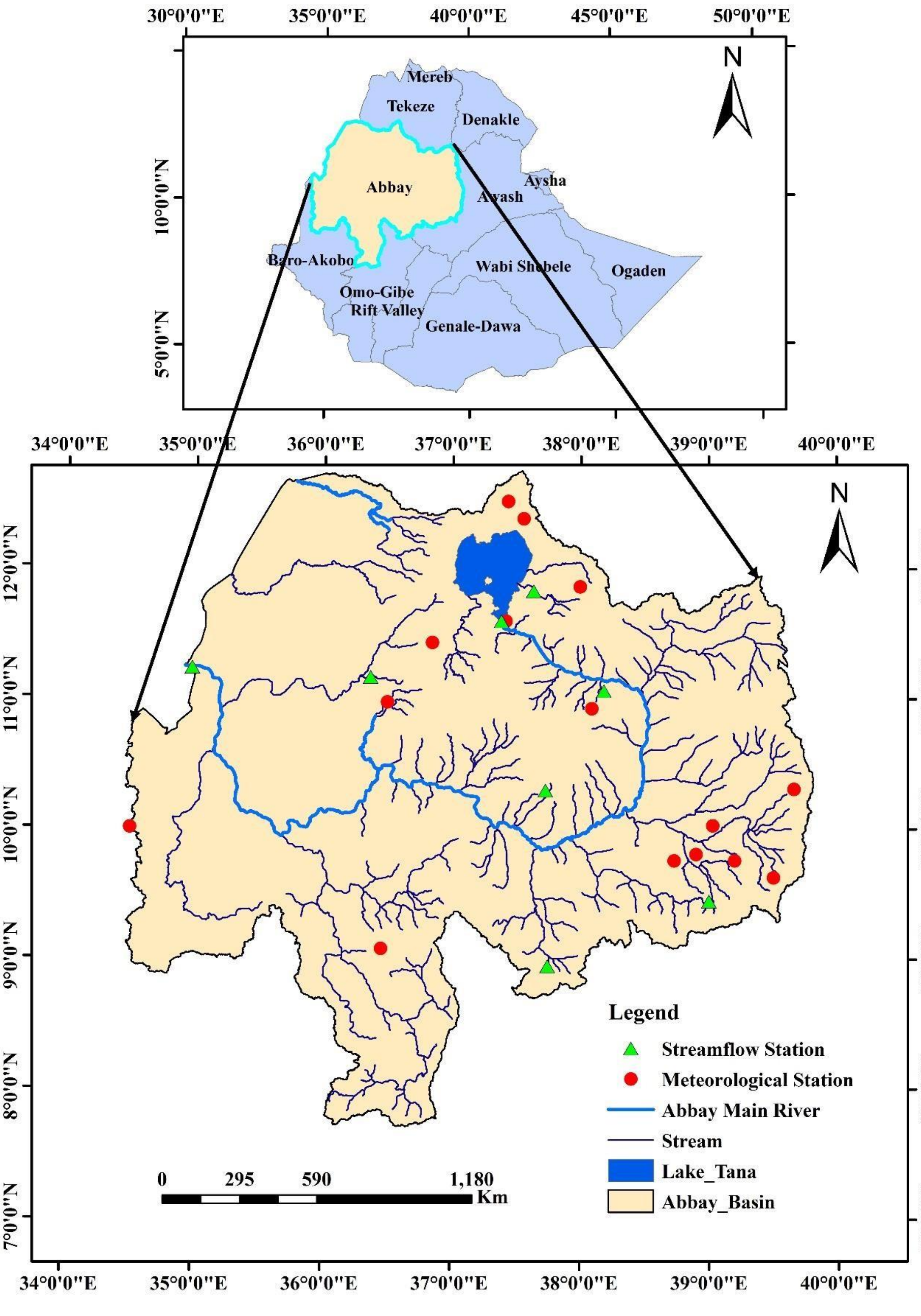


Figure 25 Location of selected hydro-meteorological stations in Abbay River Basin

5.2.2 Data Collection and Preparation

The daily precipitation and temperature data were collected from fifteen stations in the Ethiopian Meteorology Institute (EMI). For the case of drought and climate change study, at least a minimum of 30 years of data is required (European Commission, 2020). Therefore, for this study, from 1973 to 2014 (42 years) precipitation and streamflow data were collected from different representative stations for hydro-meteorological drought trend analysis. The Streamflow data were collected from the Ministry of Water and Energy of Ethiopia (MoWE). Relatively, there are many gauging stations in the basin. The selection of rainfall and streamflow stations was focused on the length of available data, quality, and coverage area. The spatial location of all stations is indicated in Table 18. As shown in Figure 25, eight streamflow stations were selected; Gummera and Bahir Dar, which represent the upper Abbay basin in the north part, Kessie, Chemoga, and Guder represent the middle part of the basin, Gilgel Belles, the Ethiopia-Sudan border, represents the downstream part of the basin, and Robigumera represents the northeast part of the basin in Jema sub-basin. In this research, the analysis was conducted at a period of months (SPI1, RDI1, and SDI1), seasonal (SPI3, RDI1, and SDI3), biannual (SPI6, RDI6, and SDI6), and annual (SPI12, RDI12, and SDI12) time scales. For the case of 1-month, 3-month, and 6-month SPI, RDI, and SDI analysis, the rainiest month (August) was considered; August, the summer season (locally Kiremt, June to August), and 6- months (February to August), respectively. Because Ethiopia receives high rainfall during these months and seasons correspondingly streamflow is also increased. To calculate these drought conditions the observed precipitation, temperature, and streamflow data were prepared in a monthly manner and used as input for DrinC software (Drought indices calculator), recently it is been widely used in different countries to determine three drought indicators such as SPI, RDI, and SDI (Vangelis, 2022). The minimum recorded data length in this study is 27 years at the Robigumera streamflow station and the maximum is 42 years in most streamflow stations and precipitation stations (see Table 18).

Table 18 Selected hydro-meteorological station location in Abbay River Basin

Hydrological Stations						
Station name	Latitude	Longitude	Area (Km2)	Annual Flow (m^3/s)	Record Year	Data Length (year)
Border	11.28	37.23	17254	1670.9	1973-2014	42
Bahir Dar	11.6	37.38	15319	115.5	1973-2014	42
Chemoga	10.3	37.73	364	5.09	1973-2008	36
Gilgele Beles	11.17	36.37	675	17.81	1973-2014	42
Guder	8.95	37.75	524	11.95	1973-2008	36
Gummera	11.83	37.63	1394	34.47	1973-2014	42
Kessie	11.06	38.18	65784	523.39	1973-2014	42
Robigumera	9.45	39	887	8.96	1983-2009	27

Meteorological Stations						
Station name	Latitude	Longitude	Elevation (m)	Mean annual rainfall (mm)	Record Year	Data Length (year)
Bahir Dar	11.6	37.42	1770	1423.88	1973-2014	42
Chagni	10.97	36.49	1614	1718.27	1973-2014	42
Gondar	12.52	37.43	1973	1161.29	1973-2014	42
Makisegnit	12.39	37.55	1912	1003.89	1973-2014	42
Gundewoin	10.93	38.09	2052	1569.47	1973-2014	42
Debre Tabor	11.87	37.99	2612	1535.97	1973-2014	42
Dangila	11.43	36.85	2116	1609.95	1973-2014	42
Mehalmeda	10.31	39.66	3084	865.42	1985-2016	32
Debre Berhan	9.63	39.5	2750	928.56	1985-2016	32
Alem Ketema	10.03	39.03	2280	1104.35	1985-2016	32
Deneba	9.76	39.2	2600	969.47	1985-2016	32
Lemi	9.81	38.9	2500	1311.75	1985-2016	32
Fiche	9.76	38.73	2784	1143.11	1985-2016	32

Assosa	10	34.51	1600	1079.02	1985-2016	32
Nekemt	9.08	36.46	2080	2065.86	1985-2016	32

5.2.3 Filling missing data

After collecting the required data from their sources, the next step is preparing the data based on the models required and in line with the objective of the task. However, the raw data may have been missing in different cases. Therefore, it is important to fill in the missing data using appropriate techniques. The most common missing data-filling techniques for meteorological data are the arithmetic mean method, normal ratio method, and inverse distance method (Mohammad-Taghi Sattari, 2017; Science, 2019). In this study, both the arithmetic means method and normal ratio methods were applied for some meteorological stations based on the percentage of the normal annual rainfall of missing data from normal annual rainfall (below 10%, arithmetic and above 10% normal ratio method) of the surrounding stations. The equation of the arithmetic means method and normal ratio methods are given below by Equations (13) and (14) respectively.

$$P_x = \frac{1}{m}[P_1 + P_2 + P_3 + \cdots P_m] \qquad 13$$

Where P_x is rainfall at the missing stations P_1, P_2, P_3, …P_m is rainfall at different stations and m is the number of known stations considered.

$$P_x = \frac{N_x}{m}[\frac{P_1}{N_1} + \frac{P_2}{N_2} + \frac{P_3}{N_3} + \cdots \frac{P_m}{N_m}] \qquad 14$$

Where P_x and N_x are the required missed rainfall and normal annual rainfall; P_1, P_2, P_3, and P_m are rainfall at different stations and m is the number of known stations.

Table 19 describes the total number of missing data days from a period of 1973 to 2014 for seven meteorological stations and from 1985 to 2016 for eight stations. As indicated from the table, Assosa and Deneba stations have relatively more missing data. The analysis showed that the normal annual rainfall of Bahir Dar, Makisegnit, Gundewoin, Fiche, and Debre Berhan stations was found below 10% of the surrounding stations' normal annual rainfall whereas, ten stations (Chagni, Dangila, Debre Tabor, Gondar, Lemi, Assosa, Nekemt, Mehalmeda, Alem Ketema, and Deneba) have a variation of above 10% of normal annual rainfall value compared to the surrounding stations. Therefore, the missing data for the former five stations were filled by using the arithmetic mean method and the later ten stations were estimated using the normal ratio method. After filling in all the missing, finally, the data were finally prepared in a monthly manner to check the homogeneity and consistency test. Besides, the streamflow missing data were filled using the regression method and the areal ratio method.

Table 19 Percentage of missing rainfall data for selected gauge station in the Abbay river basin

Station	Number of recorded data (day)	Number of missing data (day)	Missing (%)
Bahir Dar	15362	391	2.54
Chagni	15320	1915	12.46
Dangila	15320	2132	13.87
Debre Tabor	15320	1375	8.95
Gondar	15320	363	2.36
Gundewoin	15320	1852	12.05
Makisegnit	15320	173	1.12
Mehalmeda	8248	900	10.91
Debre Berhan	8248	360	4.36
Alem Ketema	8248	750	9.09
Deneba	8248	1580	19.15
Lemi	8248	1020	12.36
Fiche	8248	180	2.18
Assosa	8248	1540	18.67
Nekemt	8248	480	5.82

5.2.4 Data Quality Test

A) Consistency Test

Water resources management and planning studies require long-term hydrological and meteorological data; therefore, a test must be conducted to check the homogeneity or self-consistency of the recorded data. This is necessary because, over some time, it may happen that there will be some obstructions like trees, buildings, etc. may have emerged after the installation of the gauge, or its location might have changed or observational procedure might have changed. The inconsistency of recorded data can be checked by graphical or statistical methods including double mass curve, the Von Neumann ratio test, cumulative deviation, run test, and specific flow test. However, the double mass curve method is one of the most common and widely accepted methods for checking the consistency of rainfall and stream flow records (Amjadi et al., 2021; Eerdenbrugh et al., 2017; Weather, 1937). This method is based on the assumption that the mean accumulated precipitation for a large group of stations is not significantly affected by a change or changes in individual stations.

The consistency of all selected rainfall stations indicates that one gauging station; Nekemt is slightly deviated from a straight line compared to the remaining 14 stations. But the variation is not that exaggerated. Most stations are located in the upstream part of the river basin in the northern and northeast direction in which the area relatively received less rainfall compared to the middle and western parts of the basin. Even though the gauge stations were taken from different sub-basins of the Abbay river basin, it can be seen all stations have a straight-line relation with the mean cumulative rainfall value of all stations in the study area. Therefore, all fifteen stations are considered for further meteorological drought analysis in the basin.

B) Homogeneity Test

Homogeneous rainfall records are often required in hydrologic design. However, it is frequently occurring that rainfall data over different periods are not comparable since the measured amount of rainfall depends on such factors as the type, height, and exposure of the rain gauge, which have not always been the same. Therefore, many meteorological institutes maintain an archive with information on the rain gauge sites and the instruments used. Unfortunately, it is often not possible to specify the nature of changes in the mean amount of rainfall from the station documentation. This is partly because it is not always known how a change in the instrument or the rain gauge site may influence the measured amount of rainfall and partly because it is highly questionable whether the station information gives a complete picture of the rain gauge site during the period that the station has been in operation. Therefore, a homogeneity test is used to check the homogeneous and non – non-homogeneous stations for a specific study area and also used to determine the trend availability. The homogeneity test was obtained by determining the monthly non-dimensional value of each station within the basin (Khalil, 2021; Kocsis, 2020). It is given by Equation (15):

$$P_i = \frac{P_{av.m}}{P_{av.an}} * 100 \quad (15)$$

Where: P_i is the non-dimensional percentage (%), $P_{av.m}$ and $P_{av.an}$ are the long-term monthly average and annual rainfall respectively.

The homogeneity of fifteen rainfall stations was checked using a non-parametric ratio method in the Abbay river basin, Ethiopia. The result indicates that almost all selected stations are relatively homogeneous. But four stations, Chagni, Nekemt, Assosa, and Dangila are non-homogeneous during July and August months. Since the representative rainfall stations were collected from different sub-basins of the Abbay river basin there are high spatial variations. As a result, a slight change in inhomogeneity can be expected. However, the variation is not significant, therefore all the stations were considered for this study.

5.3 Drought Analysis Methods

Drought indices are a powerful statistical value used to monitor drought conditions and to develop an early warning system for a region. Many drought indices have been developed in the last few decades and most of them are region-specific and have some limitations in different climate regions (Kchouk et al., 2021; Zargar et al., 2004). Therefore, the selection of drought indices for a specific study area depends on many factors. The most common selection criteria are the number of input data required, data availability, the objective of the study, climate condition, novelty of the index, and validity are the factors that determine the selection of indicators (Aladaileh et al., 2019; Kchouk et al., 2021).

There are several types of drought indicators used for meteorological and hydrological drought monitoring. It is difficult to prioritize the effectiveness of one index from others due to the complex nature of drought (Kchouk et al., 2021). However, based on the literature recommendation and the objective of the index developed, it is possible to select the appropriate drought index related to the aim of the specific study. Meteorological drought can be monitored by simple to complex indices such as percentage decile (%), Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Reconnaissance Drought Index (RDI), Standardized Precipitation – Evapotranspiration Index (SPEI), etc. (Jain et al., 2015; Mercedes et al., 2022; Moreira et al., 2015; Tigkas et al., 2022). Recently the World Meteorological Organization (WMO) presents SPI as a universal meteorological drought index. It is due to its ability to monitor drought for multiple time scales and comparable between different regions or watershed drought events (Jamshidi et al., 2011; Ortiz-gómez, 2018). RDI and SPEI are the most important meteorological drought indices by incorporating the effect of potential evapotranspiration in addition to precipitation variability (Tigkas et al., 2022). Especially in a climate region highly dominated by glaciers and ice, the variation of temperature plays a great role and RDI and SPEI are very important to monitor drought trends. Even though the variability of precipitation has more impact on the development of drought phenomenon than temperature variation in Ethiopia, both SPI and RDI were selected in this study to monitor the meteorological drought variability in the Abbay river basin. Commonly, the deviation of precipitation from the long mean value is an indicator of drought starting. However, its impact is dependent on the duration of no rain times as well as the rate of evapotranspiration during the drought season. Therefore, RDI plays a great role in analyzing meteorological drought by considering the impact of temperature variability in addition to precipitation variability (Pashiardis and Michaelides, 2008; Zarch et al., 2011).

Agricultural and hydrological drought analysis indicators are more limited because of extensive input data requirements. Some of the most common agricultural drought indices are PDSI, Soil Moisture Deficit Index (SMDI) (Blue et al., n.d.) whereas hydrological drought indices are Streamflow Drought Index (SDI), Palmer Hydrology Drought Index (PHDI), Surface Water Supply Index (SWSI) (Giri et al., 2021; X. Liu et al., 2016; Zalokar et al., 2021). PHDI and SWSI need more data related to soil moisture groundwater level, and reservoir water level. However, in developing countries such as Ethiopia, it is difficult to access all the required input data. So, the simplest and most common streamflow-based drought index (SDI) was used to characterize the hydrological drought phenomena in this study (Alegre et al., 2020; Ansarifard and Shamsnia, 2018; Lucy J Barker et al., 2019; Loon and Laaha, 2015).

Therefore, in this study, the historical meteorological and hydrological droughts in the Abbay river basin in Ethiopia were analyzed by using SPI, RDI, and SDI, respectively. This analysis was considered for four-time scales; monthly (SPI1, RDI1, and SDI1), seasonal (SPI3, RDI3, and SDI3), biannual (SPI6, RDI6, and SDI6), and annual (SPI12, RDI12 and SDI12). In the Abbay river basin, the precipitation and streamflow volume is high during the summer season. Therefore, in this study, the monthly, seasonal, and biannual meteorological and hydrological drought analysis was focused on the summer season for August, June to August, and March to August.

5.3.1 Standardized precipitation index

For the first time, McKee et al. (1993) (Abara and Budiastuti, 2020), developed the standardized precipitation index (SPI) at the University of Colorado State (Arash Asadi, 2013). It is the most popular meteorological drought monitoring index. Its popularity is due to its low data requirement, statistical analysis approach, and ease of calculation as well as it can describe drought both in spatial and temporal extent (Barker et al., 2016). SPI is widely used for meteorological drought analysis. But for the long-term time scale (12, 24, and 48 months), it is also used for hydrological drought analysis in case of a lack of streamflow data (Ilmaz, 2019). However, the input data is only precipitation and does not consider the influence of temperature (Pashiardis and Michaelides, 2008).

A probability distribution function of SPI should fit the accumulated precipitation data for each time scale. Finally, the precipitation data was transferred to a standard normal distribution with a standard deviation of one and a mean of zero, respectively. The objective of transformation is to make SPI comparable in time and space (temporal and spatial variability). The gamma distribution is the most common fitted function to precipitation data in SPI calculation (Barker et al., 2016). Accordingly, SPI can be determined using Equation (16) below.

$$\mathrm{SPI} = \frac{\mathrm{Xi} - \mathrm{Xm}}{\sigma} \qquad (16)$$

Where: Xi is the value of precipitation at i^{th} month or season and year, Xm is the mean monthly, seasonal, or annual precipitation and σ is the standard deviation of recorded precipitation.

5.3.2 Reconnaissance drought index

RDI is a recent drought analysis indicator by considers the effect of temperature in drought monitoring (Tigkas et al., 2022). SPI uses only precipitation data whereas RDI uses both precipitation and temperature as input data to overcome the limitation of SPI to understand the effect of temperature on water balance (Zarch et al., 2011). RDI computation is based on the ratio of total precipitation and potential evapotranspiration. Potential evapotranspiration was estimated using maximum and minimum temperature values. The procedure of RDI value classification and analysis is the same as SPI. The classification of drought conditions is the same as SPI which ranges from -2 to 2, extreme drought to extreme wet respectively (see Table 3). The calculation of RDI is given by Equation (17):

$$RDI = \sum_{n=1}^{12} \left(\frac{Pij}{PETij}\right) \quad (17)$$

Where: P_{ij} is seasonal precipitation at i^{th} rain gauge station and j^{th} observation, PET_{ij} is seasonal potential evapotranspiration at i^{th} rain gauge station and j^{th} observation

5.3.3 Streamflow drought index

Hydrological drought is not an easy task like meteorological drought analysis. It requires many input data in the hydrologic cycle. However, Nalbantis and Tsakiris (2009) (Nalbantis, 2008) developed Streamflow Drought Index (SDI) which is a simple hydrological drought indicator using a single hydrological data, streamflow (Tigkas et al., 2015). The calculation of SDI is similar to SPI and it has the same efficiency and simplified characters as SPI. SDI is estimated using monthly streamflow volume to control hydrological drought and water supply shortage at different time scales such as short, medium, and long term. Using aggregated streamflow volumes V_{nq}, the SDI can be determined at different reference times q of the n-th hydrological year as given by Equation (18) below.

$$\text{SDI} = \frac{\text{Vn,q} - \text{Vqm}}{\text{Sq}} \quad (18)$$

Where: n = 1, 2; …, and q = 1, 2, 3, 4

Vqm and sq are the mean and the standard deviation of cumulative streamflow volumes of the reference period q as these are estimated over a long period, respectively. According to McKee (1993) and Tsakiris et al., (2009), the wetness and dryness value of SPI and SDI is between -2 and 2.

Table 20 below shows different drought categories and the extremely dry and wet values are below or equal to -2 and above 2, respectively. The number of drought classifications using SPI, RDI, and SDI varies from seven to nine, in which some classification merges slightly wet and normal values (0.5 – 0.99 and -0.5 -0.49) into -0.5 -0.99 as a normal range (Bayissa et al., 2021b; Mercedes et al., 2022).

Table 20 Hydro-meteorological drought category based on SPI, RDI, and SDI values (Ceglar, 1999)

SPI, RDI and SDI ranges	Drought Categories
> 2	Extreme wet
1.5 – 1.99	Severe wet
1.0 - 1.49	Moderate wet
-0.99 – 0.99	Near normal
-1.0 - -1.49	Moderate drought
-1.5 - -1.99	Severe drought
< -2	Extreme drought

5.4 Drought trend analysis using Mann – Kendall Test

There are several methods to detect drought trends in terms of streamflow and rainfall such as statistical approaches and rank-based tests (Pingale et al., 2016). Statistical methods include Slope based tests, Least Squares Linear Regression (LR), Sen's Slope Estimator (SS), and Rank-based tests based on Mann-Kendall (MK) test, Spearman Rank Correlation (SRC) test (Mehta, 2022). Pre-whitening, Trend pre-whitening, and Variance Correction with the Mann-Kendall test are considered in the serial correlation effect by statistical approaches (Jain and Saharia, 2013). In this study, the Mann-Kendall test is used to detect hydrological and meteorological drought trends at a 5% significance level based on the value of SDI and SPI time sequences in the Abbay river basin by using the AUTO_MK_Sen.exe software.

The Mann-Kendall (MK) test is determined using two sequential time series (Xj and Xi) from n data points in a series (Mehta, 2022). Each subsequent data value in a given time series is compared with other data of the series. The value of statistics S can be increased or decreased by 1 based on the rearrangement of the data sequence of earlier and later data values. Then the statistics S value is calculated using the two incremental and decrement data values net result. Therefore, the Mann-Kendall (MK) test statics S is estimated using Equations (19) and (20) as stated below.

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} Sign(Xj - Xi) \qquad (19)$$

$$Sign(Xj - Xi) = \{ \begin{matrix} 1; if\ Hj - XI > 0 \\ 0; if\ Xj - Xi = 0 \\ -1; if\ Xj - Xi < 0 \end{matrix} \} \quad (20)$$

where xj and xi are the data values in years j and i respectively. If the number of data points in the time series is less than 10 then the value of |S| is compared directly to the distribution S or in other cases where the number of data points in the time series is greater than 10 then the value of statistic S is distributed by the mean and variance shown in Equations (21) and (22), respectively.

$$E(S) = 0 \quad (21)$$

$$Var(S) = \frac{m(-1)(2m+5) - \sum_{k=1}^{n} k1(k1-1)(2k1+5)}{18} \quad (22)$$

Where m and k_i are the number of SPI and SDI time series and the ties of the sample time series, respectively

The Performance of the Mann-Kendall test was computed by AUTO_MK_Sen.exe and the calculated statistics Z_c test is given by Equation (23).

$$Zc = \{ \begin{matrix} \frac{S-1}{\sigma}; if\ S > 0 \\ 0; if\ S = 0 \\ \frac{S+1}{\sigma}; if\ S < 0 \end{matrix} \} \quad (23)$$

The calculated Zc statistics follow a normal distribution and positive and negative Z_c values indicate an increasing and decreasing trend for a given time series period, respectively.

The drought index plays a great role in evaluating the consequences of drought impact and in deciding various drought characteristics, such as duration (D), Severity (S), magnitude (M), and relative frequency (RF) (Eskandaripour, 2022; Soo et al., 2012). Drought duration is the time taken between consecutive drought events (onset and end of drought). The duration is from starting of the negative SDI value and turns to the positive SDI value. Drought severity is the summation of negative SDI values from the onset to the end of a drought event as defined by Equation (24). The magnitude of drought is the ratio between drought severity and drought duration which is defined by Equation (25).

$$Si = -\sum_{i=1}^{D} SDIi \quad (24)$$

$$M = \frac{S}{D} \tag{25}$$

The relative drought frequency is the ratio between the number of droughts (n) with negative SDI in drought duration and the total number of drought years in the analysis (N) (Yisehak et al., 2021), and RF is defined as Equation (26) (Spinoni et al. 2014; Wang et al. 2018):

$$RF = \frac{n}{N} * 100 \tag{26}$$

5.5 Spatial distribution analysis of drought

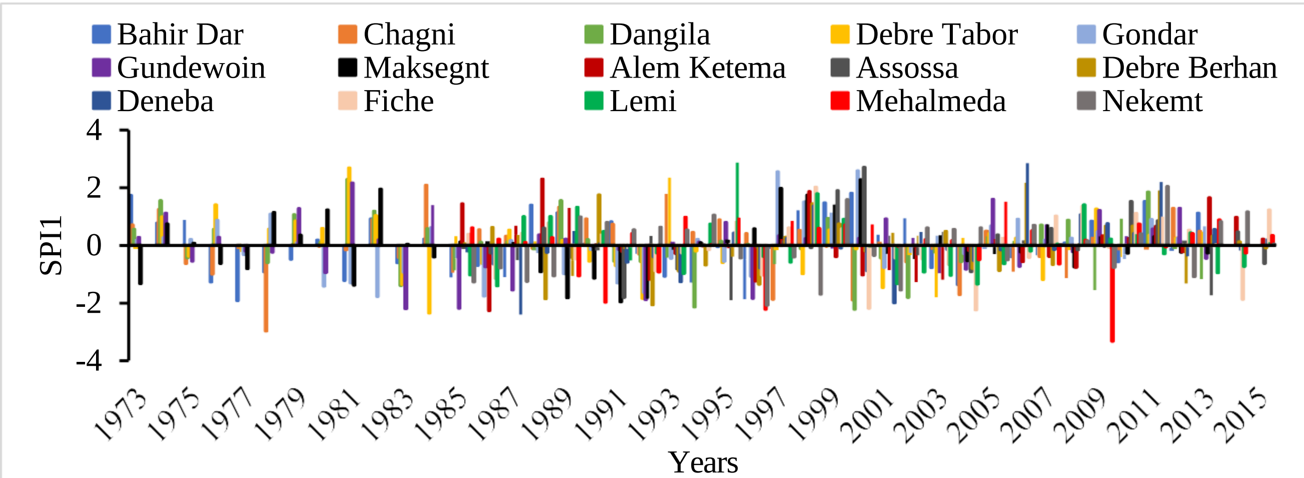
The spatial distribution of drought analysis is important for appropriate drought preparedness and early warning system development (Anose et al., 2022; Bonaccorso et al., 2003; Khairy, 2021; Mathbout et al., 2018). There are several interpolation techniques to display drought-affected areas in ArcGIS software. Among those, Inverse Distance Weighted (IDW) is suitable for heterogeneous topography like Ethiopia (Achilleos, 2018; Khouni et al., 2021). The Inverse Distance Weighted (IDW) spatial analysis tool in ArcGIS software is used to analyze the drought-prone area and its extension over the basin at a specific drought year after the temporal drought has been properly determined using SPI, RDI, and SDI. The value of selected severe and extreme drought events by SPI, RDI, and SDI is used as input for the IDW tool. This geographical analysis tool is intended to pinpoint places that are extremely prone to drought and to display the size of the coverage areas that are affected by it.

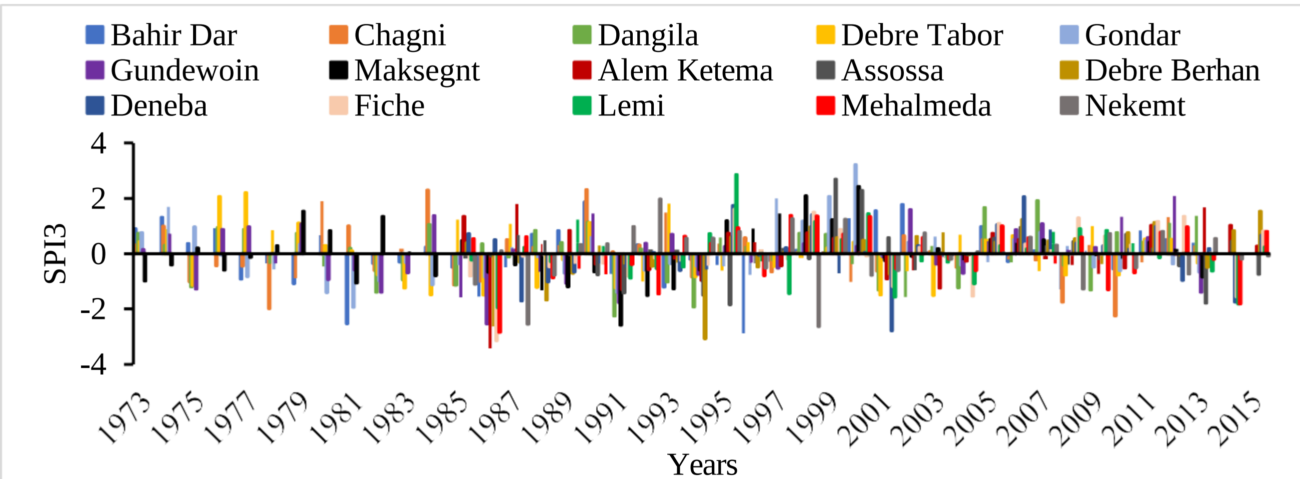
5.6 Results and discussion

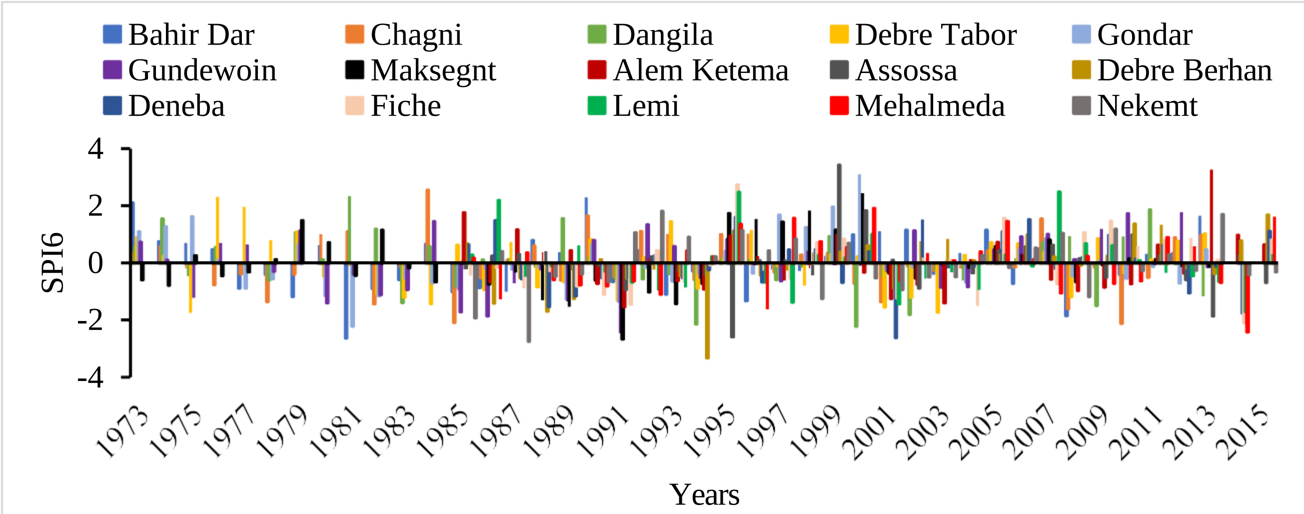
5.6.1 Meteorological drought characteristics using SPI and RDI

A meteorological drought analysis was conducted in the Abbay river basin using SPI and RDI from fifteen meteorological stations from 1973 to 2014 and 1981 to 2016 respectively. Meteorological drought analysis via SPI is mostly considered for a short time scale, one to six months (SPI1, SPI3, and SPI6). However, for areas lacking hydrological data (streamflow), SPI12 and above are used for hydrological drought analysis (Bayissa et al., 2021b; Yared A Bayissa et al., 2015a; Lemma et al., 2022). But in this study, SPI1, SPI3, SPI6, and SPI12 were computed for meteorological drought monitoring and the result indicated that drought severity increased as the time scale increased from SPI1 to SPI12 but the frequency of occurrence decreased over a long-timescale analysis. Figure 26 shows that the period 1981 to 1996 was the longest drought season and frequent moderate to severe droughts occurred for all time scales. Commonly, the periods

1981 – 1996, 2001 – 2004, and 2008 – 2010 experienced moderate to extreme drought while 1997 - 2000 were the wet period in the Abbay river basin. Y.A. Bayissa et al., 2015 (Yared A Bayissa et al., 2015b) stated that the Abbay river basin was in severe drought in the years 1978/1979, 1984/1985, 1994/1995, and 2003/2004. The result of this study also agreed with this finding but there were some additional severe drought years such as 1989, 1991, 1993, 2001, 2008, and 2010 (see Figure 4). In this river basin, extreme droughts in most gauge stations occurred in 1975, 1981, 1984, 1986, and 1991 (see Table 4).







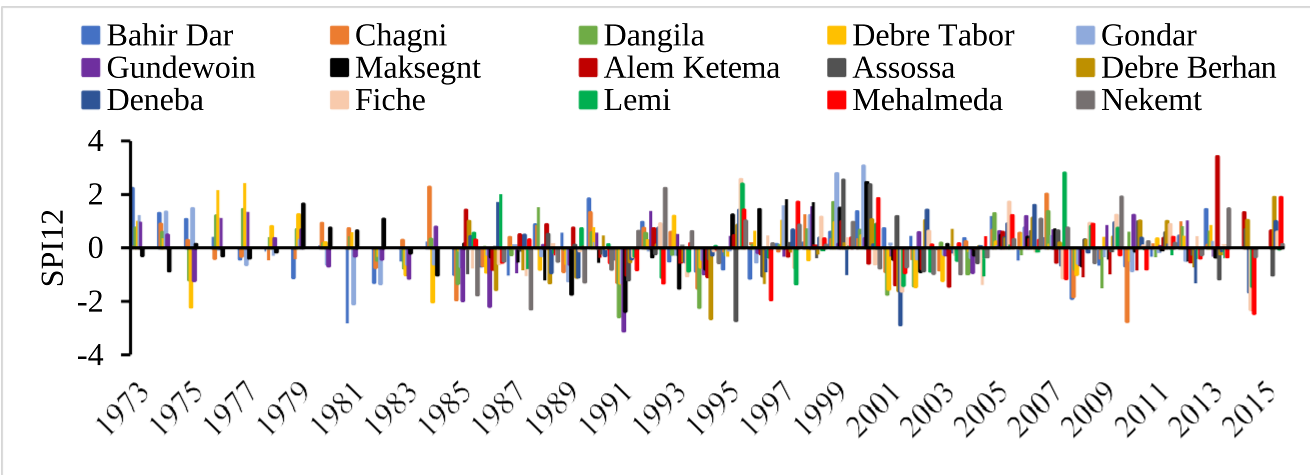


Figure 26 Meteorological drought time series in Abbay River Basin using SPI1, SPI3, SPI6, and SPI12 for selected stations

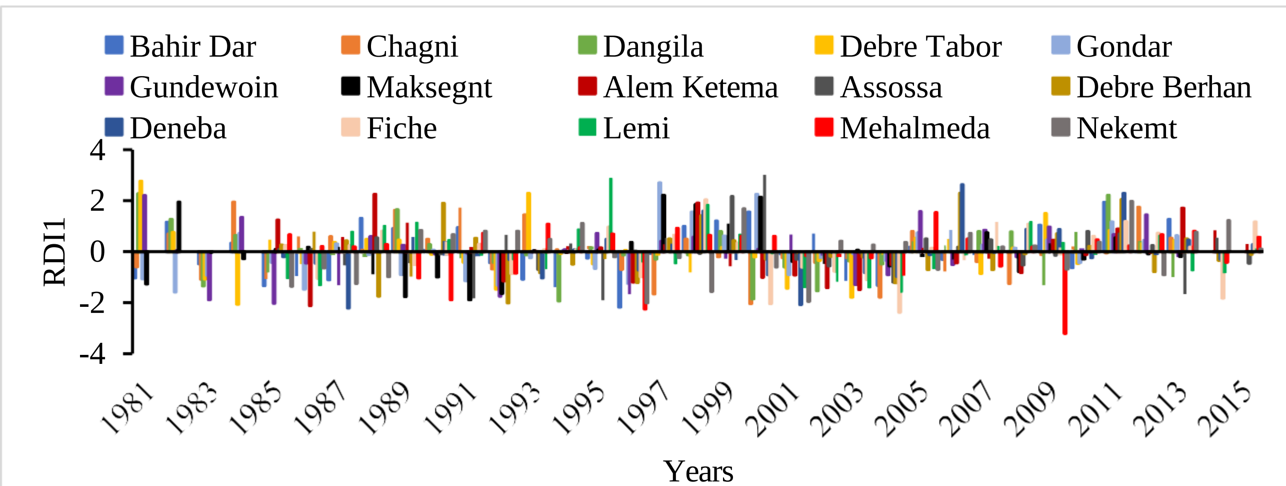
Table 21 shows that the Abbay river basin was regularly hit by severe and extreme meteorological droughts from 1975 to 2008. The result also indicates that the 1980s was the most hazardous decade compared to other decades. Spatially, the drought frequently occurred in the northern parts of the basin (Gondar, Makisegnit, and Debre Tabor) compared to other stations in the western and east-south parts (See Table 21).

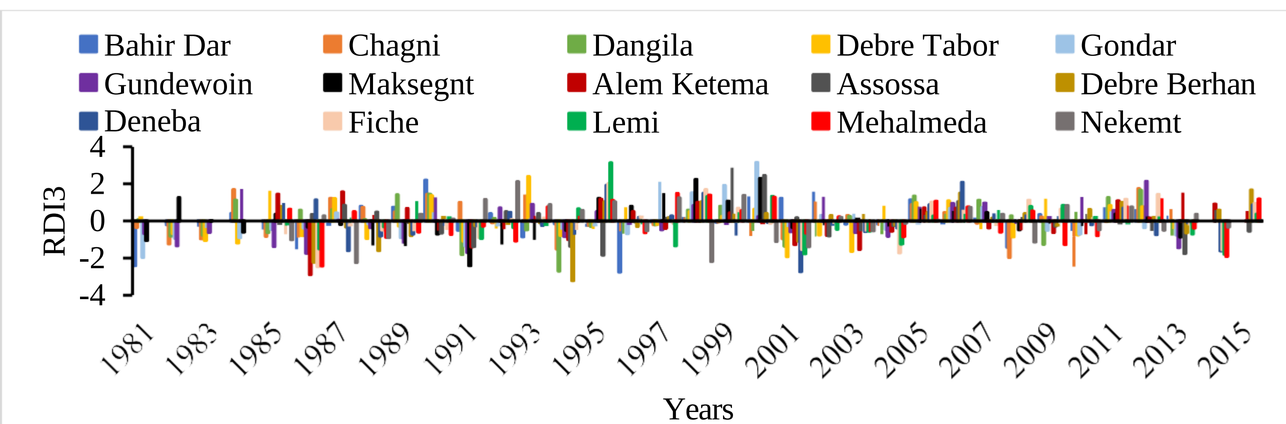
Table 21 Severely and extreme drought years in the Abbay river basin during 1973 – 2014 in SPI12

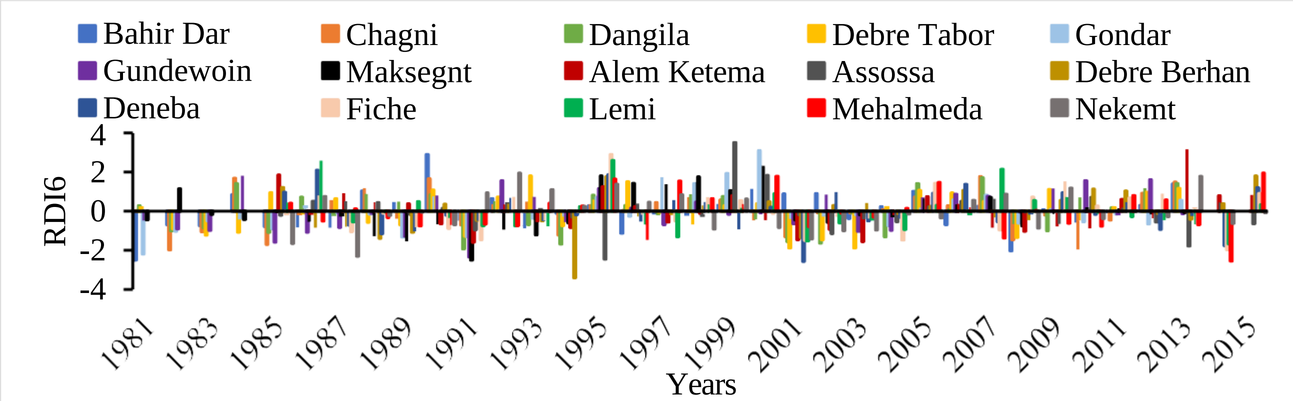
Station	Drought year	Magnitude	Frequency (%)	Drought Category
Bahir Dar	1981	-2.77	2.44	Extreme
	2008	-1.89	2.44	Severe
Chagni	1985	-1.94	7.32	Severe
	1994	-1.51		Severe
	2008	-1.82		Severe
	2010	-2.76	2.44	Extreme
Dangila	1991	-2.57	4.88	Extreme
	1994	-2.23		Extreme
	2001	-1.73	2.44	Severe
Debre Tabor	1975	-2.22	4.88	Extreme
	1984	-2.03		Extreme
	2001	-1.54	2.44	Severe
Gondar	1981	-2.10	2.44	Extreme
Gundewoin	1985	-1.98	2.44	Severe
	1986	-2.2	4.88	Extreme
	1991	-3.12		Extreme
Makisegnit	1989	-1.74	4.88	Severe
	1991	-2.37	2.44	Extreme
	1993	-1.51		Severe
Assosa	1995	-2.72	3.23	Extreme
Debre Berhan	1986	-1.56	6.42	Severe
	1994	-2.64	3.23	Extreme
Deneba	2001	-2.88	3.23	Extreme
	2014	-1.66	3.23	Severe
Fiche	2001	-1.62	3.23	Severe
	2014	-2.32	3.23	Extreme
Mehalmeda	1996	-1.94	3.23	Severe
	2014	-2.46	3.23	Extreme

Nekemt	1985	-1.76	3.23	Severe
	1987	-2.29	3.23	Extreme

RDI was computed from 1981 to 2015 for fifteen meteorological stations. As shown in Figure 27, the frequency of severe and extreme drought decreases from RDI1 to RDI12 but its severity and duration are increased. 1984, 1991, 1994, and 2001 were found the common severe drought events in most stations in the Abbay river basin. The longest duration was found from 2000 to 2004. The result of RDI highly agrees with the result of SPI in all time scales. The severe drought frequency is higher in the northern and northeast parts of the basin (Makisegnit, Gondar, Debre Tabor, Deneba, Mehalmeda) and the rear in the western part (Asossa and Nekemt).







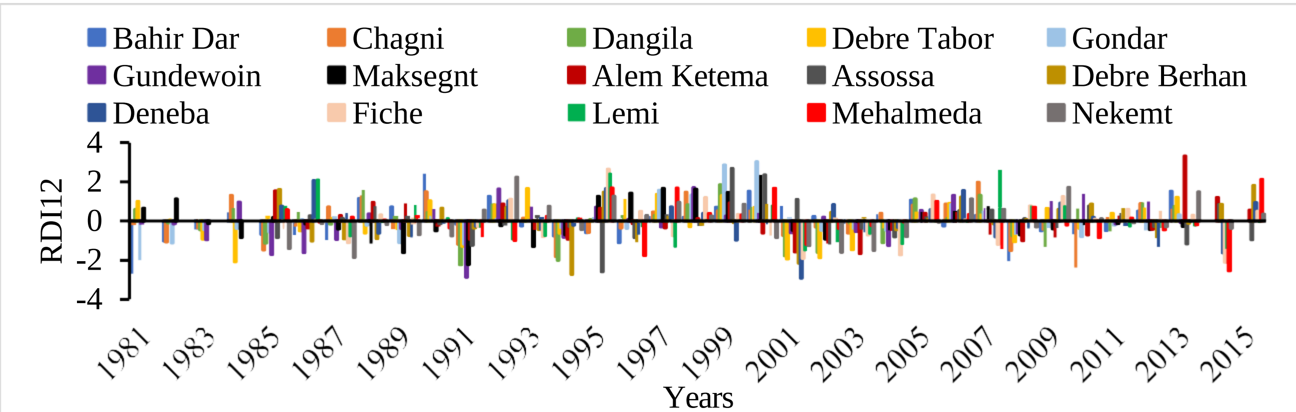
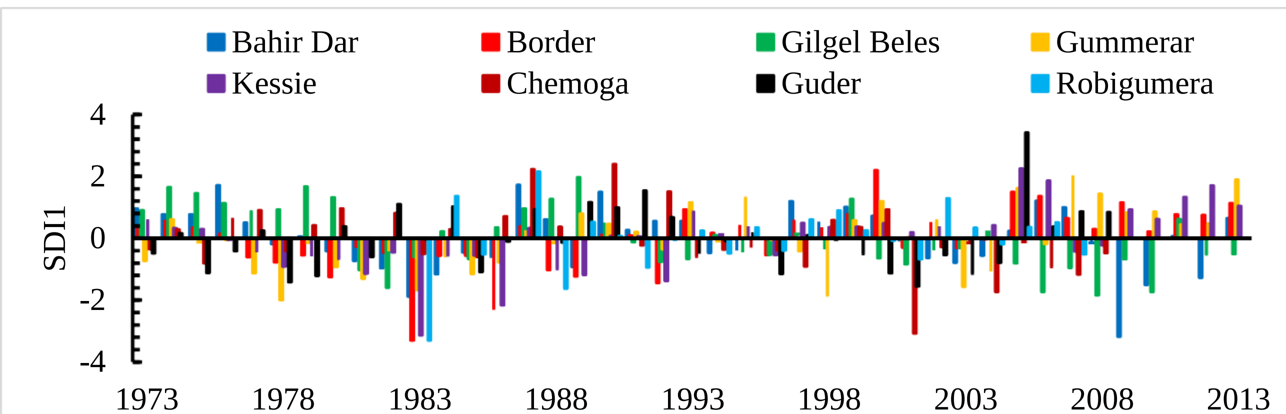


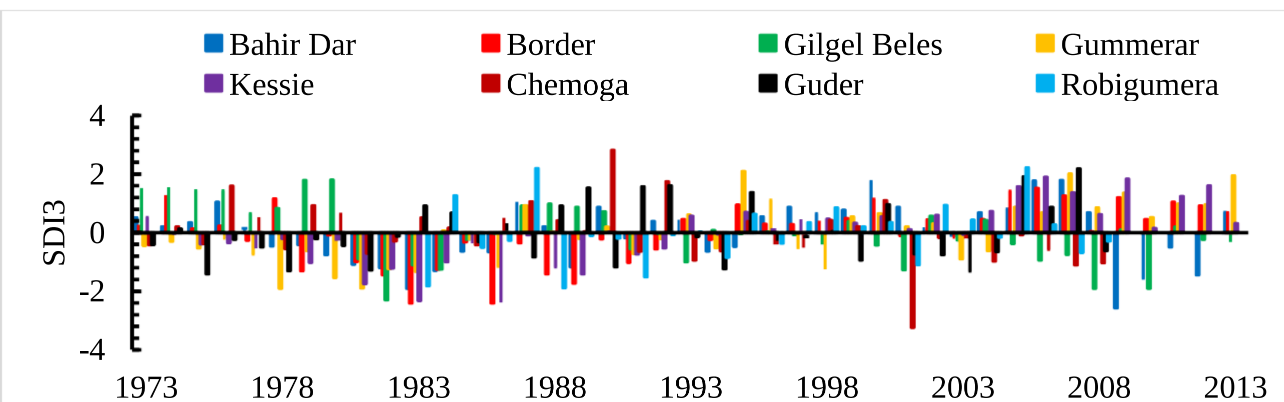
Figure 27 Meteorological drought time series in Abbay River Basin using RDI1, RDI3, RDI6, and RDI12

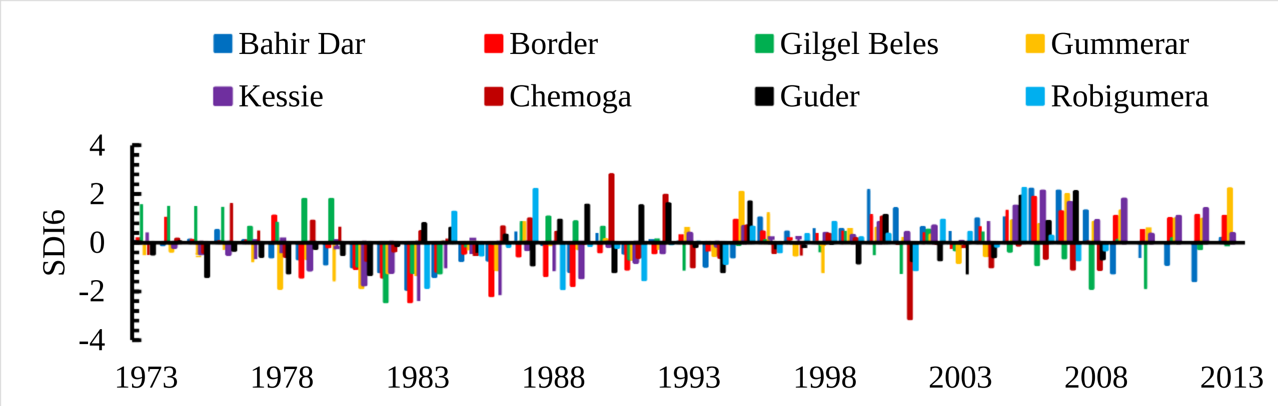
5.6.2 Hydrological droughts characterization using SDI

The hydrological drought analysis was computed using SDI by considering eight streamflow stations (Bahir Dar, Border, Gilgel Beles, Gummera, Kessie, Chemoga, Robigumera, and Guder) from 1973 to 2014 for five consecutive stations, from 1973 to 2009 for two stations, Chemoga and Guder and from 1983 to 2009 for Robigumera station (See Table 22 and Figure 28). The same as SPI and RDI, the SDI was computed for four time scales depending on different season variations (SDI1, SDI3, SDI6, and SDI12). The result showed that the SDI1 value for Border and Kessie lies under extreme drought during 1983 and 1986 whereas Chemoga and Bahir Dar stations were under extreme drought during 2001 and 2009 for SDI1 and SDI3, respectively (see Figure 28).

In Figure 28, SDI3, SDI6, and SDI12 commonly showed that from 1978 to 1987, the Abbay river Basin was highly affected by hydrological drought for ten consecutive years. In the year 1989, the central and the lower parts of the basin (Kessie and Border) were under a moderate drought but the upper part of the basin was in normal to mild drought conditions (Gummera and Bahir Dar) whereas Guder and Gilgel Beles were under wet condition, respectively. Gilgel Belles and Bahir Dar stations experienced moderate to severe drought from 2007 to 2011 whereas Gummera, Kessie, and Border stations were under wet conditions from 2005 to 2013. Generally, after 1988, the hydrological drought severity in most stations of the basin decreased. Seven streamflow stations were collected from the head to the lower parts of the river basin and nearer and the main Abbay river basin. But Robigumera is taken from the Jema sub-basin in the east-southern part of the basin and the result shows that the sub-basin was under severe drought events during 1983, 1988, and 1991. The overall result of SDI1, SDI3, SDI6, and SDI12 indicated that the Jema sub-basin is relatively wet and the effect of drought is minimal compared to the Tan sub-basin (upper) and Kessie sub-basin (middle). The result from SPI and RDI also supports the result of SDI in the Jema sub-basin.







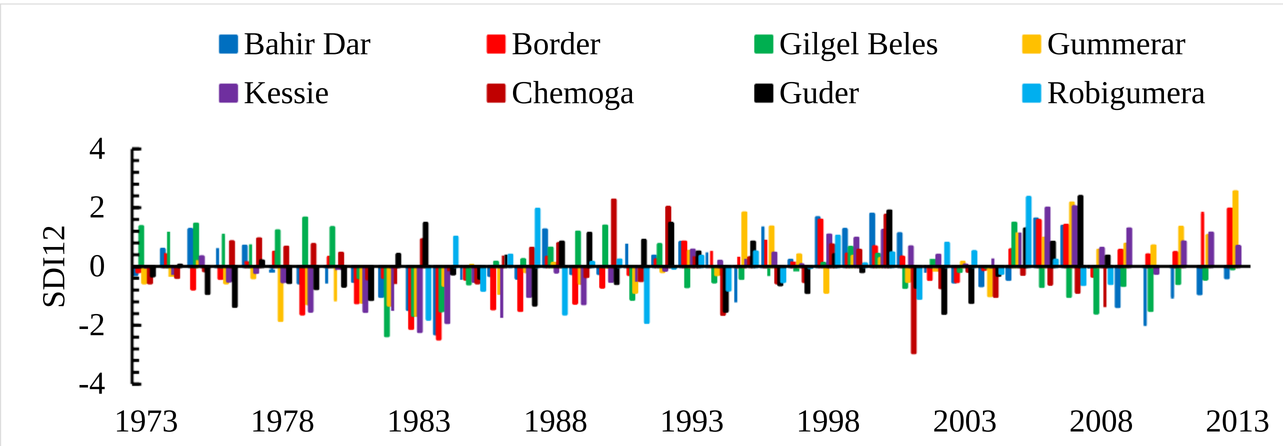


Figure 28 Hydrological drought (SDI) time series in Abbay River Basin

As shown in Table 22, four severe and one extreme drought occurred in Kessie station from a period of 1979 to 1986. Next to Kessie station, Border and Gilgel Beles stations were also highly affected by severe drought. The frequency of severe drought is minimal at Bahir Dar, Gummera, Chemoga, and Guder stations.

Table 22 Severely and extreme drought years in the Abbay river basin during 1973 – 2014 in SDI12

Station	Drought year	Magnitude	Frequency (%)	Drought Category
	1984	-2.29	2.44	Extreme
Bahir Dar	2010	-1.98	2.44	Severe
	1979	-1.62	4.88	Severe
Border	1983	-2.11		Extreme

	1984	-2.47	4.88	Extreme
	1987	-1.5		Severe
	1982	-2.35	2.44	Extreme
	1983	-1.66		Severe
	1984	-1.5	9.76	Severe
Gilgel Beles	2008	-1.59		Severe
	1978	-1.84	4.88	Severe
Gummera	1983	-1.66		Severe
	1979	-1.52	9.76	Severe
	1981	-1.53		Severe
	1983	-2.21	2.44	Extreme
	1984	-1.91		Severe
Kessie	1986	-1.69		Severe
	1994	-1.63	2.78	Severe
Chemoga	2001	-2.94	2.78	Extreme
	1994	-1.52	5.56	Severe
Guder	2002	-1.6		Severe
	1983	-1.79	11.54	Severe
	1988	-1.61		Severe
Robigumera	1991	-1.89		Severe

5.6.3 Meteorological and hydrological drought trend analysis

Meteorological and hydrological droughts trend in the Abbay river basin was computed using the Mann-Kendall (MK) test integrated with AUT_MK_Sen.exe software. The result indicated that, at the seasonal time scale (SDI3), there is significantly increasing drought trend in two streamflow stations (Gummera and Kessie), upper and middle parts of the basin respectively, and in the remaining five stations there is no significant hydrological drought trend. For the annual time scale (SDI12), three stations (Border, Gummera, and Kessie) have a significant hydrological drought trend at a 5% significant level (See Table 6). Severe and extreme drought events occurred from 1979 to 1986 for Border, Gummera, and Kessie streamflow stations. As a result, the trend analysis also results as shown in Table 23.

However, as shown in Table 24, in both seasonal (SPI3) and annual (SPI12) meteorological drought trend analysis, there is no significant trend at a 5% significance level in most stations except Debre Berhan and Fiche stations. The analysis of the meteorological drought trend using RDI also shows almost the same result as SPI, in which only Debre Berhan and Fiche have an increasing trend but other stations have no trend. Tables 23 and 24 imply that considering temperature and streamflow data in drought analysis will give better information about the drought trend than using a single precipitation variable. From this result, it is understood that monitoring hydrological drought is important in the future to manage the available water resources effectively during drought periods.

Table 23 Results of Mann – Kendall (MK) test for SDI3 and SDI12

SDI3								
Stations	Bahir Dar	Border	Chemoga	Gilgel Beles	Guder	Gummera	Kessie	Robigumera
$Z_{calculated}$	1.48	1.85	-2.08	-1.88	1.28	2.64	2.37	1.26
$Z_{critical\ (a = 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96
Trend (MK)	No trend	No trend	Decrease	No trend	No trend	**Increase**	**Increase**	No trend
SDI12								
$Z_{calculated}$	-0.1	2.13	-2.22	-1.13	1.38	2.09	2.13	0.62
$Z_{critical\ (a = 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96
Trend (MK)	No trend	**Increase**	Decrease	No trend	No trend	**Increase**	**Increase**	No trend

Table 24 Result of Mann – Kendall (MK) Test for SPI3, SPI12, RDI3 and RDI12

SPI3							
Stations	Bahir Dar	Chagni	Dangila	Debre Tabor	Gondar	Gundewoin	Makisegnit
$Z_{calculated}$	0.53	-0.33	-0.07	-0.72	0.55	1.47	0.2

$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	
Trend (MK)	No trend	No trend	No trend	No trend	No trend	No trend	No trend	
SPI12								
$Z_{calculated}$	0.85	-0.37	-0.64	-0.52	0.52	0.88	-0.03	
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	
Trend (MK)	No trend	No trend	No trend	No trend	No trend	No trend	No trend	
SPI3								
Stations	Mehalmeda	Debre Berhan	Alem Ketema	Deneba	Lemi	Fiche	Asossa	Nekemt
$Z_{calculated}$	0.82	2.99	0.51	1.37	0.27	2.70	-0.11	0.17
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96
Trend (MK)	No trend	**Increase**	No trend	No trend	No trend	**Increase**	No trend	No trend
SPI12								
$Z_{calculated}$	0.37	2.87	-0.34	-0.07	-0.83	0.93	-0.04	1.65
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96
Trend (MK)	No trend	**Increase**	No trend	No trend	No trend	No trend	No trend	No trend
RDI3								
Stations	Bahir Dar	Chagni	Dangila	Debre Tabor	Gondar	Gundewoin	Makisegnit	
$Z_{calculated}$	1.58	0.37	0.9	0.9	-0.5	2.03	0.63	
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	
Trend (MK)	No trend	No trend	No trend	No trend	No trend	**Increase**	No trend	
RDI12								
$Z_{calculated}$	0.63	0.6	0.5	0.87	0.11	1.69	-0.24	
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	
Trend (MK)	No trend	No trend	No trend	No trend	No trend	No trend	No trend	
RDI3								

Stations	Mehalmeda	Debre Berhan	Alem Ketema	Deneba	Lemi	Fiche	Asossa	Nekemt
$Z_{calculated}$	0.56	2.52	0.2	0.36	0.27	2.28	-0.71	0.5
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96
Trend (MK)	No trend	**Increase**	No trend	No trend	No trend	**Increase**	No trend	
RDI12								
$Z_{calculated}$	-0.89	2.02	-0.78	-0.71	-0.99	0.59	0.09	0.99
$Z_{critical\ (a\ =\ 0.05)}$	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96	±1.96
Trend (MK)	No trend	**Increase**	No trend	No trend	No trend	No trend	No trend	

5.6.4 Comparing Meteorological and Hydrological Drought

The distribution of rainfall in Ethiopia is highly varying from time to time and from place to place. SPI follows the variability series of rainfall in time and space. As a result, the meteorological drought trend of the Abbay river basin does not show a significant trend from 1973 to 2014 for most stations. But in two stations, Debre Berhan and Fiche have increasing trends both in SPI and RDI indices. On the other hand, streamflow measurement is taken at the outlet of the concentrated flow location of a basin. Therefore, the flow has followed an increasing or decreasing trend depending on the seasonal variation of rainfall over the basin. Therefore, the hydrological drought trend directly follows the trend of streamflow in the river; i.e., if the streamflow increases, the drought phenomenon decreases and vice versa. The result of this study reveals that the hydrological drought conditions of some streamflow stations (Gummera and Kessie) increased from 1973 to 2014 (see Table 23). The correlation of the SPI, RDI, and SDI values was computed for short, medium, and long-timescale (1 - month, 3 - months, 6 - months, and 12 - months). Table 25 indicated that the relationship between SPI, RDI, and SDI in the Abbay River basin was increased from a short time scale (1 - month to 3 - months) to a long-term time scale (6 - months to 12 - months) with a value of 0.54, 0.83, 0.84, and 0.87 respectively for SDI and SPI correlation. In the same manner, the correlation of RDI and SDI also increased from short-term to long-term timescale, except RDI6 to SDI6 is 0.72 but RDI3 to SDI3 is found 0.84. On the other hand, the correlation of SPI and RDI is excellent for all time scales with a value of 0.95. This indicates that meteorological drought analyses using SPI and RDI in this basin will result relatively the same. This result is also supported by Bayissa et al., 2021 (Bayissa et al., 2021b) in which the correlation of SPI and RDI for Kiremt (3 months) is 0.5 and for annual (12 months) is 0.85, respectively. However, the correlation of SPI and RDI in this study has a higher strength than Bayissa's finding. The analysis of the correlation between two meteorological drought indices and one hydrological drought index was considered from 1985 to 2014, which is the common data availability period for all indicators. The overall result shows that SDI has a relatively strong correlation with SPI than RDI.

Table 25 Hydro-meteorological drought indices correlation

Correlation	SPI1	SPI3	SPI6	SPI12	RDI1	RDI3	RDI6	RDI12
SDI1	**0.54**	0.63	0.49	0.51	**0.58**	0.66	0.43	0.46
SDI3	0.35	**0.83**	0.82	0.78	0.34	**0.84**	0.72	0.68
SDI6	0.29	0.81	**0.84**	0.78	0.26	0.80	**0.72**	0.66
SDI12	0.45	0.75	0.81	**0.87**	0.47	0.79	0.78	**0.83**
SPI1	1	**0.66**	0.49	0.55	**0.95**	0.65	0.41	0.54
SPI3	0.66	1.00	**0.83**	0.83	0.56	**0.95**	0.68	0.71
SPI6	0.49	0.83	1.00	**0.95**	0.43	0.85	**0.95**	0.89
SPI12	0.55	0.83	**0.95**	1.00	0.51	0.87	0.91	**0.95**

5.6.5 Spatial Distribution of Drought in Abbay River Basin

In this study, the temporal variability of hydrometeorological drought variability was assessed from fifteen meteorological stations and eight hydrological stations (streamflow stations) in the Abbay river basin. However, the temporal result gives information only about the magnitude of the drought event corresponding to the analysis time scale and it hides the spatial distribution of drought. Spatial distribution analysis has a vital role in drought early warning system development and appropriate drought mitigation measure planning. Figure 29 below indicates the spatial variability of hydrometeorological drought in the Abbay river basins for selected drought events. 1986, 1991, 1994, and 2001 were found the common moderate to extreme drought conditions for SDI, SPI, and RDI indices in most stations. In 1986, SDI12 and RDI 12 values show that most of the Abbay river basin was under severe to extreme drought (see Figure 29). On the other hand, in 1994 and 2001 the basin was affected by severe drought based on SDI 12 and RDI 12 results respectively. However, the SPI 12 spatial variability is minimal compared to SDI and RDI indices in all selected drought years. In the case of 1991, the basin was predominantly affected by moderate drought in both meteorological and hydrological drought indices. The meteorological drought spatial distribution analysis using SPI shows the minimum drought-prone area coverage compared to RDI. However, the hydrological drought severity is highly visible compared to meteorological drought results as indicated in Figure 29. This implies that investigation of hydrological drought is important to prepare good water resource management policy and drought early warning system development and mitigation measures in the Abbay river basin.

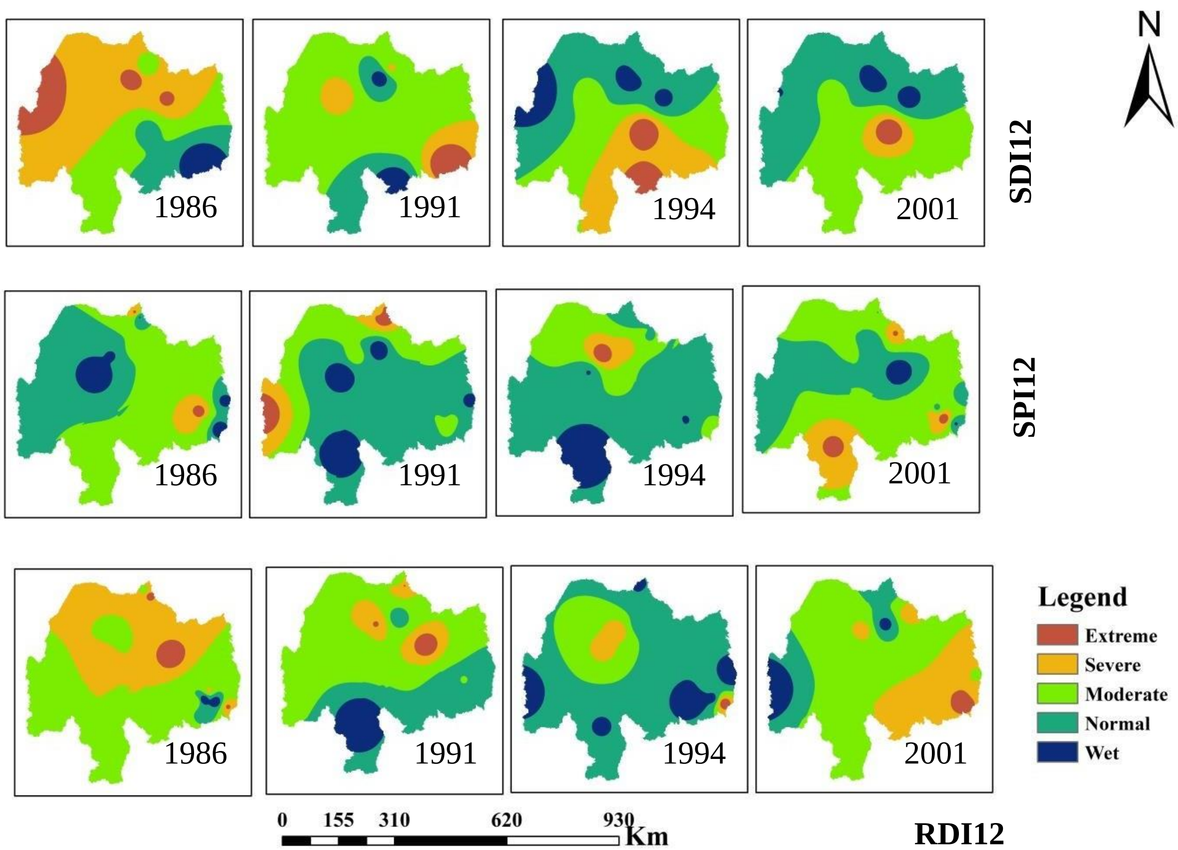


Figure 29 Spatial distribution of hydrometeorological drought in the Abbay river basin

5.7 Conclusion

In this study, the temporal-based assessment of the historical hydro-meteorological drought in the Abbay river basin, Ethiopia is presented. The analysis was conducted using 42 years of data (1973 – 2014) from fifteen meteorological stations and eight streamflow stations. The hydrological and meteorological drought time series was performed using two meteorological drought indices (SPI and RDI) and one hydrological drought index (SDI) respectively. The trend analysis was computed using the Mann-Kendall (MK) test and the result indicates that there was a positive increment of hydrological drought trend at Gummera, Kessie, and Border stations (Upper – Middle -Lower) parts of the basin, respectively for a long-timescale (SDI12). But for the case of meteorological drought, there are no significant drought trends at a 5% significant level for most stations in all time scales except Debre Berhan and Fiche which have increasing trends at SPI12 and RDI12. The most common severe hydrological drought years of the Abbay river basin were 1978, 1979, 1986, 1987, and 2010 whereas the extreme drought years were 1982, 1983, 1984, and 2001. For the meteorological drought condition, 1985, 2001, and 2008 were severe drought years, and 1975, 1981, 1984, 1986, 1991, 1994, and 2010 were extreme drought years. Commonly, 186, 1991, 1994, and 2001 were selected for spatial distribution analysis for SDI12, SPI12, and RDI12 time scales. Generally, in the year the 1980s, frequent drought events occurred in both meteorological and hydrological droughts. The relationship between meteorological and hydrological drought was increased as the time scale increased from 1 month to 12 months. SPI and RDI have a high correlation, this implies both indices are suitable for meteorological drought analysis in the Abbay river basin. The spatiotemporal drought variability of hydrological drought results shows more attention is needed for water resource management in the Abbay river basin. Recently, the Ethiopian government has planned many water resources-related projects to reduce the impact of poverty. However, hydrological drought studies are still limited in the country. Hydrological drought investigation will show the historical drought severity condition and trend of a specific area and it is possible to forecast the future hydrometeorological constraints in water resource management and infrastructure development. Therefore, this study has a vital role for decision-makers, researchers, water resource managers, and policymakers as a primary source for drought preparedness and mitigation measure development in the Abbay river basin.

6. Hydrological drought forecasting and monitoring system development using artificial neural network (ANN) in Ethiopia

Abstract

The objective of this study is to investigate and perform long–term forecasting of both streamflow and hydrological drought over Ethiopia. Observed streamflow and precipitation data are collected from 17 streamflow stations and 34 rainfall gauge stations to forecast future streamflow and hydrological drought from 2026 to 2100. Streamflow forecasting is performed using an artificial neural network (ANN) in conjunction with Python software. Observed precipitation and streamflow data from 1973 to 2014 are used to train and test the ANN model by 70 and 30% ratios, respectively. After training the model, future downscaled precipitation data from regional climate models (RCM) have been used as input data to forecast future streamflow. Three RCM models were used to downscale historical and future climate data. RACMO is found a good downscaling model for all selected stations. The linear scaling bias correction technique results in less than 2% error compared to other alternative techniques. The result indicates that ANN is a good tool to forecast streamflow in areas having a good correlation between precipitation and streamflow such as Abbay, Awash, Baro, Omo Gibe, and Tekeze river basins. But in arid areas for example Genale Dawa, Wabishebele, and Rift Valley basins, the model is not suitable because the input data (precipitation) have higher variation than the output variable (streamflow). In such areas, meteorological drought analysis and forecasting are better than hydrological drought analysis. Finally, future hydrological drought is analyzed using forecasted streamflow data as input to the streamflow drought index (SDI). The result indicates that 2028, 2036, 2042, 2044, 2062, and 2063 are the expected extreme drought years in most river basins of Ethiopia in the future. This shows that at least one extreme drought is expected in each decade in the future. Therefore, extensive research in drought analysis and forecasting is needed to develop an effective drought early warning system and water resource management policy.

Keywords: Artificial neural network, hydrological drought forecasting, linear scaling, regional climate model

6.1 Introduction

Drought results from a prolonged period of precipitation deficiency and shortage of surface and subsurface water availability (Alemu et al., 2021; Botai et al., 2021; Huang et al., 2017; Li et al., 2021). The definition of drought still depended on different perceptions but structurally it is categorized as meteorological, agricultural, hydrological, and socio-economic drought based on deficiency of precipitation, lack of surface and sub-surface water availability, and unfair water distribution between supply and demand (Wang et al., 2016).

Drought monitoring and forecasting play a great role in water resource management and early warning system development for drought and flood hazard mitigation. Artificial Neural Networks are now widely applied in a broad range of fields, including image processing, signal processing, medical studies, financial predictions, power systems, and pattern recognition among others (Modarres, 2007). Recently, several civil engineering problems such as structural damage analysis (Zhao et al., 2020b), material strength prediction (Zhao et al., 2022), buckling, and energy trapping in building blocks (Zhao et al., 2020a) have been solved using artificial neural networks. At the same time, ANN is also used in many aspects of hydrological and meteorological studies such as streamflow forecasting, groundwater analysis, precipitation forecasting, rainfall-runoff modeling, and water quality issues, flood and drought forecasting (Myronidis and Ioannou, 2018). Development in forecasting and early warning of drought phenomena is increasingly applied in many regions of the world. This is being done to mitigate the consequences of drought in vulnerable river basins and to save human life (M Wambua, 2014a).

Different drought modeling and forecasting techniques are in use today. The seasonal autoregressive integrated moving average model (SARIMA), the Adaptive Neuro-Fuzzy inference system, the Markov chain model, the Log-Linear model, and the Artificial Neural Network (ANN) model are some of the common drought-predicting models. (Barua et al., 2010; Djerbouai and Souag-gamane, 2016; Gemechu, 2021; Keskin et al., 2011; Khadr, 2016). Historically, time series-based statistical models for hydrologic drought forecasting have been applied. Regression models and autoregressive moving average (ARMA) models are typical models for statistical time series methods for forecasting. They are linear models, nevertheless, and they can only partially capture non-stationaries and non-linearity in the hydrologic data since they assume that the data are stationary (Mishra and Desai, 2006). However, the traditional statistical time series analysis in hydrology has several limitations related to non-linear variables. This problem is now overcome and improved by using robust time series predictive techniques like ANN (Zhao and Wang, 2022). Imprecise in nature, uncertainty, lack of data, and inconsistency, the physical characteristics of the region have a great influence on meteorological and hydrological variables in Ethiopia. In such circumstances, Fussy Logic techniques are renowned to be highly enhancing the modeling of such natural dynamics and variability (Barua et al., 2010; Khadr, 2016; Mishra and Desai, 2006). Drought is the most destructive natural phenomenon resulting from climate change it is usually important to analyze and monitor it on a regional scale. The fuzzy logic predictive system among the various available Artificial Intelligence techniques emerges as an advantageous technique in forecasting future hydroclimatic events such as floods and droughts. However, due to their inherent nonlinear nature and modeling flexibility, artificial neural networks (ANNs) have recently demonstrated tremendous capacity in modeling and forecasting nonlinear and non-stationary time series in hydrology and water resource engineering (Mishra and Desai, 2006). Among different drought forecasting models, the ANN model is appropriate for large and complex data sets to analyze and forecast (Boudad et al., 2018b).

The majority of water resource variables reveal a highly nonlinear behavior because of spatial and temporal variations (Noor, 2017). Therefore, to solve these nonlinear variables, one of the most attractive features is ANN modeling which can learn the exact behavior between the inputs and outputs from the examples without any kind of physical involvement (El Ibrahimi and Baali, 2017). Many applications of ANNs for prediction, forecasting, modeling, and estimation of water resource variables (i.e. water discharge, sediment discharge, rainfall-runoff, groundwater flow, precipitation, forecasting, water quality, etc.) have been found and related to river discharge and sediment (Mustafa et al., 2012). In recent years, ANNs have been used intensively for prediction and forecasting in several water-related areas, including water resource study and drought forecasting (Najah et al., 2013). It is clear that artificial neural networks constitute an emerging new technology, and their full potential for solving hydrologic problems must be explored further. ANN received a great deal in several hydroclimatic events in floods and drought forecasting for appropriate early warning system development (Allende et al., 2002; Carrão et al., 2018; Han and Singh, 2020; Jang et al., 2022; Kisi et al., 2019).

Every year drought has occurred in at least one or more countries in the world. This hydrological event has been widely concerned with water quality and water scarcity. Because hydrological drought can export or import dissolved organic carbon (DOC). However, the response relationship of DOC to hydrological drought characteristics in terms of duration and severity requires in-depth research (Wu et al., 2022). Many drought forecasting investigations indicated that artificial neural network is widely used in most water-related research due to their superior ability to forecast hydrological events from non-linear variables (Dastorani and Afkhami, 2011). There are many drought indices used to forecast future drought variability like standardized precipitation index (SPI), palmer drought severity index (PDSI), normalized vegetation index (NDV), and standardized streamflow index (SDI). The former three indices are used for meteorological and agricultural drought analysis while the latter fourth index is used for hydrological drought analysis. Recently using remote sensing instruments NVI is used to forecast drought severity but it has a limitation in areas that have no good vegetation coverage (Personal et al., 2014). Since the objective of this study is focused on hydrological drought forecasting related to climate change SDI is selected for analysis. However, the future SDI value is directly dependent on future streamflow variation and it is important primarily to forecast streamflow to estimate SDI values. Therefore, observed precipitation data at various stations near to streamflow station was used as input and a single streamflow station data was used as output to train and test ANN model performance. The statistical performance criteria such as root mean square error (RMSE), coefficient of determination (R^2), and mean absolute percentage error (MAPE) were used to check the performance of the ANN model prediction.

The major drawback of present studies in drought forecasting is using the same variable to forecast future drought conditions (Barua et al., 2010; Maca and Pech, 2016; Santos et al., 2009). Several scholars tried to forecast meteorological and hydrological droughts using ANN by introducing drought indices value as input data for the architecture of ANN (Belayneh and Adamowski, 2012; M Wambua, 2014b; Ozan Evkaya and Sevinç Kurnaz, 2021). Those scholars used the SPI time series value as input for the ANN input layer to predict one month or two months ahead. A statistical error computation result from a similar variable will result in a good performance. However, it does not give good information about the nonlinear problems. Therefore, this study is aimed to forecast future hydrological drought by integrating two different variables (precipitation and streamflow data). The historical precipitation data were used as input and historical streamflow as output in the model training. After checking the performance of ANN model streamflow prediction, the future streamflow was forecasted using downscaled precipitation data. Then the hydrological drought condition from 2026 – 2099 is forecasted using future streamflow values.

Surface and sub-surface water resources are directly related to streamflow variability. So streamflow forecasting has a great role in reservoir optimization development to mitigate future drought impacts on society (Sherif et al., 2022). Besides this streamflow forecasting using ANN is very important in water resource planning and management under poor gauged river basins (Adnan and Yuan, 2018). In streamflow time series analysis both peak flow and low flow are important issues in hydrology to develop strategic water resource management during hydrological events such as floods and droughts. Therefore, in this study streamflow is forecasted to predict the future drought condition in Ethiopia.

6.2 Materials and method

6.2.1 Description of the study area

Ethiopia is geographically located in East Africa at a latitude of 3^0 - 15^0N and a longitude of 33^0 - 48^0 E (Teshome, 2019a). There are twelve major river basins of which four are now categorized under low flow to dry basins (Mereb, Denakil, Ayisha, and Ogaden). Therefore, this study was focused on eight river basins; five are dominated by humid to temperate climate zones (Omo Gibe, Baro Akobo, Abbay, Awash, and Tekeze), respectively whereas the remaining three are dominated by semi-arid to arid climate zones (Genale Dawa, Rift Valley, and Wabishebele), respectively (Yared A Bayissa et al., 2015b; A Belayneh et al., 2014; Chemeda et al., 2010). Figure 30 shows the different climatic zones and the spatial location of selected hydrometeorological stations in the study area.

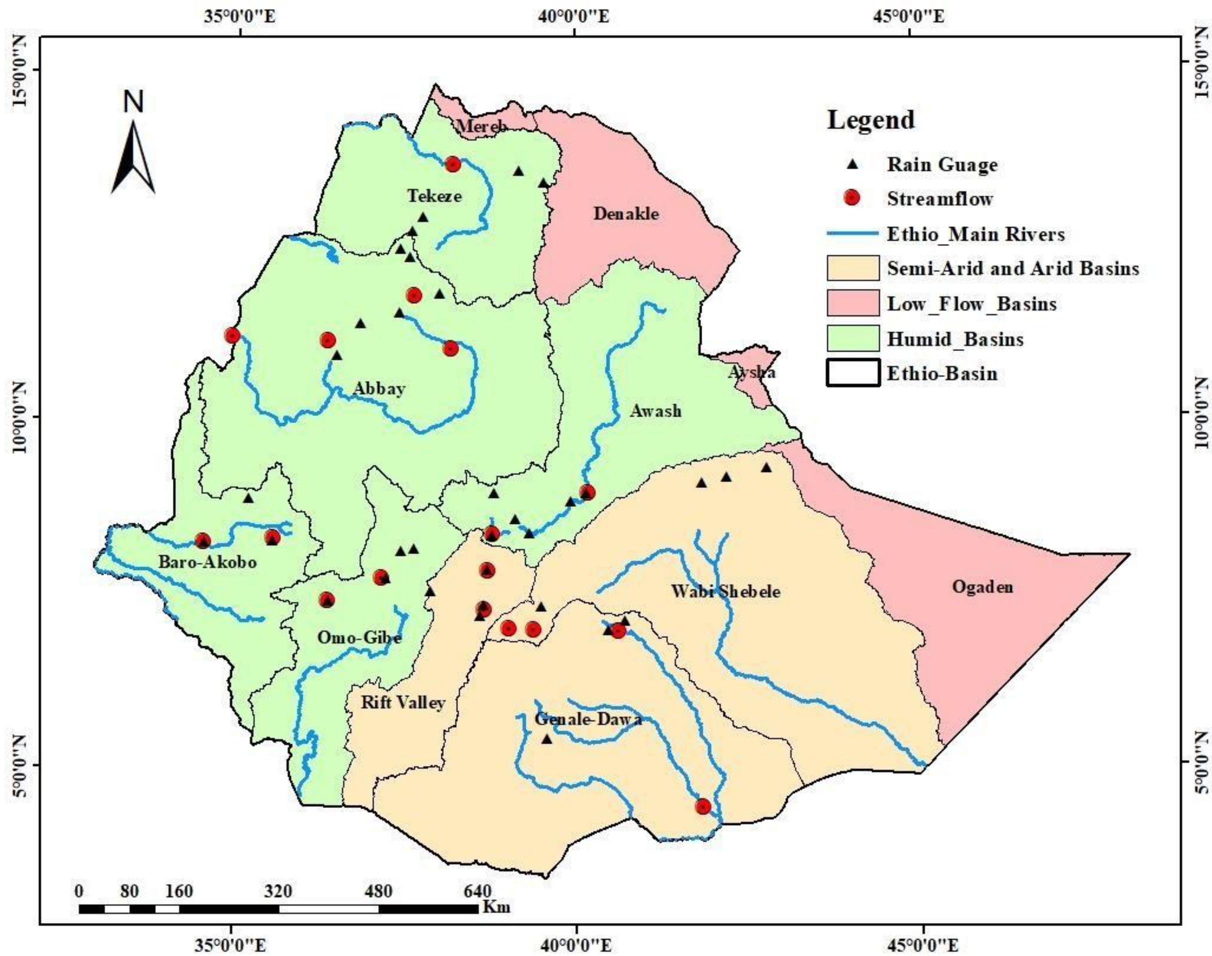


Figure 30 Major River basins in Ethiopia and spatial location of selected hydroclimatic stations

In the previous few decades, drought studies were conducted in some parts of Ethiopia with a special focus on meteorological drought assessment. However, hydrological drought analysis and long-term drought forecasting using the recent data-driven application are still not addressed. Therefore, this study addressed both streamflow forecasting and hydrological drought projection based on the historical observed data trend and future downscaled regional climatic data.

6.2.2 Data collection and preparation

Ethiopian Meteorology Institute (EMI) and the Ministry of Water and Energy (MoWE) provided daily precipitation and streamflow data, respectively. Observed rainfall data were collected from 42 stations and streamflow was from 35 stations from 1973 to 2014. However, only 34 rainfall stations and 17 streamflow stations show a good correlation to forecast future streamflow. The monthly rainfall was used as input and the mean monthly streamflow was used as an output for training and testing the artificial neural network (ANN) model using Python software. Downscaled precipitation data were also used for future forecasting of streamflow in all river basins from 2026 to 2100. Table 26 gives the geographical location of both hydrological and meteorological stations with some physical characteristics (Area and elevation) and the mean annual flow and annual rainfall of selected stations. Backpropagation multilayer perceptron (BPMLP) was used to predict future streamflow from past rainfall and streamflow.

Table 26 Basic statistical data of selected hydroclimatic stations

Hydrological Stations					
Basin	Stations	Latitude (°)	Longitude (°)	Area (Km^2)	Mean Annual flow (m^3/s)
Abbay	Gilgel Beles	11.17	36.37	675	17.81.2
	Border	11.23	34.98	17254	1670.9
	Gummera	11.83	37.63	1394	34.47
	Kessie	11.07	38.18	65784	523.39
Awash	Awash7	8.98	40.18	19110.8	17.52
	Hombel	8.38	38.78	7656	10.61
Baro	Gambela	8.25	34.58	23461	398.48
	Sorie	8.32	35.60	1622	50.8
Genale Dawa	Halewel	4.43	41.83	54093	168.63
	Weib	6.98	40.62	3576.9	11.26
Omo Gibe	Assendabo	7.75	37.18	2966	1217
	Gojeb	7.42	36.38	3577	1845.85
Rift Valley	Dedessa	7.28	38.67	156	1.12
	Kekersitu	7.85	38.72	7488	4.93
Tekeze	Embamadre	13.73	38.20	45694	258
Wabishebele	Wabi@bridge	7.02	39.03	1035	7.38
	Leliso	7.00	39.38	135	1.75
Meteorological Stations					
Basin	Stations	Latitude	Longitude	Elevation (m)	Annual rainfall (mm)

	Bahir Dar	11.60	37.42	1770	1423.9
Abbay	Gondar	12.52	37.43	1973	1161.3
	Debre Tabor	11.87	38.00	2612	1536.0
	Makisegnit	12.39	37.56	1912	1003.9
	Dangila	11.43	36.85	2116	1609.6
	Chagni	10.97	36.50	1614	1718.3
	Addis Ababa	8.98	38.80	2354	1042.8
Awash	Mojo	8.61	39.11	1763	953.8
	Awash7	8.98	40.15	923	617.4
	Metehara	8.86	39.92	944	520.7
	Melkawerer	8.40	39.32	1540	848.2
	Hombel	8.37	38.77	1743	863.8
	Alemteferi	8.90	35.23	1630	1636.4
Baro	Gambela	8.25	34.58	500	1162.6
	Metu	8.28	35.57	1711	1629.3
	Ginir	7.13	40.70	1750	1128.4
Genale Dawa	Goro	7.00	40.47	1800	938.0
	Negele	5.42	39.57	1544	690.0
	Abelti	8.17	37.63	1968	1068.5
Omo Gibe	Wolkite	8.13	37.45	2000	1232.5
	Assendabo	7.75	37.22	1764	1181.2
	Gojeb	7.42	36.38	1250	1500.3
	Arsi	7.35	38.65	1800	845.8
Rift Valley	Adamitulu	7.86	38.70	1653	836.4
	Hosana	7.55	37.87	2200	1162.2
	Shashemene	7.20	38.60	2080	791.5
	Dabat	12.98	37.75	2685	947.3
Tekeze	Hagereselam	13.65	39.17	2618	812.3
	Mekele	13.47	39.53	2257	591.2
	Ambagiorgis	12.77	37.60	2900	976.0
Wabishebele	Bisidimo	9.20	42.20	1669	717.9

Girawa	9.13	41.83	2100	973.4
Jijiga	9.33	42.78	1775	588.4
Endeto	7.34	39.49	2480	887.9

Once the relevant data was collected, missing data were filled using the arithmetic mean method and normal ratio method based on the normal annual rainfall percentage deviation with neighbor stations. In the case of Abbay, Awash, Baro, Omo Gibe, and Tekeze river basins, the percentage of missing rainfall data was insignificant. But in the arid river basins such as Genale Dawa, Rift Valley, and Wabishebele the missing was significant. After filling in some missed data, the consistency and homogeneity test was conducted on all stations using a double mass curve and non-dimensional ratio method, respectively and the analysis revealed that all selected stations were considered for streamflow forecasting and future drought analysis.

6.2.3 Downscaling climatic data and bias correction

For the last five and six decades, several researchers have conducted climate change investigations in different parts of the world. However, local climate changes force different sights of understanding the effect of natural disasters related to climate change. The successful understanding of local climate change impact has a great role in climate adaptation and early warning system development for drought and flood mitigation. Future and past (Historical) daily precipitation data were projected from Global Climate Models (GCM)and Regional Climate Model (RCM) from the African domain using CORDEX projects. Since the GCM data spatially covers a large area and its resolution is coarser (Chokkavarapu and Ravibabu, 2019), the data were generated from RCM for the Africa domain (AFR-44) historically from 1965 to 2005 and the future was from 2026 to 2100 using the RCP4.5 climate change scenario. MIROC5, KNMI, and SMHI were the driving GCM models, and RCA4, RACMO, and RCA were the corresponding RCM models selected for this study. Both the historical and future climate data were downscaled from Coupled Model Intercomparison Project Phase 5 (CHIP5). The statistical downscaling model (SDSM) was applied to project the historical and future climate data due to its superior ability to capture local scale climate variability. After bias correction using Climate Model data for the hydrological modeling (CMhyd) tool, the three models' data generation performance was checked by the coefficient of determination (R^2), and mean absolute percentage error (MAPE) using overlap year data from 1973 to 2005. Five bias correction techniques were evaluated in this study. These are delta change correction (DCC), precipitation local intensity scaling (PLIS), linear Scaling (LS), power transformation (PT), and distribution mapping for Precipitation (DMP). Finally, by comparing their percentage of error, an appropriate bias correction technique is selected.

6.2.4 Streamflow forecasting using Artificial Neural Network

Climate change is the primary cause of hydroclimatic events, floods, and drought. This climatical variability can directly affect the natural water availability such as streamflow, groundwater, reservoir, lake, etc. (Emiru et al., 2022; Mukherjee et al., 2018; Zegeye, 2018). Hydrological drought monitoring and forecasting are associated with surface and subsurface water availability. However, future streamflow forecasting is a challenging task for researchers due to its spatial and temporal variability. Drought affects the natural environment of an area when it persists for a longer period. Therefore, drought forecasting is crucial for river basin planning and management of its water and natural resource systems. In the previous ten years, neural networks have demonstrated excellent modeling and forecasting capabilities for nonlinear and non-stationary time series (Mishra et al., 2007).

Recently there have been several physical-based hydrological models to predict streamflow. But most of them require intensive input data and complex mathematical algorithms. Because the transformation process from rainfall to streamflow is complex and non-linear. Since the rainfall distribution can be influenced by temporal and spatial factors, such as duration of rainfall, and catchment characteristics. Therefore, this complex and non-linear process is not easily described by a simple model. Nowadays, the application of Artificial intelligence and Machine learning is becoming a prominent tool for many aspects of water resource studies (Khashei and Bijari, 2010; Kolarik and Rudorfer, 1994; Tealab, 2018; Wibawa et al., 2022).

In this study, ANN was applied to explore simulating the nonlinear hydrologic behavior of eight river basins to forecast future hydrological drought. In the development of ANN architecture, input selection and decision on the number of hidden layers and perceptron play a great role in the model output performance. In each river basin, the input data were selected by checking historically observed precipitation and streamflow correlation. Out of 42 rainfall stations and 32 streamflow stations, only 34 rainfall and 17 streamflow stations showed a good correlation. Therefore, two or more rainfall stations are used as input to forecast streamflow at a single station. Forty-two years of consecutive historical monthly precipitation and streamflow data were applied to train and test the ANN model. The first thirty years of data (360 months) were used for model training (70%), while the remaining twelve years of data (204 months) were used for the evaluation of model performance (30%). The architecture of the ANN structure contains three layers (input, hidden, and output), respectively (see Figure 31). To forecast the future condition of drought, first, the model is well-trained, tested, and validated using historical observed data, and the performance of the model was checked by coefficient determination (R^2), root means square error (RMSE), and mean absolute error (MAE) with the observed data. After the train and test reached recommendable statistical performance, 75-year future precipitation data (2026 to 2100) was used as an input to forecast future streamflow. Figure 31 is an illustrative example of one streamflow station forecasting in the Abbay river basin. Seven precipitation stations were used as input and streamflow at the Border station was used as the output variable. In the same manner, the remaining streamflow stations in this study were computed in the same procedure as the Border station.

R and Python programming software are used in many water resources studies such as flood inundation analysis, sediment prediction, low flow, and high flow forecasting, water quality analysis, natural disasters monitoring, and mitigation measure development. Studies indicated that Python software becomes more efficient than R and is applicable in many data-driven environments (Ozgur et al., 2021). Therefore, in this study python software was applied to forecast future streamflow using generated monthly precipitation from the Regional Climate Model (RCM) as input for Back Propagation Multi-Linear Perceptron (BPMLP). Therefore, input – the hidden – output layer architecture relation was developed by trial-and-error approach until the model performed to the acceptable range.

The performance of forecasting streamflow using ANN was performed by trial-and-error approach. The important parameters considered in trial and error are epoch, batch size, and the number of perceptrons in the hidden layer. After many trials, epoch and batch size were fixed as 100 and 64, respectively. A small number of neurons in the hidden layer results in underfitting whereas large numbers result in overfitting. Therefore, by trial-and-error procedure, appropriate numbers of neurons in the hidden layer were selected for each specific station. All the input and output variables were standardized from 0 to 1, to illuminate the time and spatial variability problem. The sigmoid function was applied between the input and hidden layer whereas a linear regression function was applied between the hidden and output layer. The sigmoid function is mainly used as an activation function in various layers of neural networks. The estimation of the sigmoid function in a backpropagation neural network approach is given by Equation 1 (Watkin, 1923). If the value of x is more negative, the output is approximately 0; and if the value of x is more positive, the output is approximately 27.

$$\sigma(x) = \frac{1}{1+e^{-x}} \qquad 27$$

Where $\sigma(x)$ is sigmoid function

The main difficulty in the artificial neural network is deciding the number of hidden layers and the number of perceptrons in each hidden layer. Increasing the number of hidden layers makes the ANN architecture more complex and the performance of the overall system is reduced. Therefore, a single hidden layer is mostly recommended by scientists (Arifin et al., 2019).

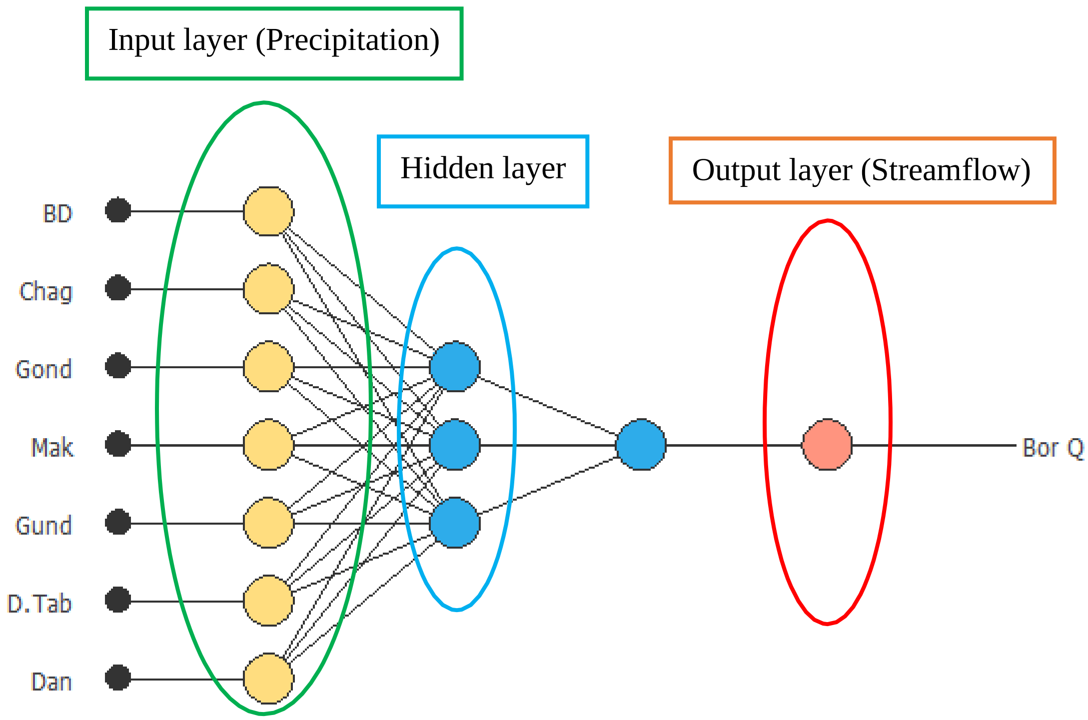


Figure 31 A three-layer feedforward neural networks Architecture for streamflow forecasting

6.2.5 Model performance measures

Statistically, there are several models of performance measuring techniques. Root Mean Square Error (RMSE), Coefficient of determination (R^2), and Mean Absolute Percentage Error (MAPE) are the most common performance measures. Those three techniques were adopted for this study to check the performance of the backpropagation multi-linear perceptron (BPMLP) model to forecast monthly streamflow using monthly precipitation data as model input. The performance evaluation of each technique is described by Equations 28, 29, and 30, respectively (Hodson, 2022; Kim and Kim, 2016; Zhang, 2017).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Q_{obs} - Q_{sim})^2}{N}} \qquad 28$$

$$r = \frac{n(\sum Q_{obs} * Q_{sim}) - (Q_{obs})(Q_{sim})}{\sqrt{[n \sum Q_{obs}{}^2 - (\sum Q_{obs})^2][n \sum Q_{sim}{}^2 - (\sum Q_{sim})^2)]}} \qquad 29$$

Where coefficient of determination (R^2) = coefficient of correlation square (r^2)

$$MAPE = \frac{1}{N} \sum_{i=1}^{n} \left| \frac{Q_{obs} - Q_{sim}}{Q_{obs}} \right| \qquad 30$$

Where n is the number of observed data, Q_{obs} and Q_{sim} are the observed and simulated streamflow data respectively.

6.2.6 Future hydrological drought characterization

There are several hydrological drought indicators applied in many countries such as Palm Hydrological Drought Severity (PHDS), Surface Water Supply Index (SWSI), and Streamflow Drought Index (SDI). However, the selection of these indicators depends on their input data requirement, simplicity, widely practiced, etc. For example, PHDS and SWSI require at least three input data and for future drought analysis, all those required data could not be easily predicted. Accordingly, the streamflow drought index (SDI) is selected for this study to characterize future hydrological drought trends in Ethiopia using forecasted streamflow data as an input. The analysis of SDI is given by Equation 31 below and Table 27 shows the hydrological drought severity levels using SDI.

$$SDI = \frac{Q - Q_m}{\sigma} \qquad 31$$

Where Q and Q_m are seasonal observed and mean streamflow, respectively and σ is the standard deviation of the observed streamflow.

Table 27 SDI values for different drought severity levels

Drought Condition	Wet	Normal	Mild Drought	Moderate drought	Severe drought	Extreme drought
Value	≥ 1.5	-0.4 – 1.4	-0.5 - -0.99	-1 - -1.4	-1.5 - -1.99	≤ -2

6.3 Results

6.3.1 Climate data bias correction

Historical and future climate data was downscaled from GCM and RCM. Finally, the data was extracted and bias-corrected using five techniques with the help of Climate Model data for the hydrologic modeling (CMhyd) tool. It is found that Linear Scaling (LS) and power transformation (PT) have a minimum error. From the three selected models, the result shows that the RACMO regional climate model (RCM) has good performance using the linear scaling bias correction technique. Except for the Omo Gibe River basin, all river basins satisfied that the RACMO model has a minimal error using the linear scaling bias correction technique whereas the Omo Gibe River basin has a minimum error using the RCA4 model, and the Linear Scaling bias correction technique also had a good performance. From Table 28, it is observed that power transformation has minimum error compared to linear scaling for MIROC5. But for RACMO and RCA4, linear scaling has a minimum error of bias. Therefore, the linear scaling technique has good performance for bias correction of downscaled climate data by reducing the error below 2% and producing better climate-simulated outcomes in all river basins as shown in Table 28. This result is agreed with (Tumsa, 2022) and the scholar found that the linear scaling bias correction technique has below 5% error.

Statistically, RACMO shows high performance than MIROC5 and RCA4 (SMHI). This result indicated that the bias-corrected future projected precipitation data generated from the RCP4.5 scenario can be directly used for future climate variabilities analysis such as streamflow forecasting and drought monitoring analysis. Since RCP 4.5 is considered for optimal temperature variation in the globe. Therefore, the RCP4.5 scenario is selected for this particular study to forecast future streamflow using projected future precipitation data.

Table 28 Comparing a bias correction technique and climate-generating models

Basin	Bias correction Technique	Model Error (%)		
		MIROC5	RACMO	RCA4
Abbay	Linear Scaling	2.43	1.67	1.89
	Power Transformation	2.31	1.89	2.17
Awash	Linear Scaling	3.57	1.44	1.96
	Power Transformation	3.06	1.48	1.90
Baro	Linear Scaling	2.14	1.12	1.22
	Power Transformation	1.95	1.28	1.29
Genale Dawa	Linear Scaling	4.00	1.54	2.63
	Power Transformation	3.93	1.68	2.53
Omo Gibe	Linear Scaling	2.55	2.43	2.01
	Power Transformation	2.50	2.37	2.03
Rift Valley	Linear Scaling	3.41	1.26	1.91
	Power Transformation	3.31	1.27	1.68
Tekeze	Linear Scaling	1.67	1.30	1.57
	Power Transformation	1.47	1.60	1.70
Wabishebele	Linear Scaling	5.88	2.37	3.98
	Power Transformation	7.06	2.80	3.43

6.3.2 Artificial Neural Network architecture development and streamflow forecasting

Table 29 shows the number of trials that found a good performance in line with selected epoch, batch size, and perceptron for different stations in Ethiopia and their corresponding statistical value of observed and simulated streamflow, respectively. The number of trials depends on the number of epochs, batch size per iteration, and the number of perceptrons in a hidden layer. The epochs and batch size were tested from 50, 100, 1000 and 16, 32, 64, 128, respectively. From many trials, 100 epochs and 64 batches size give a good performance. Then by fixing those values for all stations, the trail was repeated by changing the number of perceptron in the hidden layers.

Table 29 Parameter values used to train and test hydrometeorological data sets in ANN

Stations	Number of trials	Epochs	Batch size	Hidden layer Perceptron	Mean $Q_{obs}(m^3/s)$	σ_{obs}	Mean $Q_{sim}(m^3/s)$	σ_{sim}
Gummera	5	100	64	8	34.5	9.9	42.3	8.3
Gilge Belles	11	100	64	7	17.8	4.5	16.2	1.8
Kessie	13	100	64	8	523.7	166.5	698.9	102.6
Border	13	100	64	6	1675.7	325.5	2809.3	328.6
Awash7	4	100	64	6	57.6	17.5	65.4	6.8
Hombel	6	100	64	16	41.7	10.6	45.7	10.9
Gambela	7	100	64	8	398.5	94.3	393.2	31.6
Sorie	9	100	64	16	50.8	12.6	49.3	5.1
Assendabo	8	100	64	12	1217.5	309	1501.8	243.1
Gojeb	7	100	64	4	1845.9	433.9	1470.2	254.9
Embamadre	3	100	64	10	258	104.2	431.2	23.94
Wabishebele	5	100	64	9	7.4	2.1	9.1	1.1
Leliso	6	100	64	7	3.8	1.3	3.1	0.33

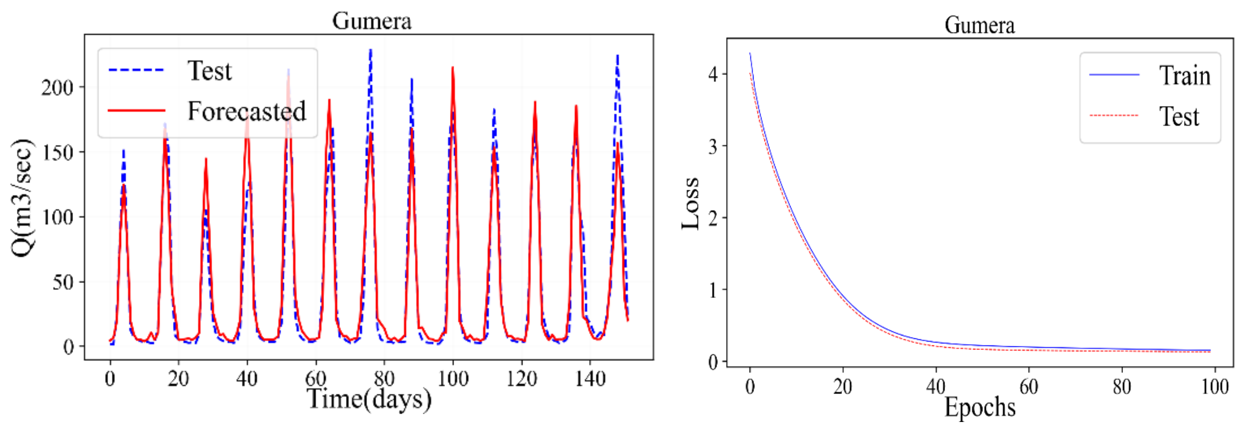
Table 30 clearly shows that relatively humid climate basins such as Abbay, Awash, Baro, Omo Gibe, and Tekeze have good prediction performance whereas the arid basins like Genale Dawa, Wabishebele and Rift Valley have low prediction performance. The reason is that the hydroclimatic variables such as precipitation and streamflow variability are higher in arid areas than in humid areas. The correlation between annual precipitation and mean annual streamflow for humid and arid basins of this study was found 0. 55 to 0.77 and 0.23 to 0.52, respectively. As a result, forecasting future streamflow using highly varied precipitation data directly affects hydrological drought prediction and water resource management. This result agreed with previous drought predictions in using forecasted streamflow in Iran by Dasstorami. M.T. and Afkhami. H (2011) (Dastorani and Afkhami, 2011). From Table 30, it is understood that the Abbay, Baro, and Omo Gibe River basins resulted in excellent streamflow forecasting performance compared to the remaining river basins. As shown in Table 26, those basins received annual precipitation above 1000 mm. Even though the RMSE and MAPE values for three arid river basins (Genale Dawa, Rift Valley, and Wabishebele) are acceptable, the R^2 value is minimal. This indicates that ANN is suitable for humid and temperate climate zones to forecast streamflow from precipitation data.

Table 30 Statistical comparison of ANN forecasting performance

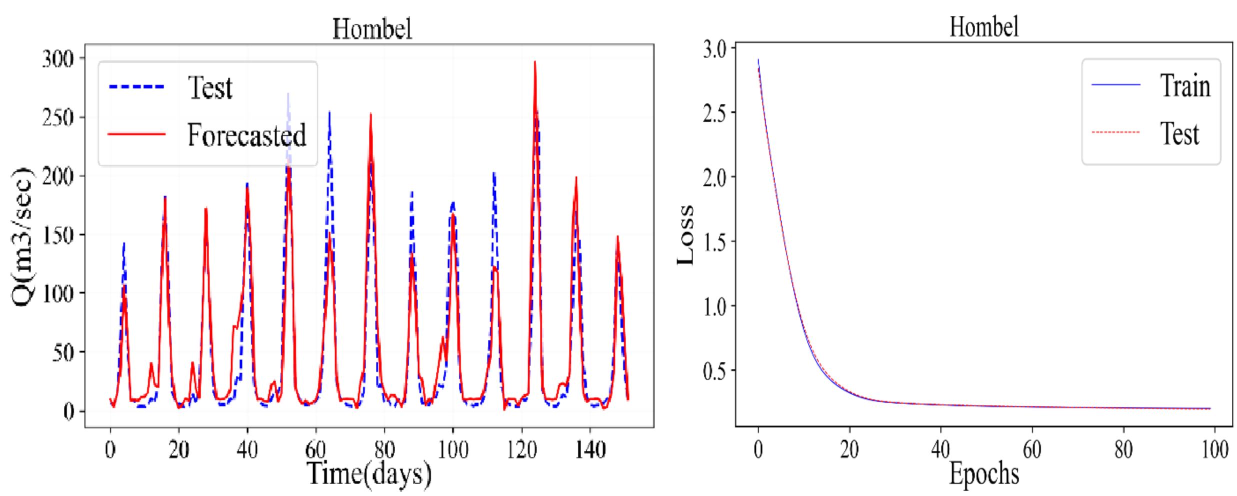
River basin	Station	Modell Architecture	RMSE	MAPE	R^2
Abbay	Gummera	3, 8, 1	1.9	1.1	0.9
	Gilgel Belles	3, 7, 1	0.83	0.47	0.83
	Kessie	3, 8, 1	3.6	2.3	0.81
	Border	4, 6, 1	11	8.32	0.84
Awash	Awash7	4, 6, 1	3.1	2.1	0.68
	Hombel	3, 16, 1	2.3	1.4	0.87
Baro	Gambela	2, 8, 1	16.1	11.6	0.77
	Sorie	3, 16, 1	2.03	1.4	0.83
Genale Dawa	Halewe	3, 8, 1	4.98	3.26	**0.59**
	Weib	2, 4, 1	12.45	9.4	**0.2**
Omo Gibe	Assendabo	3, 12, 1	6.5	4.7	0.77
	Gojeb	2, 4, 1	7.2	4.7	0.75
Rift Valley	Wosha	3, 8, 1	0.14	0.13	**0.24**
	Dedeba	3, 8, 1	1.31	0.89	**0.48**
Tekeze	Embamadre	4, 10, 1	12.5	8.8	0.7
Wabishebele	Wabishebele	2, 9, 1	5.66	4.22	**0.54**
	Leliso	3, 7, 1	1.82	1.29	**0.55**

Where 3, 8, and 1 indicate the number of input variables, Hidden perceptron, and output variable, respectively

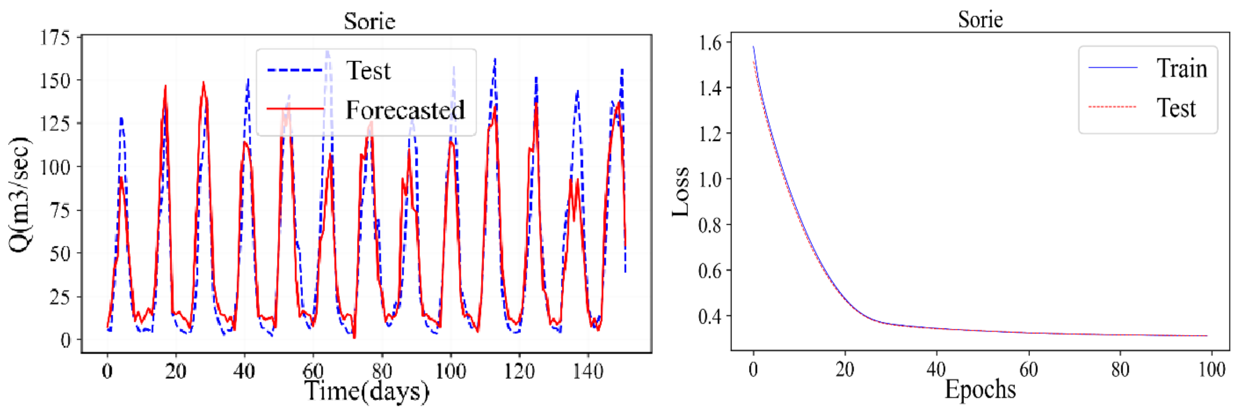
Figure 32 (a, b, c, d) shows the observed versus forecasted streamflow time series graph for the Abbay, Awash, Baro, and Omo Gibe River basins, respectively, developed using Python software and the ANN model. The result revealed that the observed and simulated fitted with good performance. The analysis was computed using precipitation data as input and streamflow data as output in the ANN model setup. From this analysis, it is observed that streamflow forecasting from precipitation data has a significant relation. As shown in Figure 32, the loss decreases as the epoch increases in all selected streamflow stations. For a selected 100 epoch and 64 batch sizes, the train and test were best performed. The ultimate goal of forecasting streamflow in this study is to see the future hydrological drought trend in Ethiopia.



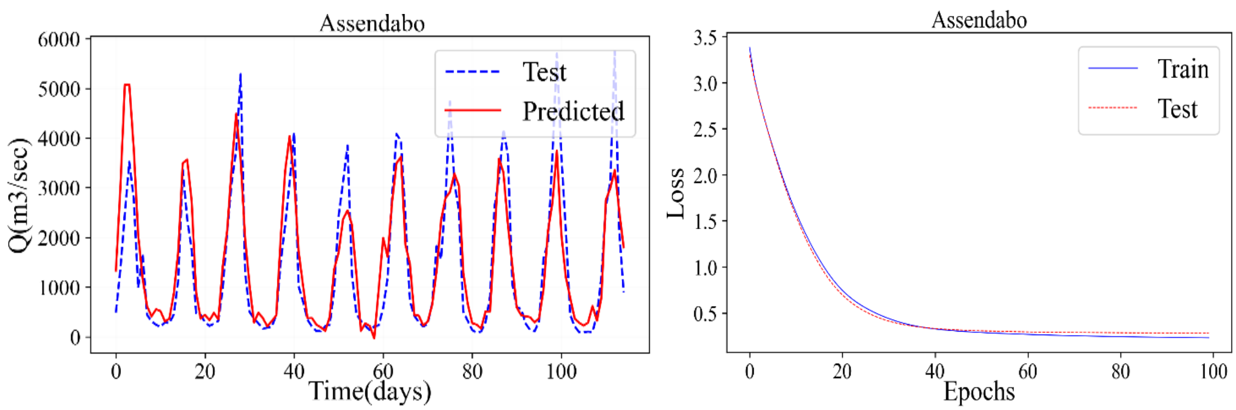
a) Gummera Station (Abbay basin)



b) Hombel station (Awash basin)



c) Sorie station (Baro basin)



d) Assendabo station (Omo Gibe basin)

Figure 32 Observed and forecasted streamflow time series plot using ANN in Python software

6.3.3 Future hydrological drought characterization

In all river basins except Genale Dawa and Rift Valley basins, the performance of streamflow forecasting using ANN indicated the possibility of using simulated streamflow time series to predict future hydrological drought conditions. Therefore, the forecasted streamflow was directly used as input for the DrinC model to predict future hydrological drought analysis. However, in this study, Genale Dawa and Rift Valley basins were excluded due to the low performance of streamflow forecasting results. Therefore, the future hydrological drought analysis was conducted for six river basins as shown in Figures 33 - 38. The analysis was considered for four time scales; monthly (SDI1), seasonal (SDI3), half-year (SDI6), and annual (SDI12) time scales. The result revealed that the frequency of drought occurrence is high for monthly (SDI1) and seasonal (SDI3) time scales compared to half-year and annual time scales (see Figure 37). However, the duration of severe and extreme drought is high for annual time-scale analysis. Therefore, for this study, the result and discussion part focused on the annual (SDI12) time scale. Future hydrological drought condition in Ethiopia is analyzed for each river basin separately.

In the Abbay river basin, four streamflow stations were considered for future drought analysis and the result indicated that the probability of severe and extreme drought occurrence from 2026 to 2041 was less in all stations. But in 2026, 2031, 2033, 2037, and 2040 moderate drought events are expected in some stations in the basin. However, Figure 33 shows that 2042 to 2045, 2049/2050, 2052 to 2054, 2062, 2065, 2072/2073, and 2097/2098 are the most expected moderate to extreme drought years in the Abbay river basin. The most severe magnitude and frequency were identified at the Gummera and Beles streamflow stations. The analysis indicated that the probability of severe drought occurrences in the future is higher in the Abbay river basin compared to other river basins.

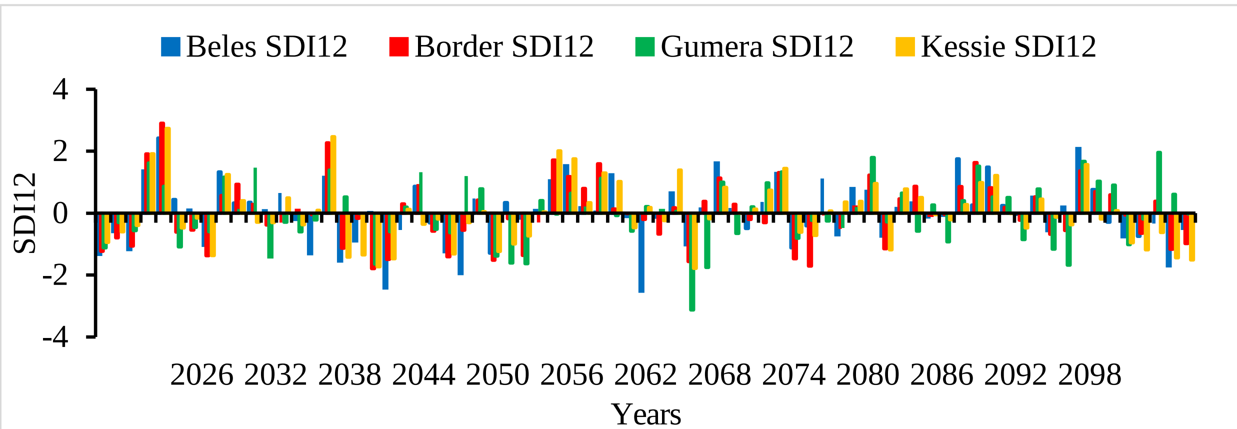


Figure 33 Future hydrological drought time series in the Abbay river basin (2026 – 2099)

Figure 34 indicates that 2036, 2042, 2063, 2079, 2086, and 2097 are severe and extreme drought events in the future in the Awash River basin. 2042, 2063, and 2097 are the common severe drought events for both the Abbay and Awash river basins. This implies that a strong water resource management strategy, early drought warning system development, and good drought preparedness policies will be important in those basins in the future. The Awash river basin is a landlocked river and is more utilized for multipurpose. Water sharing and water stress are common problems in this river basin. In the future, climate change and drought will aggravate the water-sharing problem. Therefore, a strong water resource management system and systematic water allocation approaches are needed.

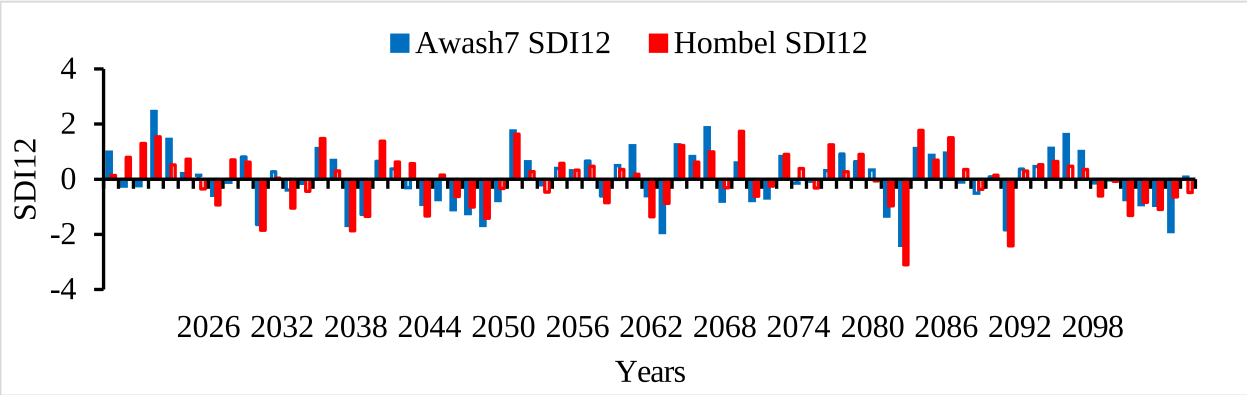


Figure 34 Future hydrological drought time series in the Awash river basin

Baro Akobo and Omo Gibe River basins receive rainfall twice a year and have good climate conditions compared to other river basins (El Afandi et al., 2016; Stojanovic et al., 2022). Although they received good rainfall, hydroclimatic disasters such as floods and droughts occurred in different parts of the basin (Stojanovic et al., 2022). However, comprehensive drought studies were yet done in both Baro Akobo and Omo Gibe River basins. Figures 35 and 36, respectively indicated that the frequency of severe and extreme drought occurrence is higher in the Baro river basin than in the Omo Gibe River basin. The future drought analysis implies that 2036, 2050, 2059, 2066, 2072, and 2086 are severe drought years 2040, 2062, and 2063 are extreme drought years for the Baro river basin whereas 2036 and 2094 are severe and 2063 are extreme drought years for Omo Gibe basin, respectively. Baro Akobo river is yet utilized but in the Omo Gibe basin there are few hydropower plants and irrigation projects are implemented in different tributaries of the main rivers; Aseendabo and Gojeb. The drastic drought in 2018 in the southern parts of Ethiopia affected the Gibe I and II hydropower plant production. During this year, the two hydropower plants produced energy below their expected potential. In the future, some hydropower plants are planned in the Baro Akobo river basin and it needs attention to consider the impact of drought resulting from climate change. Unless the construction and implementation of big developmental projects without detailed information the future hydroclimatic conditions will result in national economic crises.

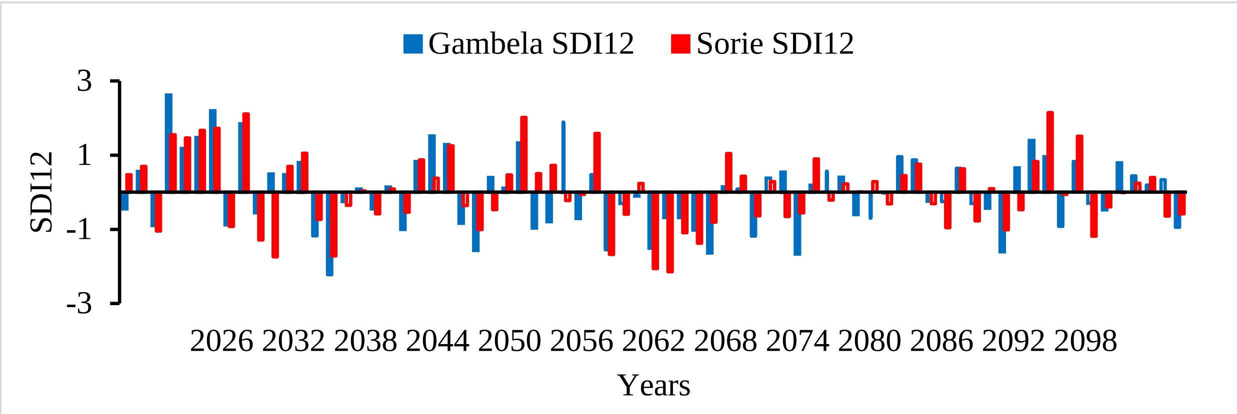


Figure 35 Future hydrological drought time series in the Baro Akobo river basin

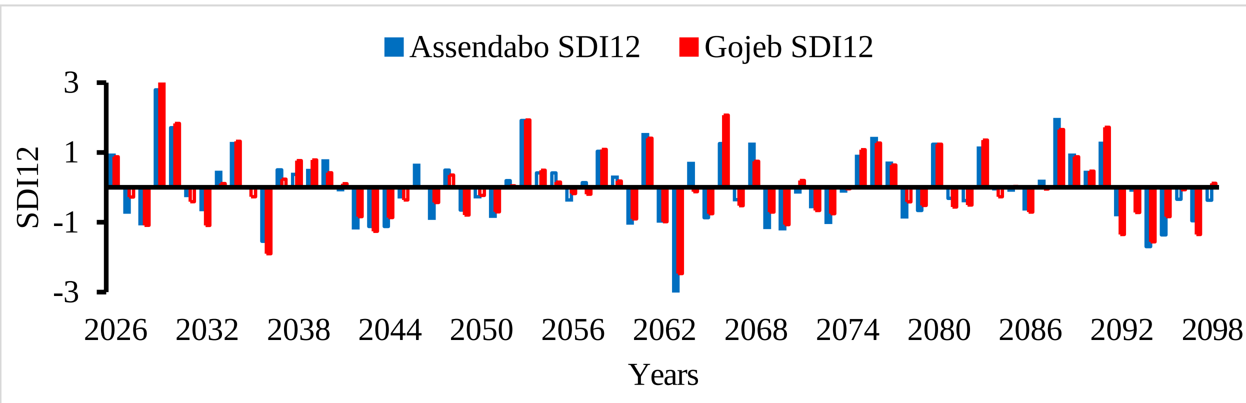


Figure 36 Future hydrological drought time series in the Omo Gibe river basin

In the Tekeze river basin, a single station data at Embamadre station was used to estimate SDI values at different time scales as shown in Figure 37. Historically northeast part of Ethiopia is frequently affected by prolonged drought phenomena (Araya and Stroosnijder, 2011; Mohammed, 2018). Gemeda (2022) also found that the northeast and southeast are the most drought-prone areas in Ethiopia (Gemeda et al., 2022). Since the Tekeze river basin is located in the northern parts of the country the result of this study also revealed the previous studies. The annual time scale (SDI12) results, 2028, 2037, 2038, 2054, 2063, 2065, and 2082 are the expected severe drought events in the Tekeze river basin. Based on the seasonal analysis, 2030 and 2053 were the expected extreme drought years. However, in hydrological drought analysis long time scale, 12 months and above is important to formulate the drought preparedness strategies and mitigation measurement development. However, the seasonal time scale result has good importance in meteorological drought analysis.

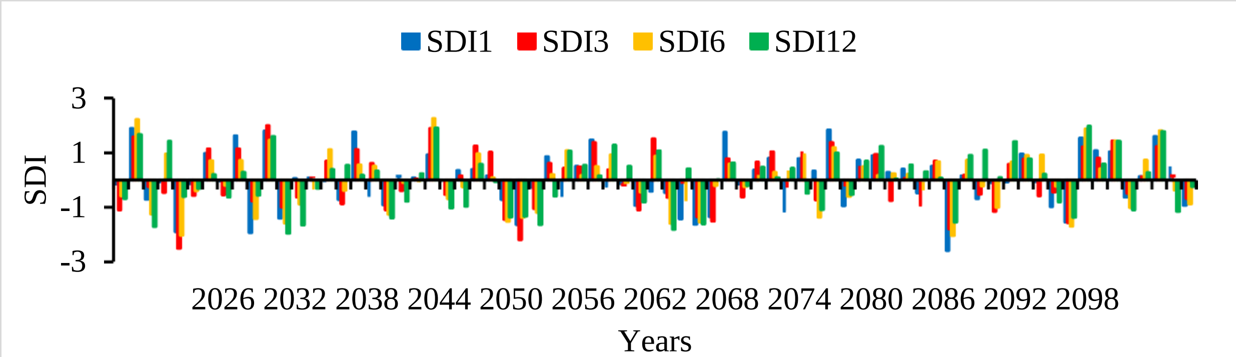


Figure 37 Future hydrological drought time series in the Tekeze river basin

Wabishebele river basin is one of the arid climate zone basins in Ethiopia. Future hydrological drought analysis was explored in this basin at two stations as shown in Figure 38. It is found that 2036, 2037, 2063, 2065, and 2072 are severe drought years whereas 2028 and 2042 are the most extreme drought years in the future in the Wabishebele river basin (see Figure 38).

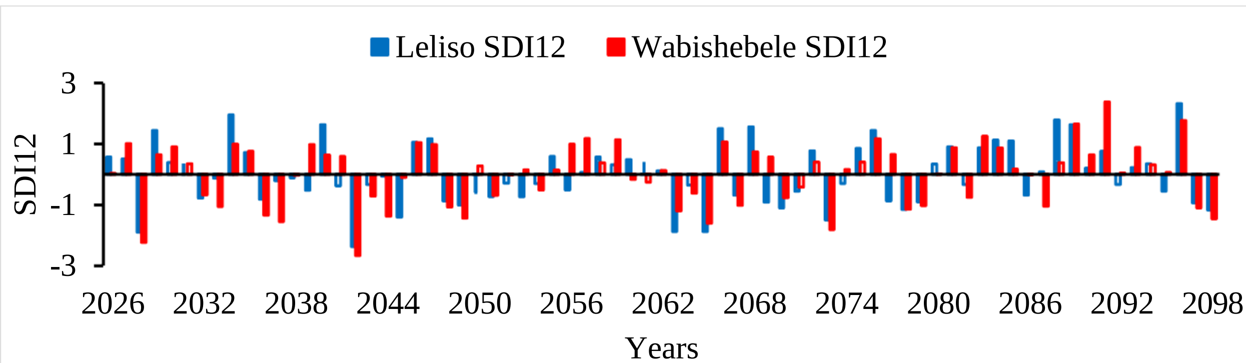


Figure 38 Future hydrological drought time series in the Wabishebele river basin

In this study, the future hydrological drought analysis was explored from 2026 to 2099 (74 years). Tables 31 and 32 show the expected future drought occurrence years at different streamflow stations in all river basins and a summary of each drought condition in a specific river basin in terms of percentage, respectively. The result also revealed that the frequency of moderate drought is increased in all river basins compared to severe and extreme drought occurrences. On the other hand, the occurrence of extreme drought is low compared to the last historical drought events in Ethiopia. For the case of the Tekeze river basin, a single streamflow station was used due to a lack of long-time recorded data as a result the probability of severe and extreme drought existence is also minimal (See Table 31).

Table 31 Summary of expected future drought years in Ethiopia at different river basins

Basins	Stations	Moderate (-1 - -.149)	Severe (-.15 - -1.99)	Extreme (≤ -2)
Abbay	Beles	2026, 2028, 2033, 2040, 2049, 2052, 2065, 2072, 2097	2042, 2050	2045, 2062
	Border	2026, 2028, 2033, 2042, 2045, 2054, 2072, 2078, 2097	2044, 2052, 2065, 2073	
	Gummera	2026, 2031, 2037,2052, 2089, 2094	2044, 2053,2054, 2066, 2090	2065
	Kessie	2026, 2033, 2042, 2043, 2045, 2049, 2052, 2053, 2065, 2078, 2096, 2097	2044, 2098	
Awash	Awash7	2043, 2049, 2052, 2078	2036, 2042, 2051, 2063, 2086, 2097	2079
	Hombel	2038, 2043, 2047, 2050, 2051, 2062, 2094, 2096	2036, 2042	2079, 2086
Baro Akobo	Gambela	2039, 2045, 2065, 2069	2050, 2059, 2062, 2066, 2072, 2086	2040
	Sorie	2028, 2035, 2050, 2064, 2065, 2086, 2092	2036, 2040, 2059	2062, 2063
Omo Gibe	Assendabo	2028, 2042, 2043, 2044, 2060, 2069, 2070, 2073, 2095	2036, 2094	2063
	Gojeb	2028, 2032, 2043, 2070, 2092, 2097	2036, 2094	2063
Tekeze	Embamadre	2044, 2048, 2052, 2053, 2073, 2090, 2094, 2097	2028, 2037, 2038, 2054, 2063, 2065, 2082	
Wabishebele	Leliso	2045, 2049, 2070, 2078, 2098	2028, 2063, 2065, 2073	2042

Wabishebele	2033, 2036, 2044, 2063, 2067, 2078, 2079, 2087, 2097, 2098	2037, 2048, 2049, 2065, 2073	2028, 2042

Table 32 Percentage of drought occurrence per year based on the number of drought years

Drought condition	Number of drought years in each River Basins					
	Abbay	Awash	Baro Akobo	Omo Gibe	Tekeze	Wabishebele
Moderate	17	11	10	13	8	13
Severe	11	6	8	2	7	7
Extreme	3	2	3	1	0	2
	Percentage of occurrence per year (%)					
Moderate	22.97	14.86	13.51	17.57	10.81	17.57
Severe	14.86	8.1	10.81	2.7	9.46	9.46
Extreme	4.05	2.7	4.05	1.35	0	2.7

6.3.4 Discussions

Climate change aggravates hydroclimatic hazards such as floods and droughts (Pahl-Wostl, 2010). To monitor and develop appropriate mitigation measures for those events, downscaling projected climate data plays a great role. Since Ethiopia is located under the Africa domain (AFR – 44) the historical and future daily precipitation data were downscaled from three regional models (MIROC5, RACMO, and RCA4) using the RCP4.5 climate change scenario. Even though the regional climate data has minimal error compared to the Global Climate Model (GCM), bias correction of raw data further reduced the projection error. In this study, five bias correction methods were applied and the result revealed that linear scaling (LS) has good performance and reduced the error below 2%. This result agreed with Nurul Nadrah's (2018) finding, which found that LS reduced climate-simulated error reduced below 3% (Aqilah Tukimat, 2018).

Hydrological drought forecasting depends on the future variability of surface water availability. However, the big challenge for hydrologists is forecasting streamflow appropriately with time and space. However, nowadays artificial intelligence and machine learning have become more popular in water resources investigation to predict streamflow in the future using data-driven models. Therefore, ANN was used in this study to forecast the streamflow of eight river basins in Ethiopia for 17 streamflow stations. The result shows that about 13 streamflow stations from Abbay, Baro Akobo, Omo Gibe, Awash, and Tekeze river basins have given good performance with an average R^2 value of 0.85, 0.8, 0.76, 0.75, and 0.7, respectively. But for the most semi-arid and arid river basins such as Genale Dawa, Rift Valley, and Wabishebele river basins the simulated performance result of the ANN model was low. Therefore, in this study, the analysis of future hydrological drought in Ethiopia was focused on six selected river basins; Abbay, Awash, Baro Akobo, Omo Gibe, Tekeze, and Wabishebele. The result revealed that Ethiopia will be stricken with severe and extreme droughts in the coming future. The most common extreme drought years identified using SDI at a 12-month time scale in the future are 2036, 2042, 2044, 2062, and 2063. Most previous drought forecasting studies were assessed for a short time scale, 1-month, 2-month, or 3-month ahead (Aghelpour, 2021; Christian et al., 2020; Raphael M Wambua, 2019). However, this study assessed long-time drought forecasting using downscale climate data from the RCP4.5 climate change scenario and by forecasted streamflow using ANN in Python software. This result agreed with the approach of (Park et al., 2014) predicting future drought in Korea using the RCP8.5 climate change scenario.

Nowadays the government of Ethiopia is on the way to implementing Green Legacy to reduce the impact of climate change and the corresponding drought. Still, water resource management and hydrological event analysis need further investigations to alleviate poverty and the consequence of drought impact on society. Therefore, this study is a starting point for future further studies, policymakers, water resource managers, decision-makers, and drought mitigation measurement development strategies. Recently using Artificial Intelligence models and machine learning has become crucial to developing drought early warning systems. So, policymakers, planners, river basin developers of the nation have to be emphasized those data-driven models in climate change and hydrological analysis studies.

6.4 Conclusion

The impact of climate change on streamflow and its consequences can be analyzed using projected climate data from GCM and RCM with observed hydroclimatic data. To minimize the effect of hydrological events on water resource projects, drought forecasting and monitoring system development are important for policymakers, drought preparedness, and water resource management sectors. This study intends to forecast long-term hydrological drought in Ethiopia using observed and projected climate data. A data-driven model such as ANN improves the problems related to non-linear and stationarity cases in water resource management analysis. The result of this study also indicated the possibility of forecasting long-time streamflow time series using precipitation data as an input for the ANN model. It is observed that humid and temperate climate zones can result in good streamflow forecasting performance compared to semi-arid and arid areas. In Ethiopia, the Abbay, Baro Akobo, and Omo Gibe River basins received mean annual precipitation of above 1200 mm, and the Awash and Tekeze river basins received mean annual precipitation between 700 to 1100 mm. Streamflow forecasting from those areas using the ANN model corresponding to areas having high precipitation results in acceptable R^2 values. Genale Dawa, Rift Valley, and Wabishebele river basins are located in the lowland parts of Ethiopia and receive low annual precipitation. The source of streamflow for these basins is Bale Mountain and other highland areas of the country. As a result, the correlation between precipitation and streamflow data is very low. Therefore, the result revealed that forecasting streamflow directly using precipitation data will not give good performance in arid areas. The future hydrological drought analysis result indicates that there will be frequent moderate drought events in all river basins and the 2030s, 2040s, and 2060s were identified as the most expected severe and extreme drought event occurrence years. High population growth rates and dynamic climate change will increase water stress and water-sharing conflict in resource-limited areas in the future. In addition to this, drought has a worthwhile impact on the overall economic growth of the nation. Therefore, the government and policymakers should have to plan long-term drought preparedness and mitigation measures to minimize the risk associated with expected hideous drought events.

The government of Ethiopia is practically focused on drought crisis management rather than risk management. Drought crisis management is a short-term drought preparedness mechanism by supplies food and water to drought-prone areas. This kind of drought preparedness does not bring a sustainable solution. Therefore, in the future, the government should shift to a new paradigm by developing a national drought policy. Currently, a proactive approach is recommended as a short-term and long-term drought mitigation mechanism. A 2021 and 2022 Green Legacy in Ethiopia is a good initiative to prevent the climate change impact on water resources such as rivers, lakes, and reservoirs as a long–term mitigation approach. So, Afforestation, and the development of alternative energy sources from solar and wind have to be strongly encouraged in the future.

7. Conclusion and Recommendation

7.1 Conclusion

Hydrological drought is related to the reduction of water availability in the surface and subsurface of the earth due to a lack of precipitation for a prolonged period. Therefore, in the future, it is important to focus on hydrological drought monitoring and forecasting in conjunction with meteorological drought to achieve the sustainable utilization of available water resources in the country and to minimize the impact of drought on the overall socio-economic activities.
In Ethiopia, many sectors such as agriculture, water supply, and hydropower are highly affected by hydrological drought and most human activities depend on these sectors. However, hydrological drought is not well-studied in the country. Particularly, Baro Akobo, Omo Gibe, Genale Dawa, and Rift Valley river basins are not been studied before. Abbay, Awash, Tekeze, and Wabishebele river basins are partially studied, more focused on meteorological drought than other droughts. This study analyzed both hydrological and meteorological drought in Ethiopia using SDI and M1SWSI and SPI and RDI, respectively to identify the most severe and extreme drought years and drought-prone areas. Meteorological drought analysis was conducted only for the Abbay river basin as a pilot point to compare the relationship between hydrological and meteorological drought indices. Accordingly, 1979, 1981,1983 1987, 1996, 1997, and 2001 were the most severe drought years, whereas 1984, 1986, 2002, and 2010 were relatively extreme drought years in all river basins in Ethiopia from 1973 to 2014. However, globally, only the 1984 severe drought event was popularly recognized and other drought years were not focused but affected food security, water supply, and hydropower production systems over the country.

Abbay, Awash, and Rift Valley river basins were frequently affected by severe hydrological drought, but for the case of Baro Akobo and Omo Gibe river basins, the frequency of severe drought was less. Genale Dawa and Wabishebele river basins were located in arid and semi-arid areas in which drought condition is dominated by their aridity nature and the occurrence of severe and extreme drought events was rare. However, mild and moderate drought events frequently occur in these basins. On the other hand, severe and extreme drought frequency relatively decreased in all river basins in the 1990s and 2000s compared to the 1970s and 1980s. The source of streamflow for all river basins is from highlands and mountainous areas. Therefore, most of the streamflow stations considered for this study were from the upstream and middle parts of the basins. Therefore, the hydrological drought conditions for these stations can represent the downstream parts of the basins. Generally, the Abbay and Awash river basins are the most populated basins and cover large investment areas in which the investigation of hydrological drought and development of drought early warning systems is important. Therefore, this study gives good information about hydrological drought conditions for all river basins for decision-makers to develop effective drought mitigation measurements in all river basins based on historical drought events and future expected drought conditions.

The trend analysis was computed using the Mann-Kendall (MK) test and the result indicates that there was a positive increment of hydrological drought trend at Gummera, Kessie, and Border stations (Upper – Middle -Lower) parts of the basin, respectively for a long-timescale (SDI12). But for the case of meteorological drought, there are no significant drought trends at a 5% significant level for most stations in all time scales except Debre Berhan and Fiche which have increasing trends at SPI12 and RDI12. The relationship between meteorological and hydrological drought was increased as the time scale increased from 1 month to 12 months. SPI and RDI have a high correlation (R^2 = 0.95), this implies both indices are suitable for meteorological drought analysis in the Abbay river basin. The common historical drought years 1986, 1991, 1994, and 2001 were selected for spatial distribution analysis for SDI12, SPI12, and RDI12 time scales in the Abbay river basin. The spatiotemporal drought variability of hydrological drought results shows more attention is needed for water resource management in all river basins.

Besides comparing hydrometeorological drought indices, this study has compared two hydrological drought indices (SDI and M1SWSI) and the result showed that the 1980s were the most prolonged hydrological drought event years in Ethiopia. SDI resulted in more frequent severe and extreme drought events occurring over the country than the M1SWSI. M1SWSI uses multi-hydrological components cumulatively as input which results in a small magnitude of drought severity and its occurrence frequency was decreased due to the aggregation of hydrological components. The number of severe drought events obtained using M1SWSI in all basins was less than 53.85% of the SDI result. Because some hydrological components were dominating the scarce data which will affect the overall analysis. The result of SDI values agreed with previous historical drought events. Therefore, SDI is the best hydrological drought index compared to M1SWSI for all river basins in Ethiopia and this index gives good information for a single river as well as basin-level drought conditions. Water supply, irrigation, and hydropower projects are more dependent on streamflow and need hydrological drought monitoring system development. Therefore, decision-makers, policy, and strategic planners, and master plan developers can use SDI for historical and future hydrological drought analysis to develop effective drought mitigation measures in Ethiopia.

A data-driven model such as ANN improves the problems related to non-linear and stationarity cases in water resource management analysis. The result of the study also indicated the possibility of forecasting long-time streamflow time series using precipitation data as an input for the ANN model. It is observed that humid and temperate climate zones can result in good streamflow forecasting performance compared to semi-arid and arid areas. In Ethiopia, the Abbay, Baro Akobo, and Omo Gibe river basins received mean annual precipitation of above 1200 mm, and the Awash and Tekeze river basins received mean annual precipitation between 700 to 1100 mm. Streamflow forecasting from those areas using the ANN model corresponding to areas having high precipitation results in acceptable R^2 values. Genale Dawa, Rift Valley, and Wabishebele river basins are located in the lowland parts of Ethiopia and receive low annual precipitation. The source of streamflow for these basins is Bale Mountain and other highland areas of the country. As a result, the correlation between precipitation and streamflow data is very low. Therefore, the result revealed that forecasting streamflow directly using precipitation data will not give good performance in arid areas.

The future projected hydrological drought analysis result indicates that there will be frequent moderate drought events in all river basins and the 2030s, 2040s, and 2060s were identified as the most expected severe and extreme drought event occurrence years. High population growth rates and dynamic climate change will increase water stress and water-sharing conflict in resource-limited areas in the future. In addition to this, drought has a worthwhile impact on the overall economic growth of the nation. Therefore, the government and policymakers should have to plan long-term drought preparedness and mitigation measures to minimize the risk associated with expected hideous drought events. To achieve this, the government has to be shifting the reactive approach into a proactive drought mitigation approach.

7.2 Recommendation

In any river basin master planning, considering extreme hydrological events like floods and drought are important issues for sustainable water resource infrastructure development and management. Otherwise, simply focusing on the investigation and assessment of the available natural resource potential in a specific river basin will never bring development. Particular attention is to be given to drought-affected areas and conjunctive use of ground and surface water has to be encouraged. Higher education institutions such as Universities and Federal to Regional water sectors have to support and encourage researchers working on climate change and adaptation because of sustainable utilization of limited water resources during a drought event. To enhance this, expanding alternative energy generation from solar and wind in addition to hydropower is important. Recently, the Ethiopian government has planned several water resources-related projects to reduce the impact of poverty. However, hydrological drought studies are still limited in the country. In this study, the hydrological drought investigation shows the historical drought severity condition and trend of a specific area and the forecasted future hydrometeorological drought also indicates the probability of constraints in water resource management and infrastructure development. Therefore, this study has a vital role for decision-makers, researchers, water resource managers, and policymakers as a primary source for drought preparedness and mitigation measure development in all river basins in Ethiopia.

Therefore, to overcome all threats indicated in this study and the existing actual problems related to natural disasters, especially drought, the following points have to be considered in the future.

- ✓ Strengthen the Green Legacy initiative
- ✓ Develop a strong national drought policy (NDP)
- ✓ Construct more dams and reservoirs
- ✓ Practice proactive mitigation approaches
- ✓ Implement integrated water resource management from principle to practice
- ✓ Use alternative energy sources such as solar and wind energy in addition to hydropower

Annex 1: Hydrological Drought Characterization in Ethiopian Major River Basins

A) Tekeze River Basin

Station	Event	D (year)	S	M	RF (%)
	1994-1996	**3**	**2.4**	**0.80**	**15.00**
	2001-2002	2	1.54	0.77	10.00
Embamadre	2008-2009	2	1.47	0.74	10.00

B) Omo Gibe River Basin

C) Awash River Basin

Station	Event	D (year)	S	M	RF (%)	Station	Event	D (year)	S	M	RF (%)
	1973-1976	4	2.74	0.685	10		1973	1	0.22	0.22	2.44
	1978-1981	4	3.1	0.775	10		1976	1	0.48	0.48	2.44
	1984-1988	5	6.42	1.284	12.5		1978-1980	3	1.43	0.48	7.32
	1990	1	0.55	0.55	2.5		1986-1990	5	4.61	0.92	12.20
	2001	1	1.58	1.58	2.5		1996-1997	2	2.37	1.19	4.88
Awash7	2011	1	1.05	1.05	2.5		1999-2002	4	4.15	1.04	9.76
	1974-1976	3	1.43	0.48	7.32		2004	1	1.18	1.18	2.44
	1978-1983	6	2.64	0.44	14.63	Wonj	2009	1	0.32	0.32	2.44
	1985-1987	3	4.53	1.51	7.32		1982	1	0.15	0.15	2.44
	1993-1994	2	0.39	0.195	4.88		1984	1	0.63	0.63	2.44
	1996	1	1.64	**1.64**	2.44		1986-1988	3	4.47	1.49	7.32
	1999	1	1.27	1.27	2.44		1997	1	0.79	0.79	2.44
Hombel	2001-2003	3	3.62	1.21	7.32		2002	1	1.08	1.08	2.44
	1973-1974	2	0.8	0.40	5.41		2004	1	0.73	0.73	2.44
	1976	1	0.43	0.43	2.70		2009-2011	3	4.27	1.42	7.32
	1978-1987	10	**8.54**	0.85	27.03	Metehara	2013	1	0.36	0.36	2.44
	1991	1	0.28	0.28	2.70		1973-1980	8	2.83	0.35	19.51
	1994-1995	2	0.8	0.40	5.41		1982-1988	7	5.77	0.82	17.07
Melka	2000-2004	5	3.44	0.69	13.51	Mojo	2000-2013	**14**	7.59	0.54	**34.15**

D) Abbay River Basin

Station	Event	D (year)	S	M	RF (%)	Station	Event	D (year)	S	M	RF (%)
	1973	1	0.28	0.28	2.44		1977	1	0.49	0.49	2.56
	1978-1987	10	7.66	0.77	24.39		1982	1	1.09	1.09	2.56
	1989-1990	2	0.48	0.24	4.88		1985-1987	3	2.85	0.95	7.69
	1995	1	1.17	1.17	2.44		1989	1	1.75	1.75	2.56
	2002-2005	4	1.78	0.45	9.76		1991	1	0.72	0.72	2.56
Bahir Dar	2009	5	5.7	1.14	12.20		1994	1	1.69	1.69	2.56
	1973	1	0.18	0.18	2.44		2001-2004	5	5.32	1.06	12.82
	1975-1976	2	1.18	0.59	4.88	G.Abbay	2008-2011	4	2.15	0.54	10.26
	1979	1	1.62	1.62	2.44		1975	1	0.35	0.35	2.56
	1981-1991	11	11.46	1.04	26.83		1977	1	0.24	0.24	2.56
	2002-2004	3	1.05	0.35	7.32		1981-1990	10	8.69	0.87	25.64
Border	2008	1	0.33	0.33	2.44		1992	1	0.31	0.31	2.56
	1981-1985	5	6.47	1.29	12.20		1995-1996	2	0.17	0.09	5.13
	1991	1	2.12	**2.12**	2.44		2000-2001	2	0.98	0.49	5.13
	1993-1997	5	2.01	0.40	12.20	Koga	2008-2001	4	4.08	1.02	10.26
	2001	1	0.72	0.72	2.44		1978-1984	7	8.7	1.24	17.95
	2003-2004	2	0.2	0.10	4.88		1986	1	1.47	1.47	2.56
G.Beles	2006-2013	8	6.53	0.82	19.51		1989	1	0.96	0.96	2.56
	1973-1984	12	10.7	0.89	29.27		1994	1	0.16	0.16	2.56
	1986-1987	2	1.08	0.54	4.88		1996-1997	2	0.9	0.45	5.13
	1989-1992	4	1.63	0.41	9.76		2001-2004	4	2.46	0.62	10.26
	1994	1	0.28	0.28	2.44	Ribb	2010-2011	2	0.71	0.36	5.13
	1998	1	0.88	0.88	2.44		1973-1975	3	1.7	0.57	8.33
	2001-2002	2	0.62	0.31	4.88		1981-1982	2	0.97	0.49	5.56
Gummera	2004	1	1	1.00	2.44		1984-1985	2	0.66	0.33	5.56
	1973	1	0.32	0.32	2.78		1989	1	0.34	0.34	2.78
	1975-1976	2	2.27	1.14	5.56		1991	1	0.49	0.49	2.78
	1978-1981	4	3.1	0.78	11.11		1994	1	1.63	1.63	2.78
	1984-1985	2	0.65	0.33	5.56		1996-1997	2	1.06	0.53	5.56
	1987	1	1.31	1.31	2.78	Chemoga	2001-2008	8	7.92	0.99	22.22
	1990	1	0.58	0.58	2.78		1980-1998	**19**	13.01	0.68	**55.88**
	1994	1	1.52	1.52	2.78	Megech	2001-2003	3	0.91	0.30	8.82
	1996-1997	2	1.51	0.76	5.56		1973-1974	2	0.25	0.13	4.88
	1999	1	0.18	0.18	2.78		1976-1992	17	**15.6**	0.92	41.46
Guder	2001-2004	4	3.82	0.96	11.11	Kessie	2010	1	0.23	0.23	2.44

E) Baro Akobo River Basin

Station	Event	D (year)	S	M	RF (%)	Station	Event	D (year)	S	M	RF (%)
	1976	1	0.99	0.99	2.44		1976	1	0.98	0.98	2.44
	1979-1982	4	3.06	0.77	9.76		1978	1	0.43	0.43	2.44
	1984-1986	3	3.46	1.15	7.32		1980	1	0.74	0.74	2.44
	1989	1	0.21	0.21	2.44		1982-1986	5	**6.48**	1.30	**12.20**
	1991	1	0.35	0.35	2.44		1989-1991	3	1.59	0.53	7.32
	1994	1	1.18	1.18	2.44		1993-1994	2	0.78	0.39	4.88
	2001-2005	**5**	6.23	1.25	**12.20**		2001-2004	4	4.43	1.11	9.76
	2008-2009	2	0.96	0.48	4.88		2008-2009	2	0.62	0.31	4.88
Gambela	2011	1	0.52	0.52	2.44	Sorie	2011	1	0.69	0.69	2.44

F) Genale Dawa River Basin

Station	Event	D (year)	S	M	RF (%)	Station	Event	D (year)	S	M	RF (%)
	1984-1985	2	0.81	0.41	6.90		1984-1988	5	1.36	0.27	16.67
	1987	1	0.64	0.64	3.45		1990-1991	2	1.44	0.72	6.67
	1990-1991	2	1.68	0.84	6.90		1996	1	0.89	0.89	3.33
	1993-1994	2	0.83	0.42	6.90		1999	1	1.27	1.27	3.33
	1998-1999	2	1.56	0.78	6.90		2001-2003	3	3	1.00	10.00
	2001-2005	5	3.91	0.78	17.24		2008	1	1.38	1.38	3.33
	2007-2008	2	1.46	0.73	6.90	Weib	2010-2011	2	3.11	**1.56**	6.67
Halawel	2012	1	0.8	0.80	3.45		1984-1988	5	2.31	0.46	16.13
	1981-1987	**7**	4.12	0.59	**21.21**		1990-1991	2	1.82	0.91	6.45
	1989-1991	3	1.43	0.48	9.09		1996	1	1.42	1.42	3.23
	1993-1994	2	0.43	0.22	6.06		1999	1	1.17	1.17	3.23
	1996	1	1.52	1.52	3.03		2001-2003	3	3.85	1.28	9.68
Shaya	1999-2005	**7**	**5.52**	0.79	21.21	Chenemsa	2007-2008	2	0.78	0.39	6.45

G) Rift Valley River Basin

H) Wabishebele River Basin

Station	Event	D (year)	S	M	RF (%)	Station	Event	D (year)	S	M	RF (%)
	1978-1980	3	2.05	0.68	7.89		1976	1	0.23	0.23	2.63
	1983-1985	3	2.36	0.79	7.89		1978-1981	4	3.49	0.87	10.53
	1987-1991	5	3.84	0.77	13.16		1984-1985	2	0.66	0.33	5.26
	1993-1994	2	0.73	0.37	5.26		1988	1	0.94	0.94	2.63
	1996	1	0.92	0.92	2.63		1990-1991	2	2.04	1.02	5.26
	1998	1	0.22	0.22	2.63		1994	1	0.22	0.22	2.63
	2001-2003	3	2.39	0.80	7.89		1996	1	0.77	0.77	2.63
Leliso	2007-2008	2	1.41	0.71	5.26		1998-199	2	0.88	0.44	5.26
	1984	1	0.37	0.37	3.23		2001-2003	3	4.06	1.35	7.89
	1987	1	0.59	0.59	3.23	Wabi	2011	1	1.43	1.43	2.63
	1989	1	0.41	0.41	3.23		1983-1987	5	2.54	0.51	16.13
	1993-1994	2	0.32	0.16	6.45		1989-1991	3	1.18	0.39	9.68
Erer	2000-2007	**8**	**10.52**	1.32	**25.81**		1995-1996	2	1.41	0.71	6.45
							1999-2004	6	3.3	0.55	19.35
						Weyb	2011	1	1.7	**1.70**	3.23

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