III) Watershed-based Soil and Water Conservation

1. Sensitivity of Stream Flow to Meteorological Drought in Andit-Tid Watershed, Central Highland of Ethiopia

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Abstract

Drought is identified as one of the environmental phenomena, and is an integral part of climate change that can happen in any geographic area. Drought can be expressed in different forms, including meteorological, hydrological, agricultural, and socioeconomic droughts. The main objective of this study was to identify the potential mechanisms through which meteorological droughts can lead to hydrological drought. DrinC software has been used to generate the indices required to examine how hydrologic variables responded to drought and climate change. Rainfall, minimum and maximum temperature have been the inputs used to calculate the indices. Evapotranspiration and future projection of stream flow, rainfall and temperature have been computed using the Hargreaves method and the ARIMA model, respectively. The findings of this study confirmed that the study area had both hydrological and meteorological droughts in 1987, 2003, and 2015. The results of index-based drought analysis showed a significant (P<0.05) correlation between hydrologic and meteorological droughts. Particularly, it was determined that there was a better association between the stream flow drought index and reconnaissance drought index than is between the standardized precipitation index. This shows how strongly evapotranspiration affects stream flow, a factor that the reconnaissance drought index takes into account while calculating its value. According to the projected scenarios for stream flow and climatic factors, all variables in the watershed will decline in the coming ten years. Investigating index-based droughts is essential to warn the public and decision-makers about coming toward droughts and help them put mitigation and adaptation plans for water management into action.

Keywords: Evapotranspiration**,** hydrological, meteorological, risk, temperature

Introduction

Drought is a complex term thathas various definitions, depending on individuals' perceptions. E.g. in a farmer's language it is "a shortage of rainfall or a long time without any rainfall during the growing season", or a period of below-average rainfall or a prolonged period of dryness that can cause damage to plants. The glossary of meteorology defines drought as a period of abnormally dry weather sufficiently prolonged for the lack of water to cause a serious hydrological imbalance in the affected area (Wilhite *et al.*,, 1987). Drought can occur virtually in all climatic zones, with its characteristics varying significantly from one region to another. It is an insidious hazard of nature. Though droughthas attracted less scientific attention than flood or cyclone, several authors found that the impact of drought can be more defenseless than flood and cyclone (Rahdari, 2016).

Droughthas been identified as one of the environmental phenomena and in fact, is an integral part of climate change that can happen in any geographical area. This phenomenon has various types such as meteorological, hydrological, and agricultural as well as groundwater drought (Shahid & Behrawan, 2008). Meteorological droughts are expressed as the basis of the degree of dryness (often in comparison to some 'normal' or average amount) and are usually measured for long-term daily or monthly records. While agricultural droughts are specifically concerned about the effects of water shortages on the growth of crops, grass, and other forage species. Therefore, agricultural drought is most closely associated with insufficiency of soil moisture that leads to losses in yield. Agriculture is usually the first sector to experience the devastating effects of drought.

Groundwater drought is a new concept introduced to emphasize the understanding of complicated hydrogeological processes concerning the change in dynamics of hydro-meteorological variables with changes in the land (Haile *et al.,* 2020; Kumar *et al.,* 2016). Hydrological droughts are more concerned with the effects of periods of precipitation shortfalls on surface or subsurface water supply (i.e., stream flow, reservoir and lake levels, groundwater, etc.) rather than with precipitation shortfalls. Hydrological droughts are usually out of phase or lag the occurrence of meteorological and agricultural droughts. Water in storage systems (e.g., reservoirs, rivers) is often used for multiple and competing purposes, further complicates the sequence and quantification of impacts. Hydrological drought is determined by the propagation of meteorological drought through the terrestrial hydrological cycle and is therefore influenced by the properties of the hydrological cycle (Bhardwaj *et al.,* 2020; Lanen, 2006; Loon, 2015).

Even though the drought starts with a rainfall deficit, it ultimately translates into a hydrological drought which indicates the reduced water availability in the rivers and groundwater aquifers. The scientific analysis of the hydrological drought is one of the many primary necessities for the development of an effective drought management plan for a region. The investigation of the hydrological drought is important due to the dependence of most of the activities (including industrial, water and power plants) to surface water resources (Faiz *et al.*, 2021; Zakhem & Kattaa, 2016). For example, the duration of drought in stream flow is crucial for hydropower production, particularly the missing volume of water compared to normal conditions (deficit volume) is more relevant. The results of hydrological drought analysis can be useful for proper water resources management including better planning for water supply and demand.

A pivotal step towards reducing the risk of stream flow drought impacts is the monitoring and analysis of the stream flow droughthazard. Traditionally quintile-based approaches such as stream flow percentiles on the threshold level method have been used to characterize the droughthazard of ongoing and past stream flow drought events. More recently the use of Standardized Drought Index (SDI) has become more popular. However, there are other approaches to computing the SDI and up to now, no consensus has been reached on which procedure is preferable (Tijdeman *et al.*, 2018). The study watershed has long-term primary meteorological and other hydrological data which have been collected since 1982. Using these data, this study aimed to investigate the relationship between drought in different periods to determine the relationship between meteorological and hydrological drought using Standardized Precipitation Index (SPI), Reconnaissance Drought Index (RDI), and Standardized Drought Index (SDI) in the Hulet Wenz river catchment. This study was expected to help in establishing basin-specific drought monitoring by advancing the understanding of how much the stream flow is sensitive to drought events. The main objectives of the study were: (1) to anticipate the Standardized Precipitation Index (SPI), Reconnaissance Drought Index (RDI), and Standardized Drought Index (SDI) due to the wide range of possible climate change and (2) to predict the likely proportional change in the annual stream flow available for the downstream in response to other climatic parameters.

Material and Methods

Description of the Study Area: This study was conducted at Andit Tid watershed, which is one of the Soil Conservation Research Project (SCRP) research stations (Fig. 1). It is situated on 39°43'E longitude and 9°48’N latitude 180 km northeast of the capital city, Addis Ababa. The watershed covers a total area of 477.6 ha, and the altitude of the catchment ranges from 3040 to 3550 m.a.s.l. The watershed is located in moist and humid agro-climatic zone. Its mean annual rainfall is 1581mm; minimum and maximum temperatures respectively are 7.5 and 17.6°C; and minimum and maximum average soil temperatures are 7.9 and 20.5°C respectively.

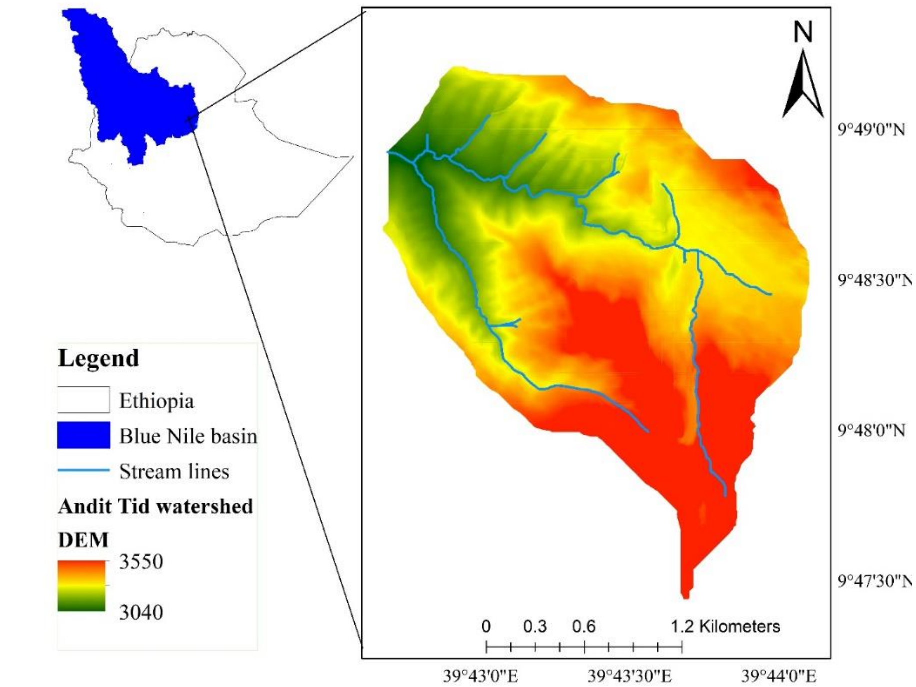

Figure 1. Location map of the study area

Methods of Data Collection and Analysis: This study was conducted by analyzing the time series of hydrologic and meteorological drought indexes. A drought Index is typically a single value used for indicating the severity of a drought and is far more useful than raw data in understanding the drought conditions over an area. SPI (standardized precipitation index) and RDI (Reconnaissance Drought Index) were two drought indices to monitor and quantify Meteorological drought while the sensitivity of stream flow to drought was identified by doing SDI (stream flow drought index).

Standardized Precipitation Index (SPI): The SPI is a measure of the likelihood of precipitation for any given period. It may be calculated for several time scales, making it applicable for both long-term hydrological applications and short-term agricultural uses. These time frames demonstrate how drought affects the availability of various water resources. Short-term precipitation anomalies affect soil moisture conditions; longer-term precipitation anomalies are reflected in groundwater, subsurface flow, and reservoir storage (Zakhem & Kattaa, 2016). The SPI can provide early warning of drought and helps for assessment of drought severity. Because of its standardization, it is particularly suited to compare drought conditions among different periods, and regions with different climatic conditions (Bonaccorso *et al.*, 2003). Due to its intrinsic probabilistic nature, SPI is the ideal candidate for carrying out drought risk analysis (Rossi & Cancelliere, 2002).

The SPI is calculated based on the long-term precipitation record for the desired period (1986 to 2020). This long-term record is fitted to a probability distribution such as gamma distribution, which is then transformed into a normal distribution so that the mean SPI for the location and desired period is zero (Koudahe *et al.*, 2017; McKee *et al.*, 1993). Positive SPI values indicate the values that are greater than median precipitation, and negative SPI indicate the values are less than median precipitation. Since the SPI is normalized, wetter and drier climates can be represented in the same way, and thus, wet periods can also be monitored using the SPI. Computation of the SPI involves fitting of a gamma probability density function to a given frequency distribution of precipitation. The parameters α and β of the gamma probability density function were estimated for the precipitation monthly time series (1, 3, 6, and 12) as analyzed by (Karavitis *et al.*, 2011; Lee *et al.*, 2023). It was developed on the basis that precipitation deficithas different impacts on groundwater, reservoir storage, soil moisture and stream flow (McKee *et al.*, 1993). The drought trend of SPI at 1, 3, 6, and 12 month time scales have been analyzed in the study area. The complete calculation procedure for the SPI can be found in McKee *et al.*, (1993), and some details are provided in Equation (1):

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Where, is a scale parameter, is a shape parameter, g(x) is the gamma probability density function, e is Euler's number for exponentiation and is the ordinary gamma function of .
Detail information about the estimation of and is stated by McKee *et al.*, (1993).

Reconnaissance Drought Index (RDI): The Reconnaissance Drought Index (RDI) has been introduced by Tigkas *et al.*, (2016) and Tsakiris (2013) as a physically based, universal and comprehensive index for the assessment of meteorological drought. It utilizes two parameters, cumulative precipitation (P) and potential evapotranspiration (PET) for specified reference periods. Recent studies have shown that temperature methods for estimating PET can be sufficient for the calculation of RDI in various regions (Tigkas *et al.,* 2013; Tigkas *et al.,* 2016). Therefore, the data requirements are limited to precipitation and temperature. Over the last decade, the RDI has been widely used in several applications worldwide (Tsakiris *et al.,* 2013). The RDI can be expressed in three forms. The initial form of the index (Ị) within a year for a reference period of k months is calculated as Equation (2) and Equation (3) (Tigkas *et al.,* 2016; Tsakiris *et al.,* 2007).

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Where, P is precipitation in mm; PET is potential evapotranspiration; is the arithmetic mean of the initial expression of RDI for kth month (Thomas *et al.,* 2015)

There are three basic ways of generating Eto namely, penman Monteith, Priestly Taylor, and Hargreaves method. Due to the ease of required input data in this experiment estimation of potential evapotranspiration used in the calculation of RDI was obtained through DrinC by using the Hargreaves method as Equation (4) (Wu, 1997);

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Where, T_{max}(°C) is the maximum average air temperature; T_{min}(°C) is the minimum average air temperature; Ra (MJ m^{-2} d^{-1}) is the extra-terrestrial solar radiation; the parameters (mm d^{-1}) and b are calibrated coefficients, determined on a monthly or yearly basis by regression analysis or visual fitting; an unadjusted version of Hargreaves equation (given by default) is given with a=0 and b=1.

However, the total precipitation cannot usually represent sufficiently the amount of precipitation that enters a reservoir, the percentage of the precipitation that contributes to groundwater recharge, the amount of water that can be used by the root system of the plants, etc. For this reason, the use of effective precipitation instead of total precipitation is proposed for RDI modification. In its processing wizard, the DrInC program offers the option to select whether to use the effective or total rainfall.

Stream Flow Drought Index (SDI): Stream flow Drought Index calculation was started according to Equation (5) (Emiru *et al.*, 2021; Wu *et al.*, 2016; Rahdari, 2016; Zeng *et al.*, 2015). If a time series of monthly stream flow volumes is available, in which i denotes the hydrological year and j represents the month within that hydrological year (j = 1 for October and j = 12 for September).

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Where, i = 1,2, …N, j = 1, 2…,12 and k = 1,2,3,4. V is the cumulative stream flow volume for the i^{th} hydrological year and the k^{th} reference period, k = 1 for October-December, k = 2 for October−March, k = 3 for October-June and k = 4 for October-September. Based on the cumulative stream flow volumes, the Stream flow Drought Index (SDI) is defined for each reference period k of the i^{th} hydrological year Equation (6)

……………………………………………………… (6)

Where, i = 1, 2… N and k = 1,2,3,4, and are the mean and the standard deviation, respectively, of the cumulative stream flow volumes of the reference period k, as these are estimated over a long time. In this definition, the truncation level is set to , although other values based on rational criteria will also be used.

Stream flow may follow a skewed probability distribution, which can be approximated well by the family of gamma distribution functions (Blum *et al.*, 2017 & Hamasha *et al.*, 2023). The distribution is then transformed to normal. Using the two-parameter log-normal distribution (for which the normalization is simply reclaiming the natural logarithms of stream flow), the SDI which is defined in Equations (7) and (8) are the natural logarithms of cumulative stream flow with mean and SD , as these statistics are estimated over a long period by (Tigkas *et al.*, 2016).

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

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i = 1,2… N and k = 1, 2, 3, 4

The annual SDI was computed for more than 34 years between 1986 and 2020. Quantities and descriptive situations of the SDI and SPI indices, which are provided in Tsakiris, (2013), have been considered in this paper to provide a better representation of drought in spatial distribution mapping. In this study, the calculations were performed using DrinC and R software (Tsakiris, 2013). DrinC has been recently used in several studies for drought assessment and monitoring. The precipitation and runoff data were fitted to the log-normal distribution function in the computation process. DrinC aims at providing a user-friendly interface for the calculation of several drought indices, with emphasis on two recently developed ones: the Reconnaissance Drought Index (RDI) and the Stream flow Drought Index (SDI). Also, the widely used Standardized Precipitation Index (SPI) was calculated. The common characteristic of the selected indices was that they require a relatively small amount of data for their calculation and the results can be easily interpreted and used in water resource management strategic planning and operational applications. The classification of drought was done following the (McKee, 1993) as presented in table below.

Table 1. Classification of drought conditions based on the standardized precipitation Index (SPI), reconnaissance drought index (RDI) and Stream flow Drought Index (SDI)

Class	Drought category	SPI, RDI and SDI values
1	Extremely wet	≥2.00
2	Very wet	1.5 ≤ (SPI, RDI and SDI) < 1.99
3	Moderately wet	1≤ (SPI, RDI and SDI) < 1.49
4	Near Normal	-0.99 < (SPI, RDI and SDI) < 0.99
5	Moderately dry	-1.49 < (SPI, RDI and SDI) ≤ -1.00
6	Severely dry	-1.99 < (SPI, RDI and SDI) ≤ -1.50
7	Extremely dry	(SPI, RDI, and SDI) ≤ -2.00

Frequency of Droughts **(F) :** The cumulative frequency (F) of drought gives an idea of the occurrence of dry sequences over a while (Caloiero *et al.*, 2016). It is obtained by reporting the cumulative number of dry sequences considering the total number of rainfall and flow data (Koffi *et al.*, 2020). The frequency of drought was computed following the Equation.

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Where, : Cumulative dry sequence size; N: total size of data.

Analysis of Correlation **(r):** To analyze the relationship between meteorological and hydrological droughts in the Hulet Wenz river catchment, the Pearson correlation coefficient between the SPI, RDI and SDI indices was calculated. The Pearson correlation coefficient is a very effective method for the analysis of potential relationships between two independent variables (López-Moreno *et al.*, 2013; Zeng *et al.*, 2015). This coefficient was calculated using R software.

Data Collection and Analysis: The 34 years of rainfall, atmospheric temperature and runoff data were collected from the study catchment station. All the indices were analyzed by using DrinC software version 1.5.73. DrinC was developed by the National Technical University of Athens Lab. of Reclamation Works & Water Resources Management in, 2007 to facilitate the procedure of the calculation of drought indices. DrinC software has been developed aiming to provide the means for the consistent calculation of various drought indices for drought analysis in research and operational applications (Tsakiris, 2013). A special routine has been added to DrinC software that can be used for the calculation of the modified RDI. The precipitation and runoff data were fitted to the log-normal distribution function in the computation process. The calculation process is performed through a graphical user interface and several options can be used for the characterization of drought. The future forecast for stream flow due to climate change was computed by using R-software by applying the Autoregressive integrated moving average (ARIMA) function. The correlations among indexes were done by using R-software.

Seasonal Forecast with ARIMA: We have restricted our attention to non-seasonal data and non-seasonal ARIMA models. However, ARIMA models are also capable of modeling a wide range of seasonal data. A seasonal ARIMA model is formed by including additional seasonal terms in the ARIMA models we have seen so far (Hyndman & George, 2014). It is written as follows:

ARIMA (p,d,q) (P,D,Q)m;

Where, m= number of observations per year. We use uppercase notation for the seasonal parts of the model, and lowercase notation for the non-seasonal parts of the model.

The results of ARIMA are measured in terms of forecast accuracy. Observed data is divided into two sets; a training set to be used in estimating the parameters and a test set to be used in measuring the accuracy of the forecast. Forecast error is the difference between the observed value (y_t) and its forecast ($\bar{y}_t$) (Alabdulrazzaq *et al.*, 2021; Athanasopoulos, 2018). The most commonly used scale-dependent measures of forecast accuracy are Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) defined in Equation (10) and Equation (11), respectively. As for scale-independent measures, the most commonly used one is Mean Absolute Percentage Error (MAPE), defined in Equation (12) (Rebelob, 2015).

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Where, *n* is the number of sample months; = is the actual observation of t^th month; = is the forecasted data value of t^th month; and m= number of observations per year (12).

If the data contain zeros, the MAPE can be infinite as it will involve division by zero. If the data contain very small numbers, the MAPE can be huge (Hyndman & George, 2014). The MAPE assumes that percentages make sense; that is, the zero on the scale of the data is meaningful. The mean absolute percentage error (MAPE) is one of the most widely used measures of forecast accuracy, due to its advantages of scale-independency and interpretability. However, MAPE has the significant disadvantage that it produces infinite or undefined values for zero or close-to-zero actual values.

Results and Discussion

Estimation of Drought Indices with Different Time Scales

Standardized Precipitation Index (SPI)

Three-Month Standardized Precipitation Index (SPI-3): The three-month standardized precipitation index (SPI-3) is presented in (Figure 2). From the analysis, it was found that October to December experienced seasonal droughts in 1990, 2003, 2012, 2015, and 2018. There were droughts from January to March in 2000, 2003, 2008, 2012, 2015, and 2018. Drought from April to June struck in 1988, 1990, and 2003. There were droughts from July to September in 1987, 1989, 2003, and 2015. Generally, 2003 and 2015 experienced drought in every season, out of all the documented seasonal droughts that occurred in the watershed. The 2015 drought in Ethiopia was also reported by another scholars (Philip *et al.*, 2018; Sjoukje *et al.*, 2017)

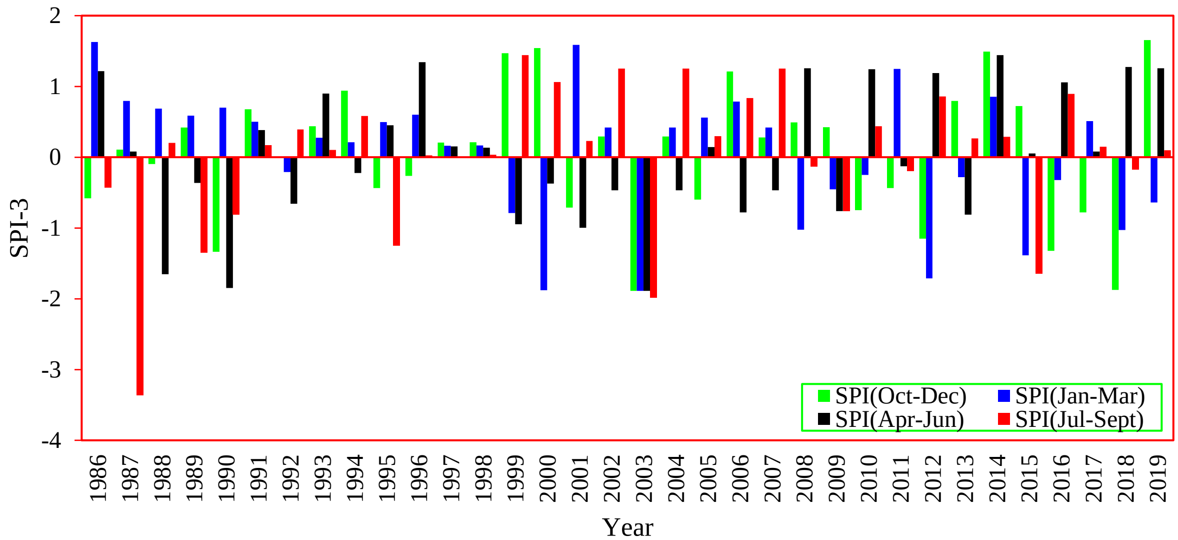


Figure 2. Three-month standardized drought index (SPI-3) of the watershed

Six-Month Standardized Precipitation Index (SPI-6): The Six-month standardized precipitation index (SPI-6) is presented in (Figure 3). Based on a 6-month time step SPI analysis, an extreme drought occurred from April to September in 1987 and 2003. The year 1987 was classified as a dry year of Ethiopia (Richman *et al.*, 2016). Drought also happened from October to March of 2003, 2012, 2015 and 2018 (Figure 3). The year 2016 (October-march) and 2009 (April-September) were affected by a moderate drought.

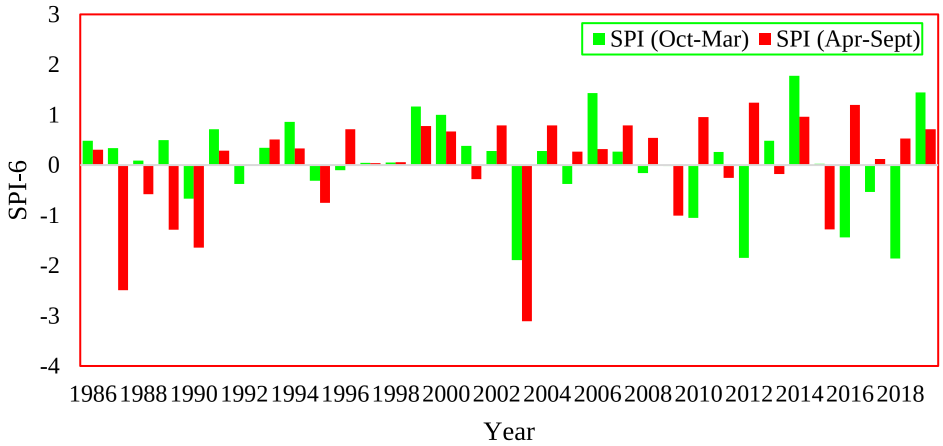


Figure 3. Six-month standardized drought index (SPI-6) of the watershed

Annual Standardized Precipitation Index (SPI-12): The historical trend of the annual standardized precipitation index is presented in (Figure 4). According to the findings, the watershed had an extreme drought with SPI<-3.74 in 2003. Furthermore, with SPI values of (-1.83) and (-1.67), respectively, it was determined that 1987 and 1990 were exceptionally dry years in the watershed's history. This result was supported by another study reported the same finding (Mattsson & Rapp, 1991). Thirdly, the SPI value for 2015 indicated that it was a moderately dry year for the watershed (-1.07). The year 1999, 2014, and 2019 were identified to be moderately wet years of the watershed. The watershed had climates that are generally close to normal for approximately 28 years, with SPI values that vary from (-1 to 1).

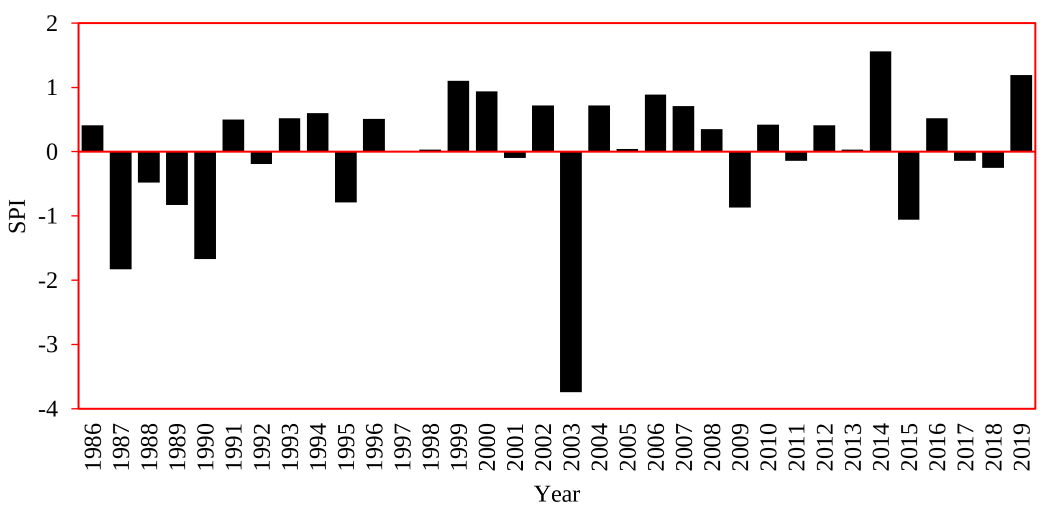


Figure 4. Annual standardized precipitation index (SPI-12) of the study watershed.

Reconnaissance Drought Index (RDI)

Three-Month Reconnaissance Drought Index (RDI-3): The three-month drought analysis with this index indicated July to September was the wettest season of the watershed. This season was the main rainy season. The remaining three seasons were moderately normal and normal. This index is generally not sensitive to seasonal drought identification for the study watershed, which is humid.

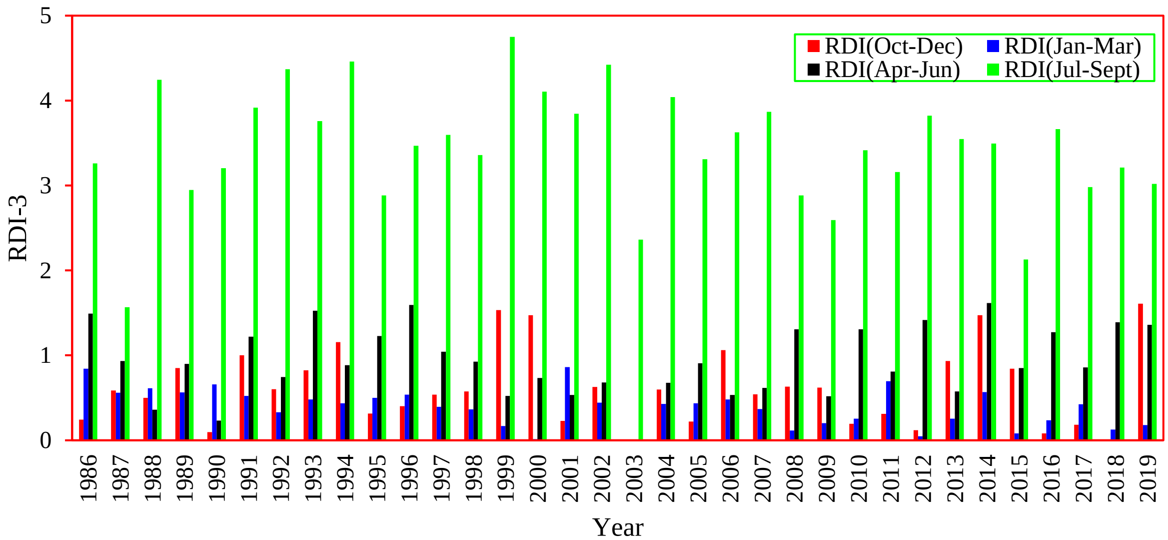


Figure 5. Three-month reconnaissance drought index (RDI-3) of the watershed

Six-Month Reconnaissance Drought Index (RDI-6): Based on RDI-6 analysis, 2003 was affected by extreme and 1987 was affected by a moderate drought**.** While the most severe dryness was observed in October-March of 2003, 2012 and 2018 (Figure 6). It was also observed that 2016 (October-march) and 2009 (April-September) were affected by severe drought. Generally, October to March is much drier than April to September in the study watershed. Similar study on the temporal drought analysis by Burka *et al.,* (2023) reported the occurrence of major drought events in the years: 1984/85, 1999/2000, 2002/3, and 2009.

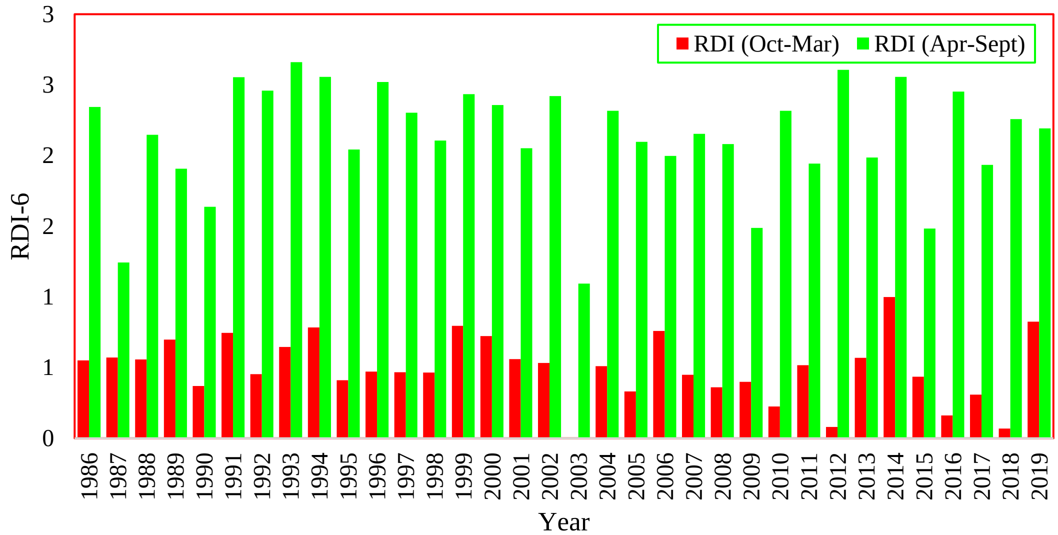


Figure 6. Six-month reconnaissance drought index (RDI-6) of the watershed

Annual-Reconnaissance Drought Index (RDI-12): The annual Reconnaissance drought index (RDI-12) is presented in (Figure 7). This index indicated that 2003 was found to be an extremely dry year of the watershed since 1986 with an RDI of (-3.65). Similarly, 1987 was found to be a severely dry year with an RDI value of (-1.68). similarly, the study on Drought sensitivity characteristics and relationships between drought indices over Upper Blue Nile basin by Kebede *et al.*, (2019) reported severe drought at Deberberehan in 1987 and 1989. The year 1990, 2009, and 2015 were found to be moderately dry years with RDI values of, (-1.09), (-1.45), and (-1.38) respectively. These years were classified as a drought affected years of Ethiopia (Karavitis *et al.*, 2011; Lee *et al.*, 2023; Richman *et al.*, 2016; Sjoukje *et al.*,, 2017). The remaining years were found to be free of drought and excess moisture. For example, the year 1991, 1993, 1994, 1999, and 2014 were found to be moderately wet years. These drought indices were found to be in a similar pattern to the standardized precipitation index.

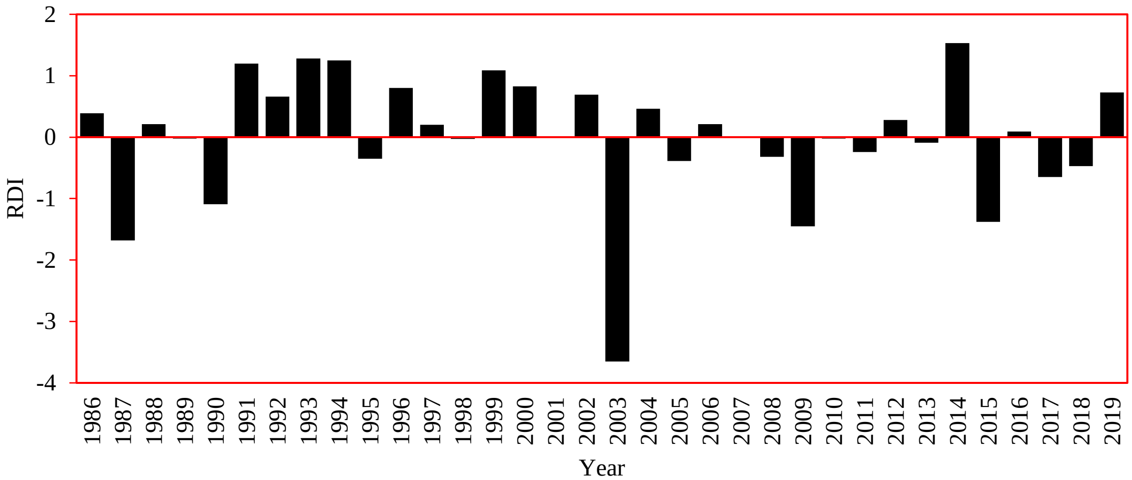


Figure 7. Annual-reconnaissance drought index (RDI-12) of the study watershed.

Standardized and Reconnaissance Drought Indices as Meteorological Drought Indices

Droughthas occurred at different times in the watershed assured by analyzing the long-term historic metrological and hydrological data. Metrological droughts were characterized by SPI and RDI indices using 1, 3, 6 and 12 month time steps. The analysis of the 1-month time scale revealed that the extreme drought occurred in the years 1987 and 2015 in July. Similarly, severe droughthappened in 1987(June), 1990 (May, June, and August), 1995 (September), 2003 (October, March, April, May, June, August, and September), 2008 (March), 2009 (September), 2015 (April) and 2018 (October). Moderate drought was also pronounced in 1988 (March and May), 1989 (May and august), 1993 (June and august), 1999 (April), 2000 (March), 2002 (May), 2004 (May), 2005, and 2006 (April), 2007 (May), 2009 (May), 2011 (October), 2012 (October and March), and 2019 (August).

Based on the 3, 6 and, 12-month time step SPI and RDI indices analysis, a higher pick of the drought was observed in the watershed in 1987 and 2003. Concerning the 3-month time scale, it was better to see the drought effects on the main rainy seasons (kiremit) and the short rainy season (B*elg*) of the watershed. The only extreme drought occurred in 1987 (July- September). Similarly, the most severe dryness has experienced in 2003 and 2015 and moderate dryness was also pronounced in 1995 in kiremit months (July- September). In agreement with this, Segele & Lamb (2005) and Viste *et al.*,(2013) reported that the kiremt season of 1987 was severely dry over

Ethiopia, particularly in the northeastern half of the country, which was primarily caused by the missing of rain in July and August. So, those incidents would have a higher risk in the study area. According to Mekonen *et al.,* (2020) the drought risk intensity was more weighted during the months of kiremt. Segele & Lamb (2005) also revealed that the greatest damaging droughts in Ethiopia are connected with the failure of kiremt rains. In the short rainy seasons also the most severe drought occurred in 2003 and 2012 (January-march).

This result mostly agreed with the ground facts of the historic drought events during the years 1970-2010 in Ethiopia presented by the EM-DAT International Disaster Database center (Yared *et al.*, 2018). According to the center, a drought occurred from June 1987 (Shewa, Wollo, Tigray, etc), from October 1989-1994, 2003-2004, and May 2008-October 2009 (Tigray, Amhara, Oromiya, etc put on as region). This depicts the performance of the drought indices' abilities in indicating historic drought events. In 2008/2009 all regions of Ethiopia and in 2015/2016 in the north, east, and southwest Ethiopia, a drought occurred and millions of people were affected (Mohammed *et al.,* 2018).

Generally, based on the above result, both indices did not show a large difference (Figure.2-7) which was similarly reported by Alemu *et al.,* (2021). Nevertheless, the RDI is more advantageous than SPI since the RDI incorporates both temperature (evapotranspiration) and precipitation data in a single index whereas the SPI includes only precipitation (rainfall) data. Similar to this study, for drought monitoring in given stations, Jamshidi *et al.,* (2011) showed that the RDI is more sensitive than the SPI to climatic conditions and therefore, the RDI was more recommended for meteorological drought monitoring. Alemu *et al.,* (2021), also reported the role of evapotranspiration is very important in drought assessment and should not be ignored. However, many scholars from different countries such as Algeria, India, the USA, Nepal, Tunisia, Kuwait, etc., also recommend the importance and suitability of SPI and RDI indices for drought monitoring, assessing and comparing meteorological and hydrological droughts (Thilakarathne & Sridhar, 2017).

Streamflow Drought Index (SDI): Based on the 35 years' time series stream flow data, the SDI has been analyzed for the reference periods, SDI-3, SDI-6, and SDI-12 described in the following subheadings.

Three-Month Stream Flow Drought Index (SDI-3): Based on the SDI-3 value the station experienced droughts during the reference period October-December in the years 1996, 1998, 2008, 2015 and 2017 (mild drought), 2003 and 2007 (moderate drought), 2001, 2012 and 2016 (severe drought), 2002 and 2005 (extreme drought). From the January-march reference period in the years 2015, 2012, 2003, 2000, and 1999 (moderate and severe droughts) have appeared. In the reference period from April-June mild and moderate droughthas been observed. However, 2013 and 2006 experienced severe and extreme drought with SDI-3 values of -1.77 and -2.16 respectively. From July to September in comparison to other periods, most of the droughts were mild. Two years, 1987 and 2015 were affected by extreme drought with SDI-3 values of -2.09 and -2.87 respectively. This may be a result of extreme and severe droughts in a similar reference period indicated above in SPI drought analysis to assure metrological drought impacts on hydrological droughts (Wale *et al.*, 2018).

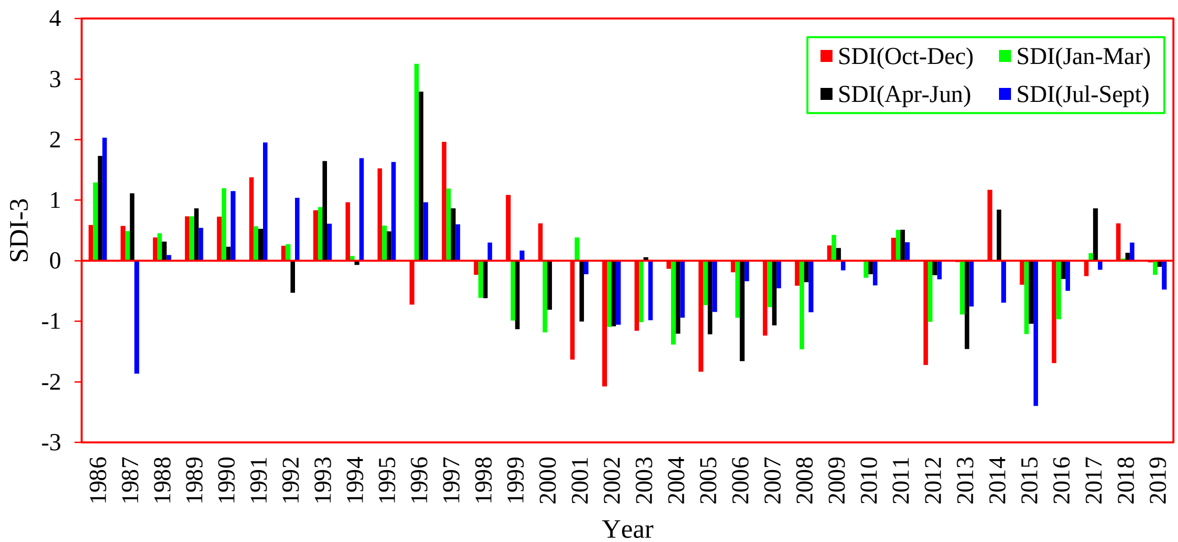


Figure 8. Three-month streamflow drought index (SDI-3) of the watershed

Six-Month Stream Flow Drought Index (SDI-6): The six-month streamflow drought index is presented in (Figure 9). For the last 35 years, drought incidents have occurred from October-March in 14 years (41.2%). From there, the years 2003, 2012, and 2016 were affected by extreme droughts with SDI-6 values of -2.55, -20.7, and -2.01 respectively, and 2005 was affected by severe droughts with SDI-6 values of -1.91. Similarly, from April-September, more droughts (50%) have occurred. However, only one extreme drought in the year 2015 with an SDI-6 value of -2.95 was experienced and the others were only moderate and mild. The SDI-6 series showed a more remarkable decrease in stream flow during the October-March period as compared with the April-September period. According to Basin & Ozkaya, (2019), a decrease in stream flow and water losses resulted in reduced use of irrigation water, because the requirement for crop irrigation was the highest at the time.

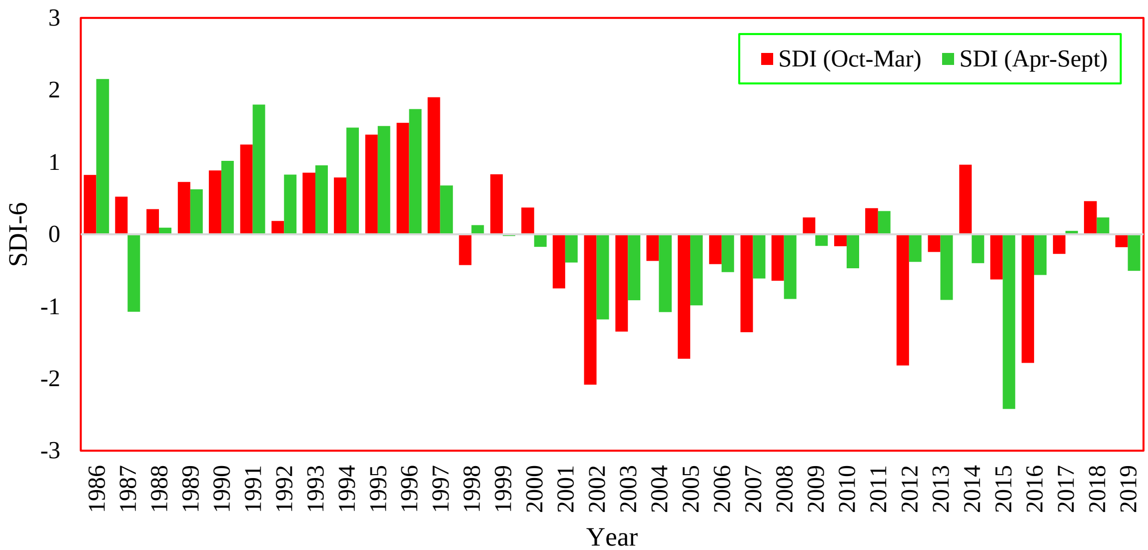


Figure 9. Six-month streamflow drought index (SDI-6) of the watershed

Annual Streamflow Drought Index (SDI-12): The annual drought index for streamflow is shown in (Figure 10). From 34 years data the annual drought (SDI-12) analysis result depicted 16 years (47%) droughthas appeared in the watershed. From these 16 years, one year (2015) got extreme drought with an SDI-12 value of -2.61 and four years (2002-2005) experienced severe drought with SDI-12 values of -1.43, -1.10, -1.05, and -1.2 respectively and the rest were mild droughts. This indicates that there was decreasing or blow average stream flow recorded in all SDI analyzing time steps. The years 1986, 1991, 1995, and 1996 were determined to be very wet years, whereas 1990, 1994, and 1997 were found to be moderately wet years, as is shown in the chart below. These wet years of streamflow had dry weather, as determined by the standard precipitation index and reconnaissance drought index.

For instance, the standardized precipitation index classified 1990 as a moderately dry year, but there was a water deficit in the stream. Such events might occur since there are insuffcent structures to facilitate water infiltration into the ground. As a result, rainwater directly transforms into runoff and flow. But beginning in 1998, the watershed's hydrologic conditions almost always showed signs of being fairly dry. The absence of excessive rainfall is the primary cause, but it is also anticipated that the rainfall is not instantly converting in to runoff. Since there have been several attempts to conserve soil and water in the watershed since 1995, these intervention activities may have an impact on the streamflow (Dile *et al.,* 2018; Sultan *et al.,* 2018).

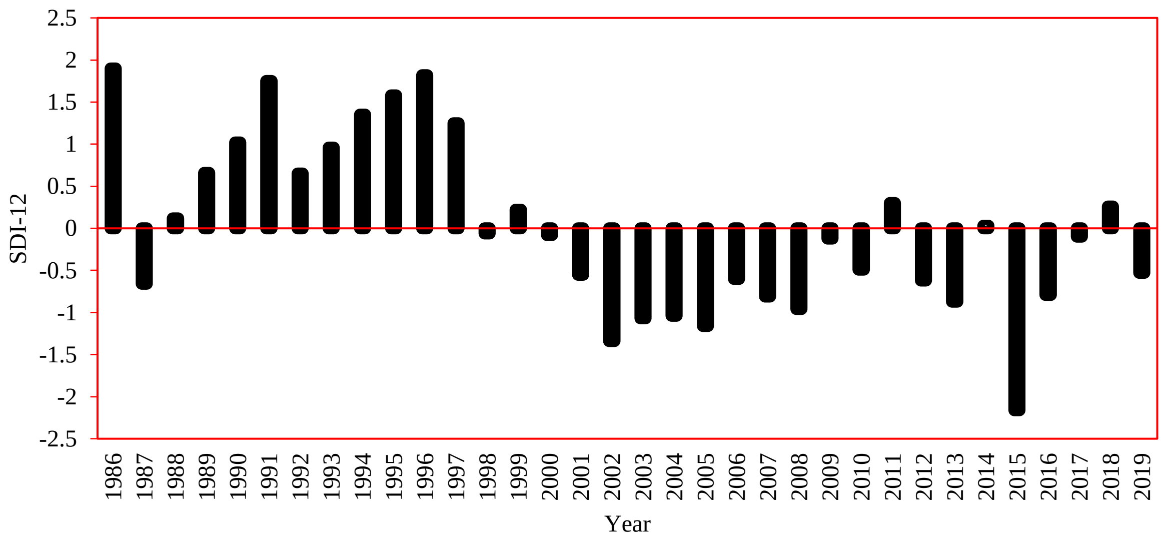


Figure 10. Annual-streamflow drought index (SDI-12) in the study watershed

Sensitivity of Streamflow to Drought: For sensitivity analysis, it was better to investigate the relationship of stream flow with drought and climatic parameters (Basijokaite & Kelleher, 2021; Malede *et al.,* 2022). The impacts of drought on stream flow were analyzed with establishing a correlation between annual stream flow data and annual SDI values.

Relationship between Meteorological and Hydrological Droughts: To analyze the relationship between climatic and hydrological droughts in a basin, the correlation coefficients between the SPI, RDI, and SDI were calculated for different time scales. Similar findings by Boudad *et al.*, (2018); Lohpaisankrit & Techamahasaranont, (2021) reported positive relationship between meteorological and hydrological droughts. The correlation coefficient between the RDI and SPI was found to be the highest ranging from 87% to 99% in all time scales. The occurrence of climatic droughts is one or two months earlier than the hydrological droughts in the watershed. Hence, the occurrence of a meteorological drought two months earlier could be an early warning signal of a hydrological drought, and the occurrence of a meteorological drought one month earlier usually could cause the occurrence of hydrological drought.

The correlation between the 3-month drought indices, SPI, RDI and SDI were found to be significantly correlated (Figure 11). January to March seasonal analysis confirmed that the watershed was equally affected with both meteorological and hydrological droughts. July to September, the streamflow was not affected by meteorology as illustrated in Figure 11. Since these were the watershed's primary rainy months, there may be more factors besides climatic ones that affect streamflow. The biophysical characteristics of the watershed may have an impact on the proportional change in streamflow caused by meteorological factors (Lv *et al*., 2021).

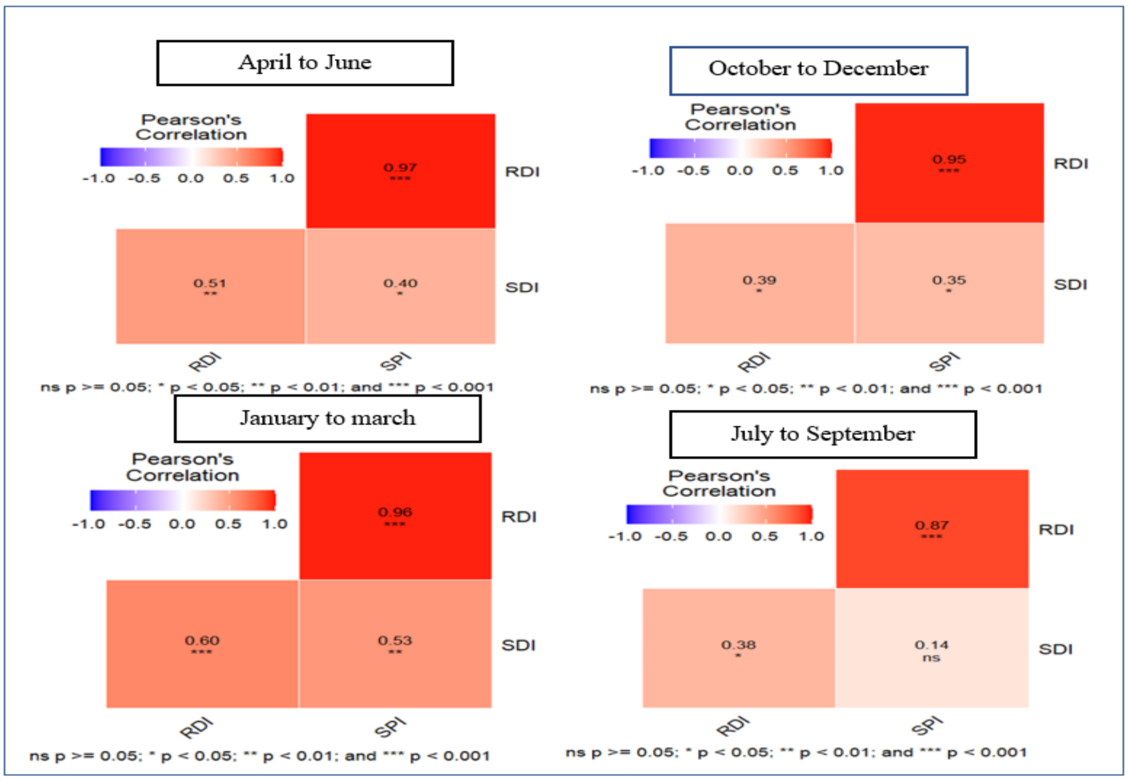


Figure 11. The correlation chart of three-month drought indices

The six-month drought analysis indicates that all drought indices were found to be significantly correlated, even though, the SPI and SDI were found to be highly correlated than Standardized Precipitation Index (SPI) and Stream flow Drought Index (SDI) and Reconnaissance Drought Index (RDI) (Figure 12). However, there was no noticeable relationship between SDI and SPI from April to September. Compared to reconnaissance drought index, streamflow drought index shows weaker correlation with standardized precipitation index. Reconnaissance drought index, which takes evapotranspiration into account while calculating streamflow, is said to be more cautious than standard precipitation index.

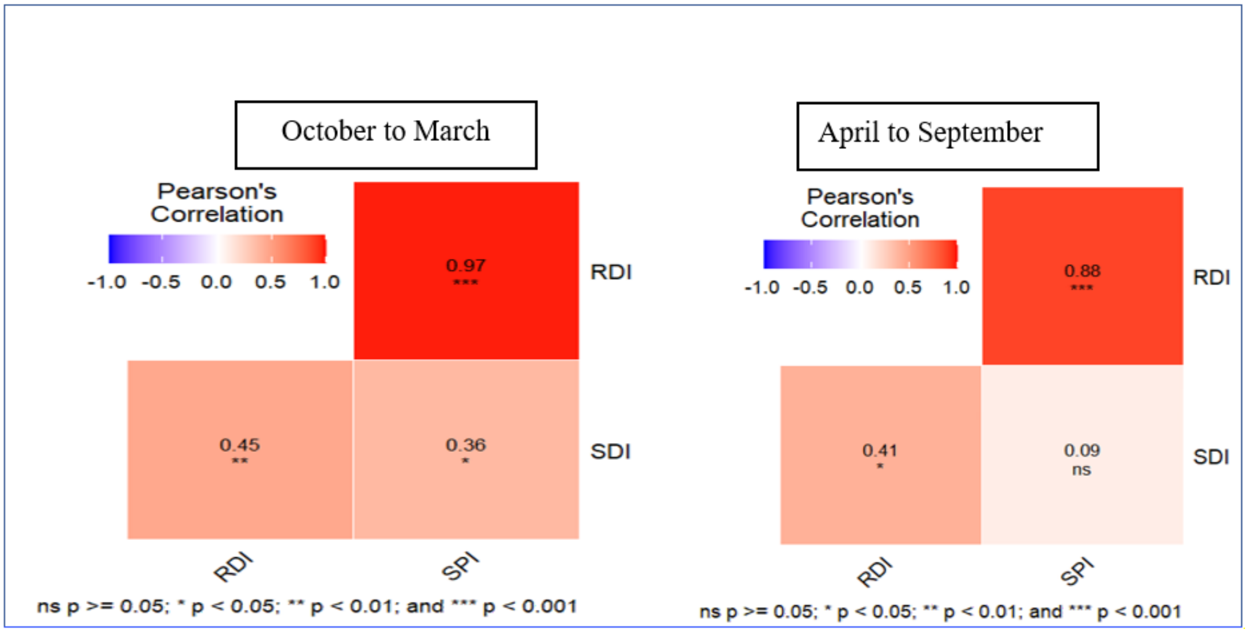


Figure 12. The correlation chart of six-months drought indices

Correlation coefficients for 12 months between SPI and SDI were not significant but there has been a significant correlation between SDI and RDI (Figure 13). The correlation coefficient for 12 months between SPI and SDI was around 10%, which is the smallest among the four different time scales. The higher values indicate that climate has a significant impact on the hydrological process on the annual time scale. However, human activities would clearly have an impact on hydrology and water supplies at shorter time spans. Similarly, streamflow is more heavily influenced by the reconnaissance drought index than the standardized drought index in the annual drought analysis. While there was a weak correlation between the streamflow drought index and the standardized drought index, the correlation between the streamflow drought index and the reconnaissance drought index was rather significant (Figure 13).

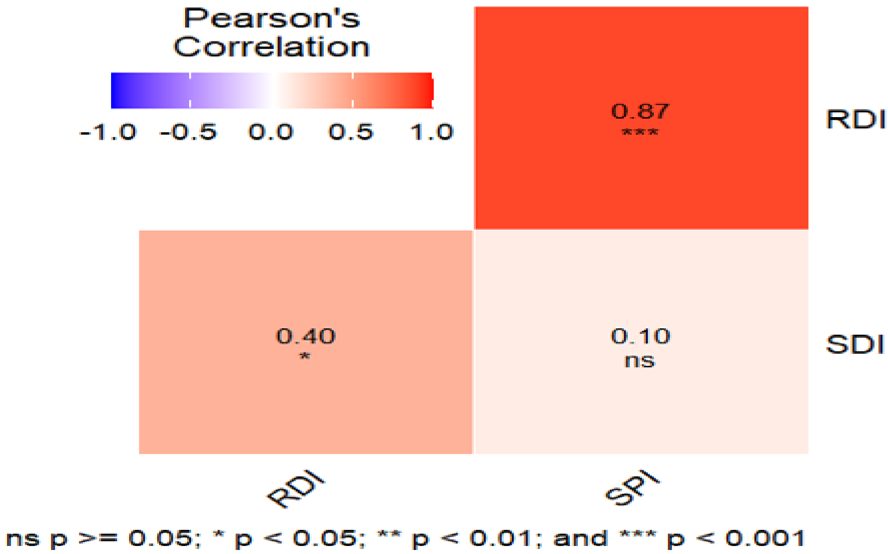


Figure 13. The correlation chart of annual drought indices

In all time correlation analyses (Figure 11-13); 1, 3, 6, and 12 months, RDI and SDI have better correlation and all correlations are significant ($P<0.05$). This is the result of the inclusion of many climatic parameters like Eto during the calculation of RDI. RDI by utilizing the Eto can be very sensitive to climatic variability, utilization of the RDI would seem to serve a better purpose (Khalili *et al.*, 2011; Memon & Shah, 2019). From the result of the correlation between SDI and RDI, we can confirm that the stream flow is highly affected by evapotranspiration.

Compared to correlations between other pairs of meteorological indices, correlations involving SDI were generally low. According to Yared *et al.*, (2018), it is based on river flow, which is a combination of surface flow, interflow, and base flow (or groundwater flow), and is expected to have a certain lag time with meteorological droughts. This might be one of the possible reasons of the absence of correlation with other drought indices.

The change in climatic parameters also plays a crucial role in the station stream flow change. According to Turoglu, (2016), the changes in annual and seasonal mean values of temperature and precipitation have a direct impact on surface runoff and therefore flow characteristics of rivers are likely to be very sensitive to climate changes. Regression analyses were carried out to understand the relationship between climatic parameters (precipitation, temperature and calculated evapotranspiration) and the resulting stream flow. Based on the analysis, annual stream flow was negatively correlated with temperature (-0.19) and potential evapotranspiration (-0.63) and positively correlated with precipitation. The watershed stream flow was more sensitive to evapotranspiration than rainfall and temperature.

Prediction of Future Stream Flow and Climatic Variables: The annual rainfall, temperature and stream flow trends have been forecasted using Autoregressive Integrated Moving Average (ARIMA) model (Figure 14 to 16). Hydrological drought prediction has a representative role in water resource management. Alawsi *et al.*, (2022) reported that drought forecasting is a critical component of drought hydrology which plays a vital role in risk management, drought preparedness and mitigation. Based on Autoregressive Integrated Moving Average (ARIMA) model, hydrological drought could project for the coming near future periods. As shown in (Figure 14) the stream flow of the study watershed will be decreasing in the coming ten years. The blue color in the graph represents the future projected streamflow using the black colored observed historical streamflow.

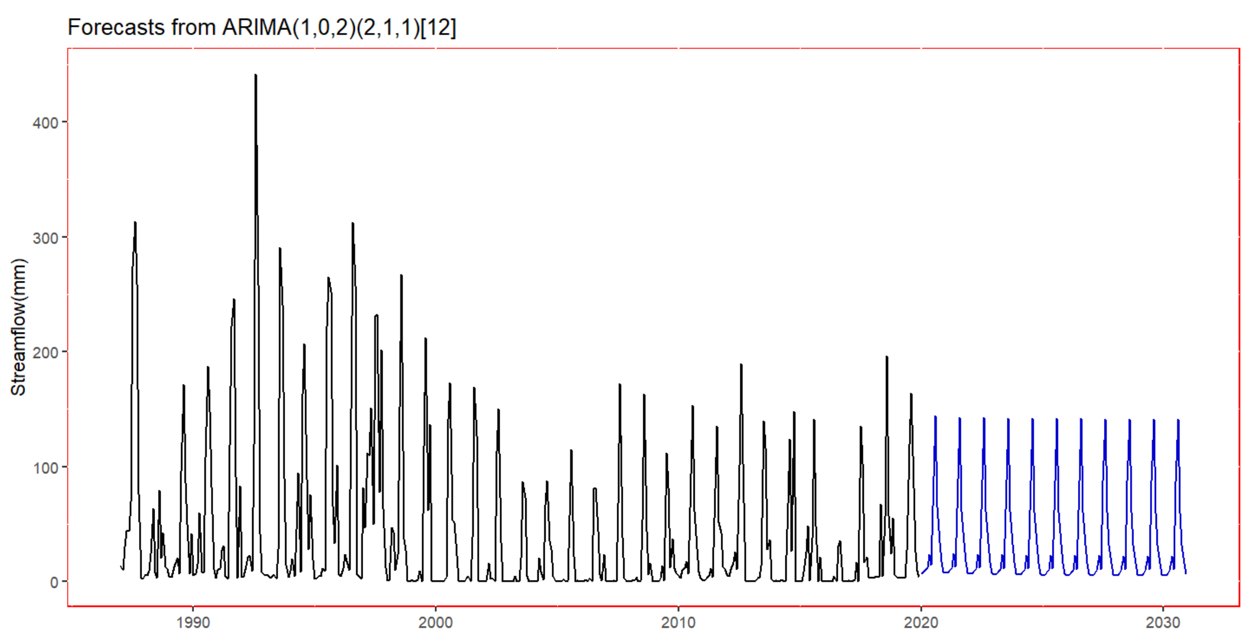


Figure 14. The historical (black line) and the future projected (blue line) streamflow of the study watershed

The rainfall of the watershed also indicated decreasing trend for the coming ten years, as illustrated in (Figure 15).

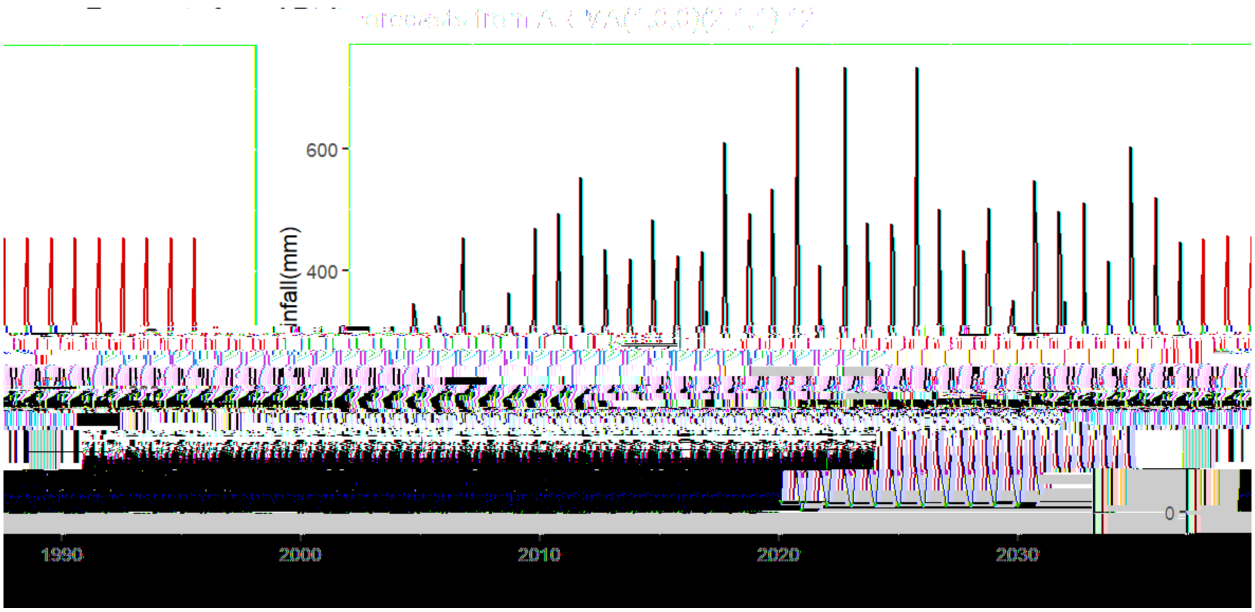
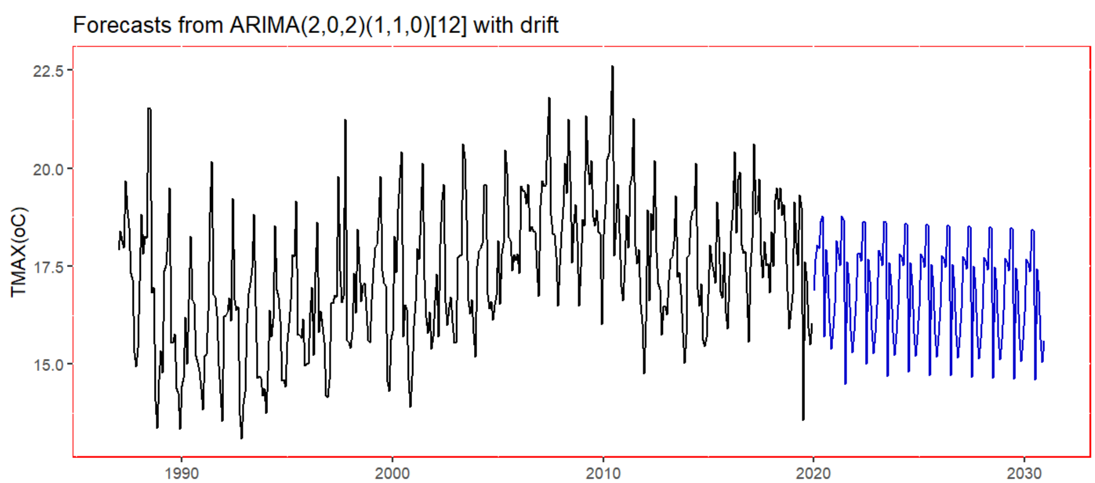


Figure 15. The historical (black line) and the future projected (blue line) rainfall of the study watershed

Additionally, it was determined that the maximum and minimum temperatures would be decreasing over the coming ten years. However, the rate of decrease is not remarkable.



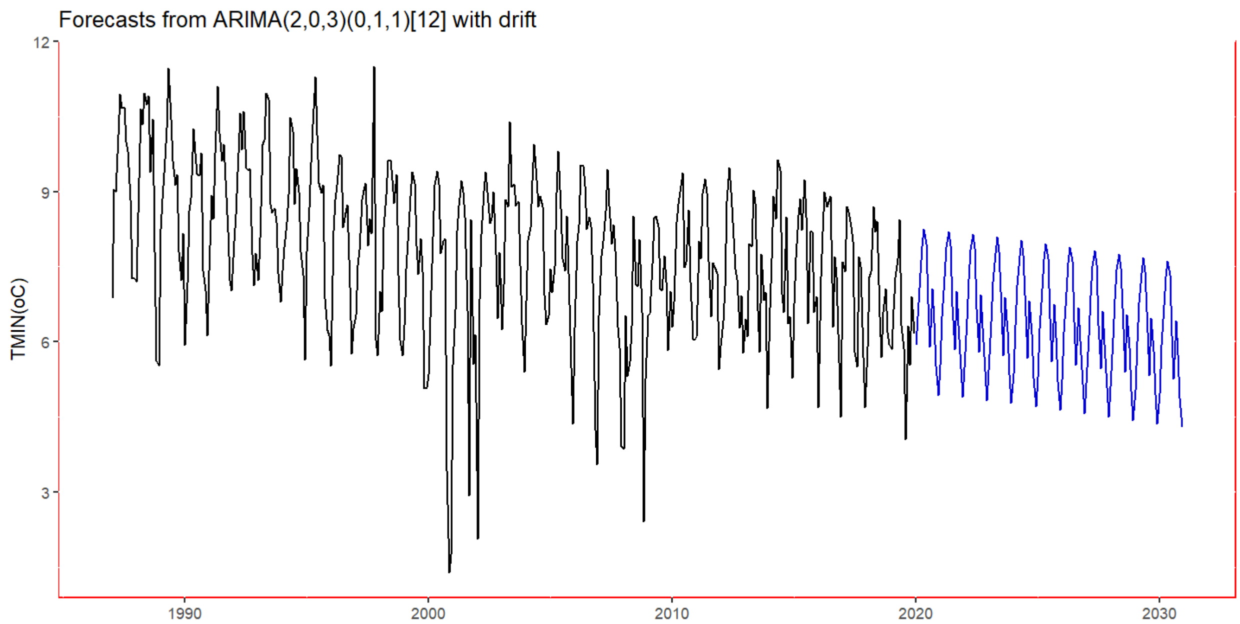


Figure 16. The historical (black line) and future projected (Blue line) minimum and maximum temperature of the study watershed

As indicated below the future predicted stream flow showed a decreasing trend proportionally to the observed data trends that help for the proper use and management of the resource. Datta *et al.*, (2021), reported that accurate prediction helps water managers with proper planning, utilization of limited water resources and distribution of available water to different sectors and avoid catastrophic consequences.

Prediction Accuracy Assessment: MAPE value of 4.4% and 10.1% in forecasting maximum and minimum temperature means that the average difference between the forecasted value and the actual value is 4.4% and 10.1% respectively (Table 2). With this metrics, the prediction model can be considered as a very accurate model. Similarly, the RMSE and MAE values of these two climatic parameters are very small; this is an indicator for the accuracy of the prediction model. Whereas the infinity and maximum value of MAPE is the result of '0' or near'0' values in our actual observed rainfall and runoff data respectively. As indicated in the equation, ithas a division for the actual value, at this time if there is '0' value in the actual data, therefore there will be undefined (infinity) value for MAPE.

Table 2. Statistics measuring the forecasting accuracy of ARIMA model

Forecasted parameters	Forecasted years	RMSE	MAE	MAPE
Rainfall (mm)	10	72.91	49.21	∞
Streamflow (mm)	10	37.08	21.65	1884.83
Minimum Temperature (oC)	10	0.87	0.61	10.10
Maximum Temperature (oC)	10	1.02	0.75	4.40

Conclusion and Recommendation

The sensitivity of streamflow to meteorological droughts was investigated using 35 years of rainfall, temperature and stream flow data in Andit Tid watershed. Standardized precipitation index (SPI) and Reconnaissance drought index (RDI) were used to analyze metrological drought and Stream flow drought index (SDI) which was used for hydrological drought analysis. Data were analyzed using DrinC, R software and Microsoft Excel. Based on the analysis both metrological and hydrological droughts were experienced in the study watershed at different periods (1, 3, 6, and 12 months). From different periods of drought analysis 1986, 2003, and 2015 were identified to be extremely dry years in the watershed. The results of a correlation analysis between drought indices showed that metrological drought indices had higher correlations between one another. There is also a strong correlation between the hydrological and meteorological droughts indices at (P 0.05). The correlation between the streamflow drought index (SDI) and reconnaissance drought index (RDI) was higher than that between the standardized precipitation index (SPI). This streamflow behavior demonstrated its high reaction to evapotranspiration than the actual temperature. Generally, the drought indices in the watershed were better correlated during dry seasons than during wet seasons. It was determined through analysis of the watershed's future hydrologic and meteorological conditions that all streamflow, rainfall, and temperature will decrease during the next ten years. Given the aforementioned results, it is preferable to take action to reduce climate change through water harvesting and management strategies.

References

Alabdulrazzaq, H., Alenezi, M. N., Rawajfih, Y., Alghannam, B. A., Al-Hassan, A. A., & Al-Anzi, F. S. (2021). On the accuracy of ARIMA based prediction of COVID-19 spread. *Results in Physics*, *27*, 104509. https://doi.org/10.1016/j.rinp.2021.104509

Alawsi, M. A., Zubaidi, S. L., Al-Bdairi, N. S. S., Al-Ansari, N., & Hashim, K. (2022). Drought Forecasting: A Review and Assessment of the Hybrid Techniques and Data Pre-Processing. *Hydrology*, *9*(7), 1–23. https://doi.org/10.3390/hydrology9070115

Alemu, Z. A., Dioha, E. C., & Dioha, M. O. (2021). Hydro-meteorological drought in addis ababa: A characterization study. *AIMS Environmental Science*, *8*(2), 148–168. https://doi.org/10.3934/environsci.2021011

Athanasopoulos, R. J. H. and G. (2018). *Forecasting: Principles and practice*. Monash University, Australia.

Basijokaite, R., & Kelleher, C. (2021). Time-Varying Sensitivity Analysis Reveals Relationships Between Watershed Climate and Variations in Annual Parameter Importance in Regions With Strong Interannual Variability. *Water Resources Research*, *57*(1), 1–21. https://doi.org/10.1029/2020WR028544

Bhardwaj, K., Shah, D., Aadhar, S., & Mishra, V. (2020). Propagation of Meteorological to Hydrological Droughts in India. *Journal of Geophysical Research: Atmospheres*, *125*(22), 0–3. https://doi.org/10.1029/2020JD033455

Blum, A. G., Archfield, S. A., & Vogel, R. M. (2017). On the probability distribution of daily streamflow in the United States. *Hydrology and Earth System Sciences*, *21*(6), 3093–3103. https://doi.org/10.5194/hess-21-3093-2017

Bonaccorso, B., Bordi, I., Cancelliere, A., Rossi, G., & Sutera, A. (2003). Spatial Variability of Drought: An Analysis of the SPI in Sicily. *Water Resources Management*, *17*(4), 273–296. https://doi.org/10.1023/A:1024716530289

Boudad, B., Sahbi, H., & Manssouri, I. (2018). Analysis of meteorological and hydrological drought based in SPI and SDI index in the Inaouen Basin (Northern Morocco). *Journal of Materials and Environmental Science*, *9*(1), 219–227. https://doi.org/10.26872/jmes.2018.9.1.25

Burka, A., Biazin, B., & Bewket, W. (2023). Drought characterization using different indices, theory of run and trend analysis in bilate river watershed, rift valley of Ethiopia. *Frontiers* *in Environmental Science*, *11*(June). https://doi.org/10.3389/fenvs.2023.1098113

Caloiero, T., Sirangelo, B., Coscarelli, R., & Ferrari, E. (2016). An analysis of the occurrence probabilities of wet and dry periods through a stochastic monthly rainfall model. *Water (Switzerland)*, *8*(2). https://doi.org/10.3390/w8020039

Datta, B., Roy, D. K., Kelley, J. J., & Stevens, B. (2021). *Prediction of Impending Drought Scenarios Based on Surface and Subsurface Parameters in a Selected Region of Tropical Queensland , Australia*. 605–631. https://doi.org/10.4236/jwarp.2021.138033

Dile, Y. T., Tekleab, S., Kaba, E. A., Gebrehiwot, S. G., Worqlul, A. W., Bayabil, H. K., Yimam, Y. T., Tilahun, S. A., Daggupati, P., Karlberg, L., & Srinivasan, R. (2018). Advances in water resources research in the Upper Blue Nile basin and the way forward: A review. *Journal of Hydrology*, *560*, 407–423. https://doi.org/10.1016/j.jhydrol.2018.03.042

Emiru, N. C., Recha, J. W., Thompson, J. R., Belay, A., Aynekulu, E., Manyevere, A., Demissie, T. D., Osano, P. M., Hussein, J., Molla, M. B., Mengistu, G. M., & Solomon, D. (2021). Impact of Climate Change on the Hydrology of the Upper Awash River Basin, Ethiopia. *Hydrology*, *9*(1). https://doi.org/10.3390/hydrology9010003

Faiz, M. A., Zhang, Y., Ma, N., Baig, F., Naz, F., & Niaz, Y. (2021). Drought indices: aggregation is necessary or is it only the researcher's choice? *Water Supply*, *21*(8), 3987–4002. https://doi.org/10.2166/ws.2021.163

Haile, G. G., Tang, Q., Li, W., Liu, X., & Zhang, X. (2020). Drought: Progress in broadening its understanding. *Wiley Interdisciplinary Reviews: Water*, *7*(2). https://doi.org/10.1002/WAT2.1407

Hamasha, M. M., Obeidat, M. S., Alzoubi, K., Shawaheen, G., Mayyas, A., Almomani, H. A., Al-Sukkar, A., & Mukkatash, A. (2023). Symmetry of gamma distribution data about the mean after processing with EWMA function. *Scientific Reports*, *13*(1), 1–13. https://doi.org/10.1038/s41598-023-39763-6

Jamshidi, H., Khalili, D., Zadeh, M. R., & Hosseinipour, E. Z. (2011). Assessment and comparison of SPI and RDI meteorological drought indices in selected synoptic stations of Iran. *World Environmental and Water Resources Congress 2011: Bearing Knowledge for Sustainability - Proceedings of the 2011 World Environmental and Water Resources Congress*, *41173*(May 2014), 1161–1173. https://doi.org/10.1061/41173(414)120

Karavitis, C. A., Alexandris, S., Tsesmelis, D. E., & Athanasopoulos, G. (2011). Application of the Standardized Precipitation Index (SPI) in Greece. *Water (Switzerland)*, *3*(3), 787–805. https://doi.org/10.3390/w3030787

Kebede, A., Raju, J. P., Korecha, D., Takele, S., & Nigussie, M. (2019). Drought sensitivity characteristics and relationships between drought indices over Upper Blue Nile basin. *Journal of Water and Land Development*, *43*(1), 64–75. https://doi.org/10.2478/jwld-2019-0064

Khalili, D., Farnoud, T., Jamshidi, H., Kamgar-Haghighi, A. A., & Zand-Parsa, S. (2011). Comparability Analyses of the SPI and RDI Meteorological Drought Indices in Different Climatic Zones. *Water Resources Management*, *25*(6), 1737–1757. https://doi.org/10.1007/s11269-010-9772-z

Koffi, B., Kouadio, Z. A., Kouassi, K. H., Yao, A. B., Sanchez, M., & Kouassi, K. L. (2020). Impact of Meteorological Drought on Streamflows in the Lobo River Catchment at Nibéhibé, Côte d'Ivoire. *Journal of Water Resource and Protection*, *12*(06), 495–511. https://doi.org/10.4236/jwarp.2020.126030

Koudahe, K., Kayode, A. J., Samson, A. O., Adebola, A. A., & Djaman, K. (2017). Trend Analysis in Standardized Precipitation Index and Standardized Anomaly Index in the Context of Climate Change in Southern Togo. *Atmospheric and Climate Sciences*, *07*(04), 401–423. https://doi.org/10.4236/acs.2017.74030

Kumar, R., Musuuza, J. L., Van Loon, A. F., Teuling, A. J., Barthel, R., Ten Broek, J., Mai, J., Samaniego, L., & Attinger, S. (2016). Multiscale evaluation of the Standardized Precipitation Index as a groundwater drought indicator. *Hydrology and Earth System Sciences*, *20*(3), 1117–1131. https://doi.org/10.5194/hess-20-1117-2016

Lee, C., Seo, J., Won, J., & Kim, S. (2023). Optimal Probability Distribution and Applicable Minimum Time-Scale for Daily Standardized Precipitation Index Time Series in South Korea. *Atmosphere*, *14*(8). https://doi.org/10.3390/atmos14081292

Lin Zhao, Jianjun Wu, and J. F., Zhao, L., Wu, J., & Fang, J. (2016). Robust response of Streamflow drought to different timescales of meteorological drought in Xiangjiang river basin of China. *Hindawi Publishing Corporation Advances in Meteorology*, *2016*, 1–8. https://doi.org/10.1155/2016/1634787

Lohpaisankrit, W., & Techamahasaranont, J. (2021). Analysis of precipitation and streamflow data for drought assessment in an unregulated watershed. *Environment and Natural*

Resources Journal, *19*(2), 112–121. https://doi.org/10.32526/ennrj/19/2020202

López-Moreno, J. I., Vicente-Serrano, S. M., Zabalza, J., Beguería, S., Lorenzo-Lacruz, J., Azorin-Molina, C., & Morán-Tejeda, E. (2013). Hydrological response to climate variability at different time scales: A study in the Ebro basin. *Journal of Hydrology*, *477*, 175–188. https://doi.org/10.1016/j.jhydrol.2012.11.028

Lv, X., Liu, S., Li, S., Ni, Y., Qin, T., & Zhang, Q. (2021). Quantitative Estimation on Contribution of Climate Changes and Watershed Characteristic Changes to Decreasing Streamflow in a Typical Basin of Yellow River. *Frontiers in Earth Science*, *9*(October), 1–13. https://doi.org/10.3389/feart.2021.752425

Malede, D. A., Agumassie, T. A., Kosgei, J. R., Linh, N. T. T., & Andualem, T. G. (2022). Analysis of rainfall and streamflow trend and variability over ETB River watershed, Abbay basin, Ethiopia. *Environmental Challenges*, *7*(April), 100528. https://doi.org/10.1016/j.envc.2022.100528

Mattsson, J. O., & Rapp, A. (1991). The recent droughts in western Ethiopia and Sudan in a climatic context. *Ambio*, *20*(5), 172–175.

Mekonen, A. A., Berlie, A. B., & Ferede, M. B. (2020). Spatial and temporal drought incidence analysis in the northeastern highlands of Ethiopia. *Geoenvironmental Disasters*, *7*(1). https://doi.org/10.1186/s40677-020-0146-4

Memon, A. V., & Shah, N. V. (2019). Assessment and Comparison of SPI and RDI Meteorological Drought Indices in Panchmahals District of Gujarat, India. *International Journal of Current Microbiology and Applied Sciences*, *8*(08), 1995–2004. https://doi.org/10.20546/ijcmas.2019.808.233

Mohammed, Y., Yimer, F., Tadesse, M., & Tesfaye, K. (2018). Meteorological drought assessment in north east highlands of Ethiopia. *International Journal of Climate Change Strategies and Management*, *10*(1), 142–160. https://doi.org/10.1108/IJCCSM-12-2016-0179

Ozkaya, A., & Zerberg, Y. (2019). A 40-year analysis of the hydrological drought index for the Tigris Basin, Turkey. *Water (Switzerland)*, *11*(4). https://doi.org/10.3390/w11040657

Philip, S., Kew, S. F., van Oldenborgh, G. J., Otto, F., O'Keefe, S., Haustein, K., King, A., Zegeye, A., Eshetu, Z., Hailemariam, K., Singh, R., Jjemba, E., Funk, C., & Cullen, H. (2018). Attribution analysis of the Ethiopian drought of 2015. *Journal of Climate*, *31*(6), 2465–2486. https://doi.org/10.1175/JCLI-D-17-0274.1

Rahdari, M. R. (2016). *Investigate the relationship between hydrological and meteorological droughts in Karaj dam Basin Investigate the relationship between hydrological and*

Environmental Management, *61*(5), 860–874. https://doi.org/10.1007/s00267-018-1005-x

Thilakarathne, M., & Sridhar, V. (2017). Characterization of future drought conditions in the Lower Mekong River Basin. *Weather and Climate Extremes*, *17*(June), 47–58. https://doi.org/10.1016/j.wace.2017.07.004

Thomas B. McKee, N. J. D. and J. K. (1993). THE RELATIONSHIP OF DROUGHT FREQUENCY AND DURATION TO TIME SCALES. *Eighth Conference on Applied Climatology*, 818–824. https://doi.org/10.1002/jso.23002

Thomas, T., Jaiswal, R. K., Nayak, P. C., & Ghosh, N. C. (2015). Comprehensive evaluation of the changing drought characteristics in Bundelkhand region of Central India. *Meteorology and Atmospheric Physics*, *127*(2), 163–182. https://doi.org/10.1007/s00703-014-0361-1

Tigkas, D, Vangelis, H., & Tsakiris, G. (2013). The RDI as a composite climatic index. *Eur Water*, *June 2014*. http://www.ewra.net/ew/pdf/EW_2013_41_02.pdf

Tigkas, Dimitris, Vangelis, H., & Tsakiris, G. (2016). Introducing a Modified Reconnaissance Drought Index (RDIe) Incorporating Effective Precipitation. *Procedia Engineering*, *162*, 332–339. https://doi.org/10.1016/j.proeng.2016.11.072

Tijdeman, E., Hannaford, J., & Stahl, K. (2018). Human influences on streamflow drought characteristics in England and Wales. *Hydrology and Earth System Sciences*, *22*(2), 1051–1064. https://doi.org/10.5194/hess-22-1051-2018

Tsakiris, D. T. V. V. T. (2013). The RDI as a composite climatic Index. *European Water*, *41*, 17–22.

Tsakiris, G., Pangalou, D., & Vangelis, H. (2007). Regional drought assessment based on the Reconnaissance Drought Index (RDI). *Water Resources Management*, *21*(5), 821–833. https://doi.org/10.1007/s11269-006-9105-4

Turoglu, H. (2016). Sensitivity of Streamflow To Climate Change in Melen River Basin (Nw Turkey). *16th International Multidisciplinary Scientific Conference SGEM2016, Book 3*, *1*(SGEM2016 Conference Proceedings, ISBN 978-619-7105-61-2 / ISSN 1314-2704), 645–652. https://doi.org/10.5593/SGEM2016/B31/S12.084

Van Lanen, H. A. J. (2006). Drought propagation through the hydrological cycle. *IAHS-AISH Publication*, *308*, 122–127.

Van Loon, A. F. (2015). Hydrological drought explained. *Wiley Interdisciplinary Reviews: Water*, *2*(4), 359–392. https://doi.org/10.1002/WAT2.1085

Viste, E., Korecha, D., & Sorteberg, A. (2013). Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology*, *112*(3–4), 535–551. https://doi.org/10.1007/s00704-012-0746-3

Wale Worqlul, A., Taddele, Y. D., Ayana, E. K., Jeong, J., Adem, A. A., & Gerik, T. (2018). Impact of climate change on streamflow hydrology in headwater catchments of the upper Blue Nile Basin, Ethiopia. *Water (Switzerland)*, *10*(2). https://doi.org/10.3390/w10020120

Wilhite *et al.*, (1987). The Role of Definitions Understanding : the Drought Phenomenon : The Role of Definitions *. *Westview Press*, *August 2013*, 11–27.

Wu, I. (1997). The Hargreaves Evapotranspiration Model. In *CTAHR Fact Sheet* (Issue 106). http://hl-128-171-57-22.library.manoa.hawaii.edu/bitstream/10125/12218/1/EN-106.pdf

Yared Bayissa, Shreedhar Maskey, Tsegaye Tadesse, S. J. van A., & Semu Moges, A. van G. and D. S. (2018). Comparison of the Performance of Six Drought Indices in Characterizing Historical Drought for the Upper Blue Nile Basin, Ethiopia. *Geosciences*, *8*(81). https://doi.org/10.3390/geosciences8030081

Zakhem, B. A., & Kattaa, B. (2016). Investigation of hydrological drought using cumulative standardized precipitation index (SPI 30) in the eastern Mediterranean region (Damascus, Syria). *Journal of Earth System Science*, *125*(5), 969–984. https://doi.org/10.1007/s12040-016-0703-0

Zeng, X., Zhao, N., Sun, H., Ye, L., & Zhai, J. (2015). Changes and relationships of climatic and hydrological droughts in the Jialing River basin, China. *PLoS ONE*, *10*(11), 1–14. https://doi.org/10.1371/journal.pone.0141648