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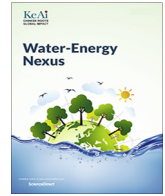
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Research Paper

Sensitivity of streamflow to meteorological drought in the Andit Tid watershed, Ethiopia

Ayele Desalegn Woldemariam^{*}, Kebede Bekele Atlaw, Tilahun Getachew Abebe, Getacher Kassa Mitiku

Amhara Agricultural Research Institute, Debre Birhan Agricultural Research Center, P.O. Box 112, Debre Birhan, Ethiopia

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ABSTRACT

Drought is an environmental phenomenon and an integral part of climate change that can occur anywhere. Drought can take different forms, including meteorological, hydrological, agricultural, and socioeconomic droughts. The main goal of this study was to identify how meteorological droughts can cause hydrological droughts. The study confirmed that the area experienced both hydrological and meteorological droughts in 1987, 2003, and 2015. Index-based drought analysis results showed a significant ($P < 0.05$) correlation between hydrological and meteorological droughts. Particularly, it was determined that there was a better association between the Streamflow Drought Index and Reconnaissance Drought Index than between the Standardized Precipitation Index. This demonstrates how strongly evapotranspiration influences streamflow, a factor that the Reconnaissance Drought Index considers when calculating its value. Based on projected scenarios for streamflow and climate factors, all variables in the watershed are expected to decline up to 2030, other than maximum temperature. From the prediction process results, SARIMA caught better the seasonality of temperature than rainfall or streamflow. Investigating index-based droughts is essential to warn the public and decision-makers about impending droughts and help them put mitigation and adaptation plans for water management into action.

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1. Introduction

Drought is a multifaceted natural hazard; its definition varies across individual perceptions. It is generally a prolonged period of below-average rainfall that disrupts water availability, causing damage to plants. The glossary of meteorology defines drought as a period of abnormally dry weather sufficiently severe to introduce a hydrological imbalance to a certain area (Wilhite et al., 1987). Although drought evolves spontaneously and receives very little attention than often-happening flooding and cyclones, the impacts of drought can be equal to or more devastating on a substantial spatial and temporal coverage in all climatic zones (Rahdari, 2016).

Drought has been identified as one of the environmental phenomena and is an integral part of climate change. It is classified into several interconnected forms, including meteorological, hydrological, agricultural, and groundwater drought, which indicate the spread of water deficits in climate, soil, and hydrology (Shahid and Behrawan, 2008). Meteorological drought is the continuous decrease in precipitation and often triggers agricultural drought, which is associated with soil moisture deficit affecting

crop and forage productivity. Groundwater drought is a recently emerged drought type highlighting the delayed and complex response of aquifer systems to hydro-meteorological anomalies and land-surface changes (Haile et al., 2020a,b; Kumar et al., 2016). Hydrological droughts are a more concerning drought type characterized by the decline in river discharge, reservoir storage, lake levels, and groundwater availability. It is influenced by catchment characteristics, land use, and water management practices, causing hydrological drought to lag behind meteorological drought (Bhardwaj et al., 2020; Van Lanen, 2006, 2015).

Even though the drought starts with a rainfall deficit, it ultimately transfers into a hydrological drought, which means 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. The analysis of the hydrological drought is important due to the dependence of most of the industrial, water, and power plants' activities on surface water resources (Faiz et al., 2021; Zakhem and Kattaa, 2016). For example, the duration of drought in streamflow is crucial for hydropower production, particularly the missing volume of water compared to normal conditions, which is more relevant. The results of hydrological drought analysis can be useful for proper water resources

^{*} Corresponding author.

E-mail address: ayeledesalegn5@gmail.com (A.D. Woldemariam).

management, including better planning for water supply and demand. Despite the importance of hydrological drought, long-term assessments of how meteorological drought signals propagate into streamflow remain limited in many regions. Studying this relationship is believed to be essential for improving drought early-warning systems, water allocation planning, and climate-risk management. Index-based approaches, when applied to multi-decadal hydro-meteorological datasets, offer a robust means of quantifying drought characteristics and assessing catchment sensitivity to climatic extremes. To describe the drought hazard of current and past streamflow drought episodes, quintile-based techniques, such as streamflow percentiles on the threshold level method, have been employed traditionally. However, this study employed the recently popular Streamflow Drought Index (SDI) to calculate streamflow sensitivity to meteorological drought.

This study investigated the comprehensive sensitivity analysis of streamflow to meteorological drought using 34 years of hydrological and meteorological datasets recorded from the Andit Tid watershed. By integrating key drought indices, namely the Standardized Precipitation Index (SPI), Reconnaissance Drought Index (RDI), and SDI and drought propagation characteristics, this study elucidates how streamflow responded to meteorological anomalies. Through this analysis, the study sought to ensure our knowledge of how delicate the sensitivity of streamflow is under meteorological drought incidents. This study aims not only to contribute valuable insights into the sensitivity but also to help as an input during the establishment of basin-specific drought monitoring strategies. This finding also provides basic scientific evidence that can support improved drought preparedness, water resource sustainability, and adaptive strategies in increasing climate variability. Ultimately, the insights from this study can inform policymakers and stakeholders, leading to more resilient water management practices in the Andit Tid watershed and similar regions susceptible to drought.

2. Materials and methods

2.1. Description of the study area

This study was conducted at the Andit Tid watershed, which is one of the Soil Conservation Research Project (SCRIP) research stations. It is situated at 39°42.5'–39°44'E longitude and 9°47.5'–9°49'N latitude (Fig. 1), 180 km northeast of the capital city of the country. The watershed covers a total area of 477.6 ha, and the altitude of the catchment ranges from 3040 to 3550 m above sea level. The watershed is located in the moist and humid agro-climatic zone. Its mean annual rainfall is 1581 mm; minimum and maximum temperatures are 7.5 °C and 17.6 °C, respectively.

2.2. Methods of data collection and analysis

This study was conducted by analyzing the time series of hydrologic and meteorological drought indices. 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 and RDI were two drought indices to monitor and quantify Meteorological drought, while the sensitivity of streamflow to drought was identified using SDI.

The 34 years of rainfall, temperature, and streamflow data were collected from the Andit Tid watershed station. The missing data in the streamflow from 2009 to 2011 were filled using Markov Chain Monte Carlo (MCMC) methods in XLSTAT.

All the indices were analyzed by using DrinC software version 1.5.73. This software was intended to give a means for the consistent calculation of numerous drought indices for drought analysis in research and operational applications (Tsakiris, 2013). A special routine has been added to the DrinC software for calculating the modified RDI. In the computation process, precipitation and runoff data were fitted to the log-normal distribution function. The calculation is carried out through a graphical user interface with several options for characterizing drought. The future streamflow forecast, considering climate change, was computed using R software with the Seasonal Autoregressive Integrated Moving Average (SARIMA) function. Correlations among the indices were analyzed to understand how meteorological drought propagated into hydrological drought.

2.2.1. Standardized Precipitation Index (SPI)

Due to its temporal flexibility to calculate, SPI is applicable for both long-term hydrological applications and short-term agricultural uses. 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). SPI has an intrinsic probabilistic nature, and this characteristic makes it an ideal index for carrying out drought risk analysis (Rossi and Cancelliere, 2002).

In the case of this study, it's calculated based on the long-term precipitation record for the desired period of 1986–2020. This long-term record is fitted to a 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). The values of SPI are categorized and defined in a Table, and the meaning of each value is defined as follows: positive SPI values indicate values that are greater than the median precipitation, and negative SPI values indicate values that are less than the median precipitation.

Its calculation is through fitting a gamma probability density function to a given frequency distribution of precipitation. The two parameters α and β of the gamma probability density function were estimated for the precipitation with a monthly, 3-month, 6 month and, and annual time periods (Karavitis et al., 2011; Lee et al., 2023). It was developed on the basis that precipitation deficit has different impacts on groundwater, reservoir storage, soil moisture and streamflow (McKee et al., 1993). Following these procedures, the SPI at a monthly, 3-month, 6 month and, and annual time scales has been analyzed for the study watershed. The complete calculation procedure of SPI is presented in Eq. (1) following McKee et al. (1993).

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (1)$$

where β is a scale parameter, α is a shape parameter, $g(x)$ is the gamma probability density function, e is Euler's number for exponentiation and $\Gamma(\alpha)$ is the ordinary gamma function of α . Detailed information about the estimation of β and α is stated by McKee et al. (1993).

2.2.2. Reconnaissance Drought Index (RDI)

To sufficiently represent the effective precipitation that is expected to contribute to groundwater recharge and precipitation not pass through the root system, effective precipitation instead of total precipitation has been used during the computation of RDI of

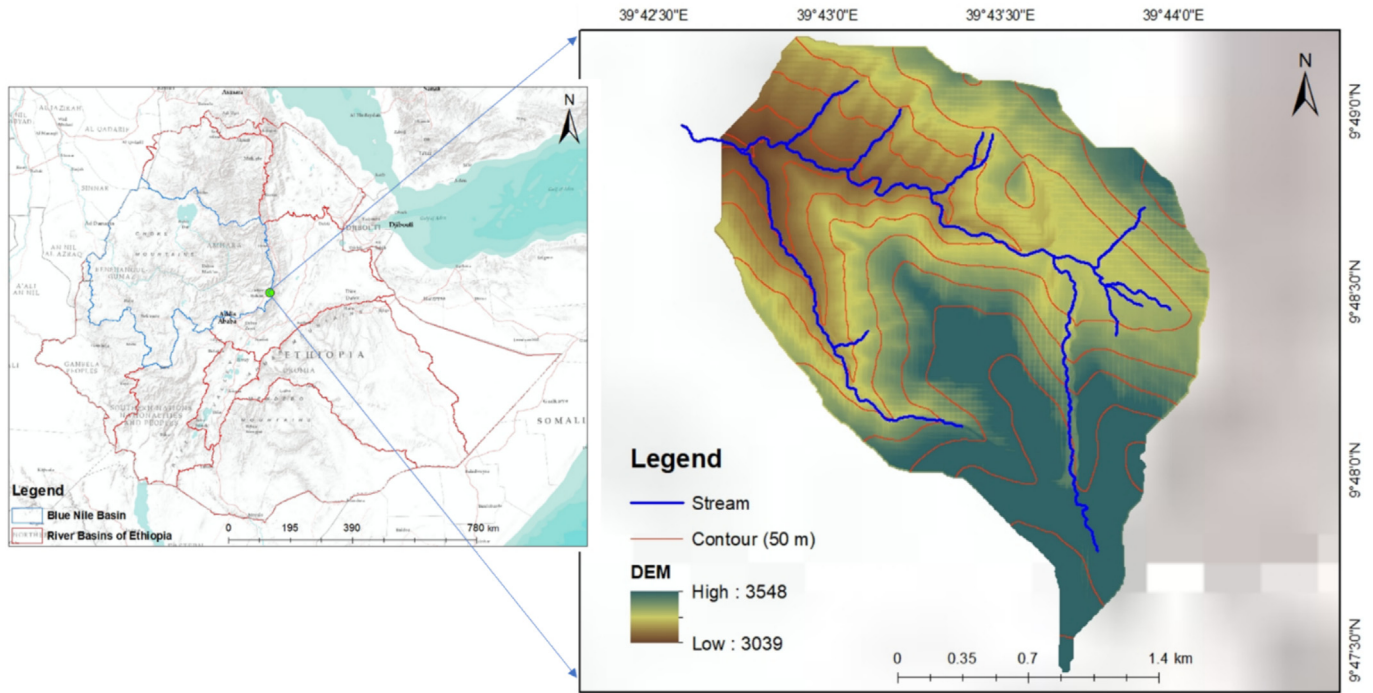


Fig. 1. Location map of the study area.

this study. The RDI was introduced by Tigkas et al. (2016) and Tsakiris (2013) as a physically based universal index utilized cumulative precipitation (P) and potential evapotranspiration (PET) for specified reference periods. The initial form of the index (I) within a year for a reference period of k months is calculated as Eqs. (2) and (3) (Tigkas et al., 2016; Tsakiris et al., 2007).

$$a_k = \sum_{j=1}^k p_{ij} / \sum_{j=1}^k PET_{ij} \quad (2)$$

$$RDI_{n(i)} = (a_k / a_{k-1}) \quad (3)$$

where p is precipitation in mm, and PET is potential evapotranspiration, a_k is the arithmetic mean of the initial expression of RDI for the k th month (Thomas et al., 2015).

Because of the lack of required data for the computation of PET in a more advanced way, this study was obligated to use the Hargreaves method (Eq. (4)) (Wu, 1997) for this study.

$$ET_0 = a + b * \frac{1}{\lambda} * 0.0023 * \left(\frac{T_{max} + T_{min}}{2} + 17.8 \right) * \sqrt{T_{max} - T_{min}} * R_a \quad (4)$$

where T_{max} and T_{min} are the maximum and minimum temperatures ($^{\circ}\text{C}$); R_a is the extra-terrestrial solar radiation ($\text{MJ m}^{-2} \text{d}^{-1}$); a & b are calibrated coefficients with default values of $a = 0$ & $b = 1$.

2.2.3. Streamflow Drought Index (SDI)

SDI calculation was performed following Eq. (5) (Emiru et al., 2021; Zhao et al., 2016; Rahdari, 2016; Zeng et al., 2015). For a time series of monthly streamflow volumes available, i denotes the hydrological year, and j represents the month within that hydrological year ($j = 1$ for October and $j = 12$ for September).

$$V_{i,k} = \sum_{j=1}^{3k} Q_{ij} \quad (5)$$

where $i = 1, 2, \dots, N$, $j = 1, 2, \dots, 12$ and $k = 1, 2, 3, 4$. V is the cumulative streamflow 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 streamflow volumes, the SDI is defined for each reference period k of the i th hydrological year, Eq. (6)

$$SDI_{i,k} = (V_{i,k} - \bar{V}_k) / S_k \quad (6)$$

where $i = 1, 2, \dots, N$ and $k = 1, 2, 3, 4$, $\bar{V}_k$ and S_k are the mean and the standard deviation, respectively, of the cumulative streamflow volumes of the reference period k , as these are estimated over a long time. In this definition, the truncation level is set to $\bar{V}_k$, although other values based on rational criteria will also be used.

The SDI, which is defined in Eqs. (7) and (8), is the natural logarithm of cumulative streamflow with mean $\bar{V}_k$ and $S_{y,k}$, as these statistics are estimated over a long period (Tigkas et al., 2016).

$$SDI_{i,k} = (y_{i,k} - \bar{Y}_k) / S_{y,k} \quad (7)$$

where $i = 1, 2, \dots, N$ and $k = 1, 2, 3, 4$ and:

$$y_{i,k} = \ln(V_{i,k}) \quad (8)$$

where $i = 1, 2, \dots, N$ and $k = 1, 2, 3, 4$.

The classification of the drought indices of all SPI, RDI, and SDI was done following McKee et al. (1993) as presented in Table 1.

Table 1

Classification of drought conditions based on the computed SPI, RDI, and SDI values.

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

2.2.4. Correlation analysis

Pearson correlation between the SPI, RDI, and SDI indices was performed to look at the rate of propagation of meteorological drought in to hydrological systems. It is reported as an effective method for the analysis of potential relationships between two independent variables (López-Moreno et al., 2013; Zeng et al., 2015). In this research, correlation analysis has been computed using the R software.

2.2.5. Seasonal forecast with SARIMA

SARIMA was shown to be superior to the older version of the so-called ARIMA because of its strong capacity to identify the seasonality of the variables (Kumari and Muthulakshmi, 2024; Nwokike et al., 2020; Yavuz, 2025). To take into consideration recurrent seasonal trends, it incorporates seasonal components such as the seasonal autoregressive (P), differencing (D), moving average (Q), and period length (m). Determining the values of p, d, and q, as well as P, D, and Q by examining the time series' partial autocorrelation and autocorrelation functions is the first stage in estimating a SARIMA model. These functions aid in determining which lag values are important enough to be included in the model. Maximum likelihood estimation can be used to fit the model to the data after parameters have been established.

$$\text{SARIMA}(p,d,q)(P,D,Q)m;$$

where m is the number of observations per year. This research considered using uppercase notation for the seasonal parts of the model and lowercase notation for the non-seasonal parts of the model.

The results of SARIMA are measured in terms of forecast accuracy. The observed data is divided into two sets: a training values to be used in estimating the parameters and a test values 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 Eqs. (9) and (10), respectively. As for scale-independent measures, the most commonly used one is Mean Absolute Percentage Error (MAPE), defined in Eq. (11) (Rebelob, 2015).

$$\text{MAE} = \frac{1}{n-m} \sum_{t=m+1}^n |y_t - \bar{y}_t| \quad (9)$$

$$\text{RMSE} = \sqrt{\frac{1}{n-m} \sum_{t=m+1}^n (y_t - \bar{y}_t)^2} \quad (10)$$

$$\text{MAPE} = \frac{1}{n-m} \sum_{t=m+1}^n \left| \frac{y_t - \bar{y}_t}{y_t} \right| * 100 \quad (11)$$

where n is the number of sample months; y_t is the actual observation of t th month; $\bar{y}_t$ is the forecasted data value of t th month; and m is the number of observations per year (11).

2.3. Data diagnostic test and quality checking

Prior to conducting the prediction, we carried out a series of diagnostic checks to ensure the reliability and suitability of the data for time series modeling. These checks included the QQ quantile plot to assess the normality of the data, which helps identify deviations from a normal distribution. we used the correlogram to examine the presence of autocorrelation within the time series,

which is essential for selecting appropriate model parameters. The standard residual plot was employed to evaluate the randomness and constant variance of residuals, ensuring that the model assumptions were not violated. Additionally, a histogram was used to visually inspect the data distribution and detect any skewness or irregular patterns. These preliminary analyses provided confidence in the data quality and informed the appropriate configuration of the SARIMA model for accurate forecasting.

3. Result and discussion

3.1. Estimation of drought indices with different time frames

Drought has occurred at different times in the watershed, as assured by analyzing the long-term historical meteorological and hydrological data. Metrological droughts were characterized by SPI and RDI indices using 1, 3, 6, and 12-month time steps.

3.1.1. One-month Drought Indices values

In this study, the one-month drought occurrence was explored by categorizing the severity class of drought as extreme, severe, or moderate. In July 1987 and 2015, there was an extreme drought. Similarly, severe droughts were seen 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 droughts were also seen 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).

According to the 3-month, 6-month, and annual time step SPI and RDI indices analysis, the watershed experienced a higher peak of drought in 1987 and 2003. On a three-month timescale, it was more practical to examine the drought's effects on the watershed's main rainy season (Kiremit) and short rainy season (Belg). The severe drought occurred in 2003 and 2015. The only extreme drought occurred in the Kiremit of 1987. Moreover, moderate dryness was seen in 1995 during the kiremit months. So, those incidents would have a higher risk in the study area. Similar research by Segele and Lamb (2005) and Viste et al. (2013) reported that the kiremit season of 1987 was severely dry over Ethiopia, particularly in the northeastern half of the country. According to Mekonen et al. (2020), the drought risk intensity was more weighted during the months of the kiremit season. The most damaging historical droughts in Ethiopia are connected with the failure of kiremit rain (Segele and Lamb, 2005). This argument is valid because the majority of the highlands in Ethiopia have a time-bound rainy season, with bimodal rainfall concentrated from January to March and June to September of each year. From June to September, also known as Kiremt, is the main rainfall season not just in the highlands but throughout the country, and a lack of rainfall during this rainy season directly causes the region to suffer from drought. Even during the short rainy season (January–March), the most severe drought occurred in 2003 and 2012. 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 (Bayissa et al., 2018). According to the center, a drought occurred in June 1987 (Shewa, Wollo, Tigray), from October 1989 to 1994, 2003 to 2004, and May 2008 to October 2009 (Tigray, Amhara, Oromiya). Drought occurred and millions of people were affected in 2008 throughout Ethiopia, and in 2015 in the north, east, and southwest Ethiopia (Mohammed et al., 2018).

This explanation of the monthly, 3-month, 6-month, and yearly droughts mentioned and discussed is based on the values of SPI

and RDI, and there was no significant difference between the two indices, as stated by Alemu et al. (2021). Nevertheless, the RDI is more advantageous than SPI since the RDI incorporates both temperature and precipitation data in a single index, whereas the SPI includes only precipitation data. Similarly, Jamshidi et al. (2011) showed that the RDI is more responsive to climatic circumstances than the SPI, and hence the RDI is more suited for meteorological drought monitoring. Alemu et al. (2021) also reported that the role of evapotranspiration is very important in drought assessment and should not be ignored.

3.1.2. Three-month Drought Indices values

This section is visually illustrated in Fig. 2, which presents the three-month (quarterly) SPI, RDI, and SDI values in a single composite chart.

3.1.2.1. SPI-3. 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 scholar (Philip et al., 2018; Sjoukje et al., 2017).

3.1.2.2. RDI-3. Based on the three-month drought analysis using this index, the watershed's primary rainy season, which runs from July to September, had severe drought in 1987 (RDI = -3.24), 2003 (RDI = -1.62), 2009 (RDI = -1.22), and 2015 (RDI = -2.05). In 1988, 1990, 1999, 2001, 2003, and 2009, there was a chance of drought during the other rainy season, which runs from April to May. According to the calculation of all three months' drought indices, 2003 was the year with the most drought-affected years throughout the period taken into consideration for this study. Additionally, the indices' values demonstrated that the watershed's agroecological class was humid.

3.1.2.3. 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 to June, mild and moderate drought has 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 ensure meteorological drought impacts on hydrological droughts (Wale Worqlul et al., 2018).

3.1.3. Six-month Drought Indices values

This section is visually illustrated in Fig. 3, which presents the six-month (half-year) SPI, RDI, and SDI values in a single composite chart.

3.1.3.1. SPI-6. 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 in Ethiopia (Richman et al., 2016). Drought also happened from October to March of 2003, 2012, 2015, and 2018 (Fig. 3). The years 2016 (October–March) and 2009 (April–September) were affected by a moderate drought.

3.1.3.2. RDI-6. With an RDI value less than negative 1, it was discovered that two years (1987 and 2003) experienced drought from May to September, while five years (1987, 1990, 2003, 2010, 2015) from the studied period had drought from October to March. A 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. The data chart trends

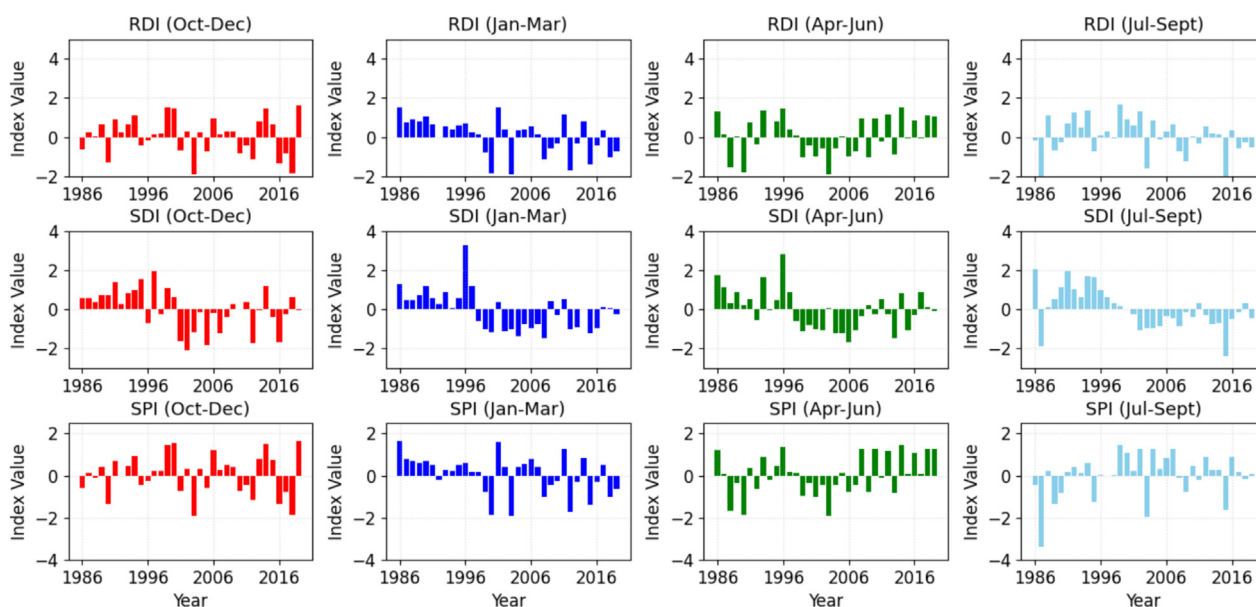


Fig. 2. Three-month drought indices of RDI, SDI, and SPI.

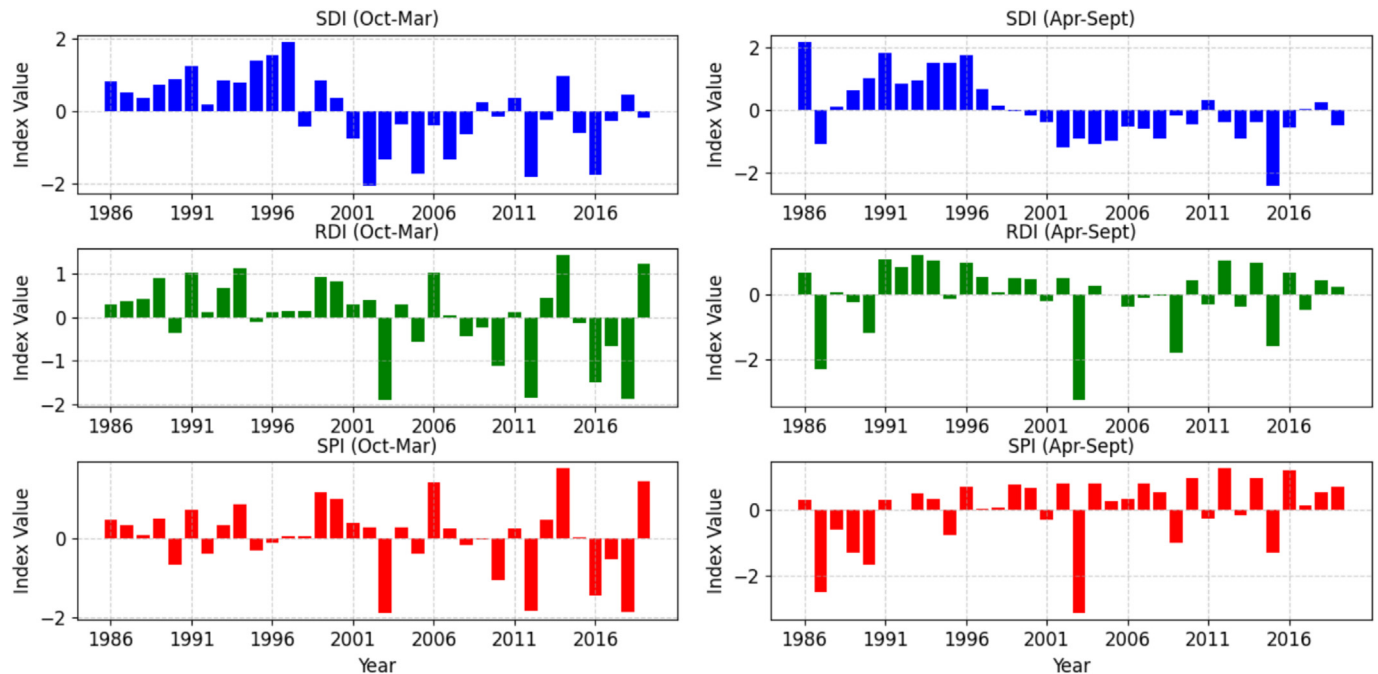


Fig. 3. The six-month drought indices value for all SDI, SPI and RDI.

for this index are nearly identical to those of the SPI value for the same time frame (Fig. 3).

3.1.3.3. SDI-6. For the last 34 years, drought incidents have occurred from October to March in 14 years (41.2%). From there, the years 2003, 2012, 2016, and 2005 were affected by extreme droughts with SDI-6. Similarly, from April to September, more droughts (50%) have occurred. However, only one extreme drought

in the year 2015, with an SDI-6 value of less than -2.0 , was experienced, and the others were only moderate and mild. The SDI-6 series showed a more remarkable decrease in streamflow during the October–March period as compared with the April–September period. According to Ozkaya and Zerberg (2019), a decrease in streamflow and water losses resulted in reduced use of irrigation water, because the requirement for crop irrigation was the highest at the time.

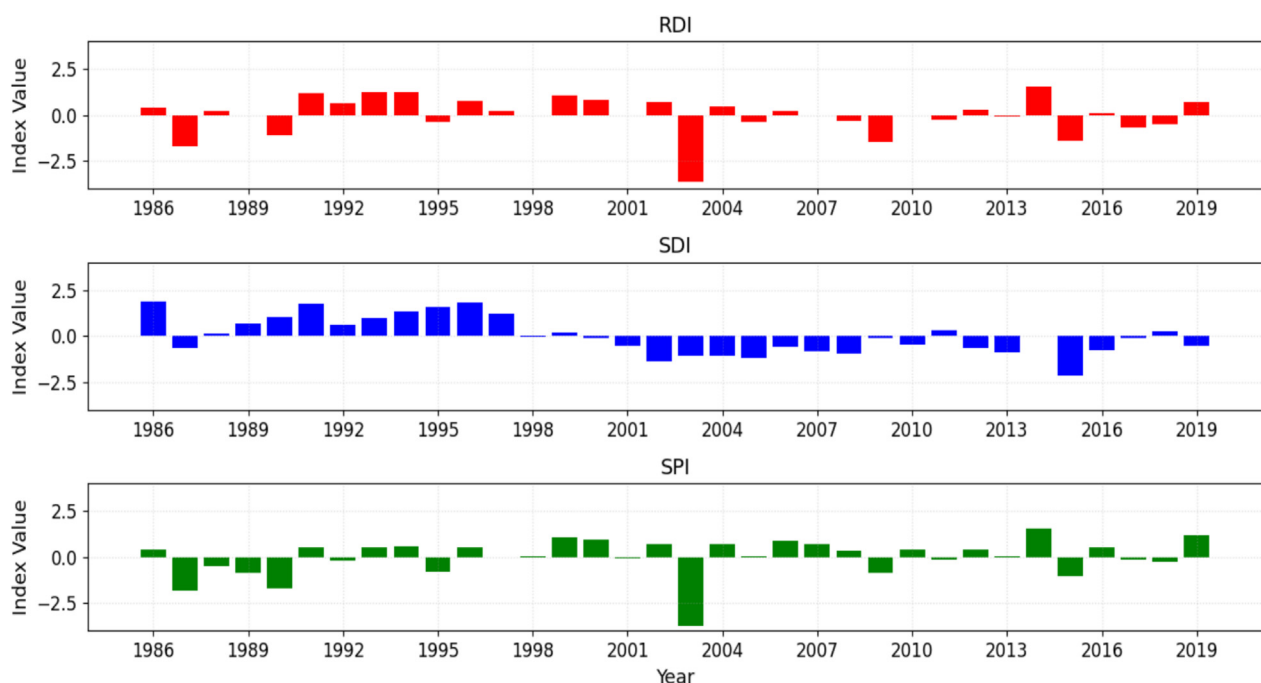


Fig. 4. The annual drought trends over time in RDI, SDI and SPI viewpoints.

3.1.4. Annual Drought Indices values

This section is visually illustrated in Fig. 4, which presents the annual values of SPI, RDI, and SDI in a single composite chart.

3.1.4.1. SPI-12. The long-term trend of the annual SPI, as shown in Fig. 4, highlights distinct drought and wetness episodes in the watershed. Notably, the year 2003 experienced an extreme drought, with an SPI value below -3.74 , the lowest in the observed period. Additionally, 1987 and 1990 were found to be exceptionally dry years, with SPI values of -1.83 and -1.67 , respectively, aligning with the findings of Mattsson and Rapp (1991). In contrast, 2015 was classified as a moderately dry year ($\text{SPI} = -1.07$). Moderately wet conditions were observed in 1999, 2014, and 2019. Over the entire study period, the watershed experienced near-normal climatic conditions for around 28 years, with annual SPI values ranging between -1 and $+1$. These trends suggest that, despite some severe and moderate drought episodes, the watershed's overall climate has remained relatively stable, with fluctuations falling within normal climatic variability most of the time.

3.1.4.2. RDI-12. This index indicated that 2003 was found to be an extremely dry year for the watershed since 2003, 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 the Upper Blue Nile basin by Kebede et al. (2019) reported severe drought at Debre Birhan in 1987 and 1989. The years 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 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 years 1991, 1993, 1994, 1999, and 2014 were found to be moderately wet years.

3.1.4.3. SDI-12. The analysis of the annual drought (SDI-12) indicate that droughts occurred in 16 years (47%) of the period. Among these, one year (2015) experienced an extreme drought with an SDI-12 value of -2.16 , and four years (2002–2005) experienced severe droughts with SDI-12 values of -1.43 , -1.10 , -1.05 , and -1.2 , respectively. The remaining years experienced mild droughts. This suggests that there was consistently below-average streamflow recorded across all SDI analysis periods. The years 1986, 1991, 1995, and 1996 were identified as very wet years, while 1990, 1994, and 1997 were classified as moderately wet years, as shown in the chart below. These wet years of streamflow coincided with dry weather conditions, as indicated by the SPI and RDI.

For instance, the SPI classified 1990 as a moderately dry year, but there was a water deficit in the stream. Such events might occur since there are insufficient structures to facilitate water infiltration into the ground. As a result, rainwater directly transforms into runoff and flows. 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 will not instantly convert into 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).

3.1.5. Sensitivity of streamflow to meteorological drought

The correlation analysis among the three-month drought indices revealed important seasonal relationships. As shown in Fig. 5, out of the 12 possible index pairs, 11 showed statistically

significant correlations ($P < 0.05$), indicating meaningful associations between specific drought indices during certain seasons. The strongest correlation was observed between the RDI and the SPI in all quarters, with a correlation of from 89% to 99%. This suggests a strong linkage between drought-indicating conditions during this period. The next strongest correlations were found between RDI and SDI, with the correlation coefficient value of between 39% and 60%, RDI and SDI (April–June) at 50%, and RDI and SDI (January–March) at 60%. These results reflect how rainfall and water demand jointly influence drought conditions across various seasons. Notably, all indices were significantly correlated in October–December, January–March and April–June, suggesting that these seasons exhibit consistent interrelationships among drought indicators. However, for the July–September period, only RDI and SPI and RDI and SDI were significantly correlated, possibly due to variable rainfall patterns or delayed hydrological responses. The biophysical characteristics of the watershed may also have an impact on the proportional change in streamflow caused by meteorological factors (Lv et al., 2021). From July to September, the streamflow was not affected by drought. Since these were the watershed's primary rainy months, there may be more factors besides climatic ones that affect streamflow.

For sensitivity analysis, it was better to investigate the relationship of streamflow with climatic parameters (Basijokaite and Kelleher, 2021; Malede et al., 2022). Similar findings by Boudad et al. (2018) and Lohpaisankrit and Techamahasaranont (2021) reported a positive relationship between meteorological and hydrological droughts.

The six-month drought indices correlation analysis reveals strong interrelationships among the indices, with all showing statistically significant correlations (Fig. 6). Notably, the highest correlations were found between the RDI and the SPI, particularly from October to March (97%) and April to September (87%). These strong correlations suggest that both indices effectively capture similar drought signals over longer time scales. In contrast, the correlation between the SDI and SPI was insignificant from April to September (9%), and a smaller significant relationship was observed from October to March (36%). This indicates that streamflow responses to precipitation may lag or be influenced by additional hydrological processes. Compared to SPI, the RDI shows a closer relationship due to its consideration of both precipitation and evapotranspiration, making it more responsive to climatic water demand. Thus, RDI appears to be a more cautious and comprehensive indicator for long-term streamflow assessment.

The annual drought indices correlation analysis revealed significant relationships in two of the three index pairs. As illustrated in Fig. 7, the strongest correlation was observed between the SPI and the RDI, with a value of 90%, indicating a strong climatic influence on drought conditions. A moderate but still significant correlation (39%) was found between RDI and the SDI, while the SPI-SDI pair showed a weak and statistically insignificant correlation (10%). This weak SPI-SDI relationship suggests that precipitation alone does not fully explain streamflow variability on an annual scale. The low correlation between SPI and SDI at the annual level, compared to shorter time scales, may reflect delayed hydrological responses and the cumulative effects of climate over time. The stronger influence of RDI on streamflow highlights the importance of considering evapotranspiration in drought assessments.

In all time correlation analyses (Figs. 5–7), at 3 months, 6 months, and 12 months, RDI and SDI show better correlations, and all are statistically significant ($P < 0.05$). This is due to the inclusion of many climatic parameters, such as Eto, in the calculation of RDI. Using RDI appears to be very sensitive to climatic variability due to the use of ETo in its determination processes (Khalili

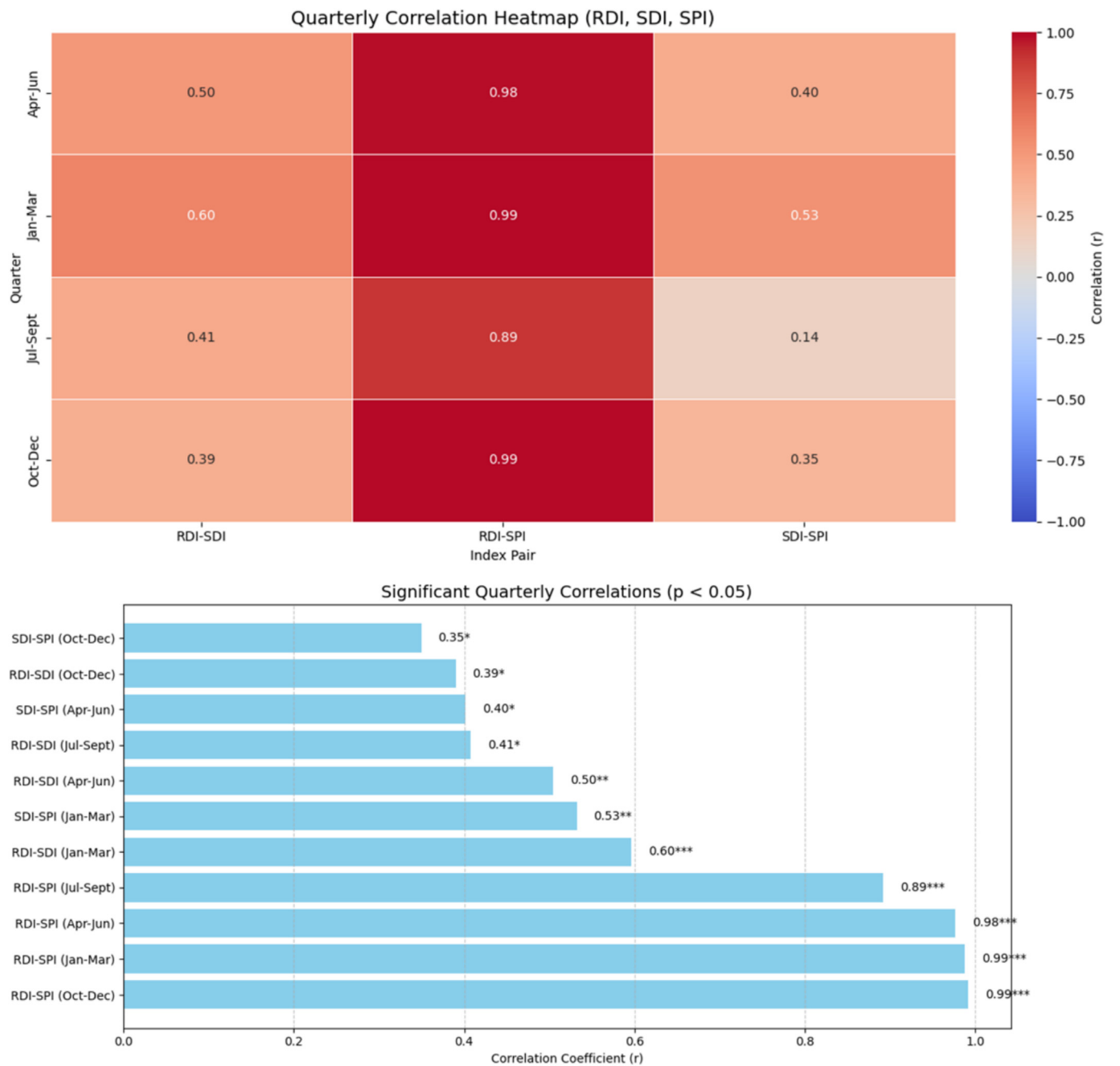


Fig. 5. The correlation chart of SPI, RDI, and SDI over the three-month time frames.

et al., 2011; Memon and Shah, 2019). From the result of the correlation between SDI and RDI, we can confirm that the streamflow is highly affected by evapotranspiration.

Compared to correlations between other pairs of meteorological indices, correlations involving SDI were generally low. According to Bayissa 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 for the insignificant correlation with other drought indices, particularly with SPI.

3.1.6. Diagnostic tests result

The results of the diagnostic tests confirmed that the data could be used for forecasting the future. All Q-Q plots show that, with very few exceptions, the observed data quantiles nearly match the theoretical normal distribution, as seen in Figs. 8 and 9. This lends credence to the data normality assumption. The unexistence of significant autocorrelation is further confirmed by the correlograms, which show that the residuals are independent, a crucial feature of a well-fitting model. The test reflects the underlying data patterns, as evidenced by the standardized residual plots, which also show consistency with a normal distribution and no notable

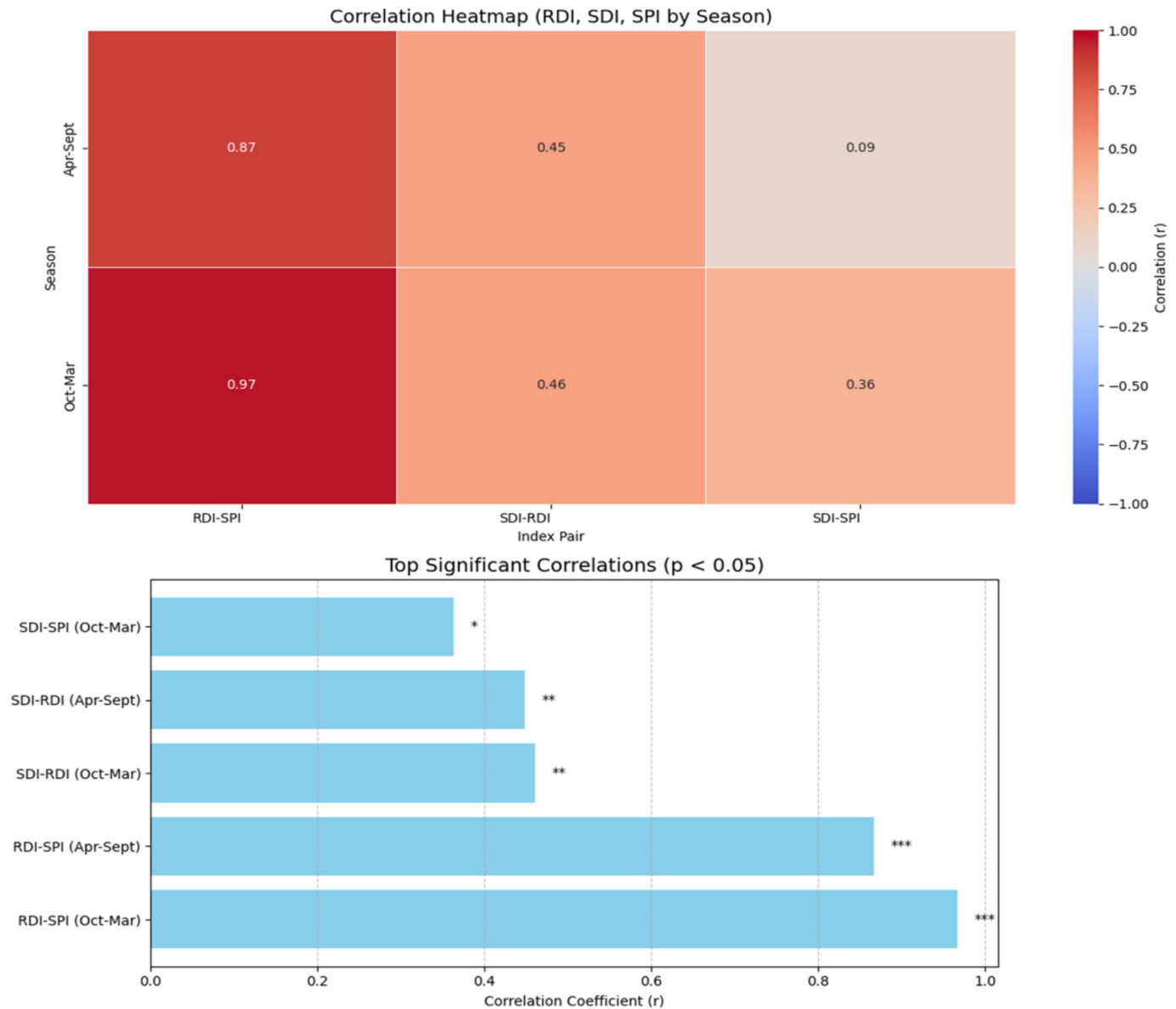


Fig. 6. The correlation chart of SPI, RDI, and SDI over a six-month time frame.

outliers. Furthermore, the histograms show no noticeable skewness to the right or left, supporting the idea that the data are normally distributed and suitable for precise prediction. The Kernel Density Estimate (KDE), shown in orange colour, directly follows the Standard Normal Distribution ($N(0,1)$) in blue colour in the histogram. The strong resemblance of KDE and the theoretical normal curve $N(0,1)$ of the minimum and maximum temperature data shows the temperature data is more normally distributed than the rainfall and streamflow (Fig. 8). In the case of rainfall and streamflow, the peak and very low in season variation of records, the kernel density exhibits peaks and deviations from the standard normal distribution bell (Fig. 9).

3.2. Prediction of future streamflow and climatic variables

The annual rainfall, temperature, and streamflow trends have been forecasted using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model as indicated in Figs. 10 and 11.

Based on the SARIMA model, hydrological drought is projected to intensify in the near future. As illustrated in the chart, the red-colored line indicates future projected streamflow, derived using the blue-colored historical streamflow data and green-colored model validation years (2018–2019). The model forecasts a slight decline in streamflow up to 2030, which closely mirrors the observed historical trends. This reduction has occurred with the projected increase in maximum temperature and decrease in minimum temperature, which contributes to higher evapotranspiration and reduced water availability and the undefined projected rainfall trend. A combination of decreased atmospheric moisture and increased surface energy fluxes, especially due to soil degradation in the highland regions, might be a cause for this asymmetric warming pattern. While other research, [Manatsa et al. \(2008\)](#) and [Seleshi and Zanke \(2004\)](#), has also noted rises in maximum temperatures with varied trends in minimum temperatures, in the central Ethiopian highlands. These results highlight how crucial it is to include specific land-atmosphere interactions in climate

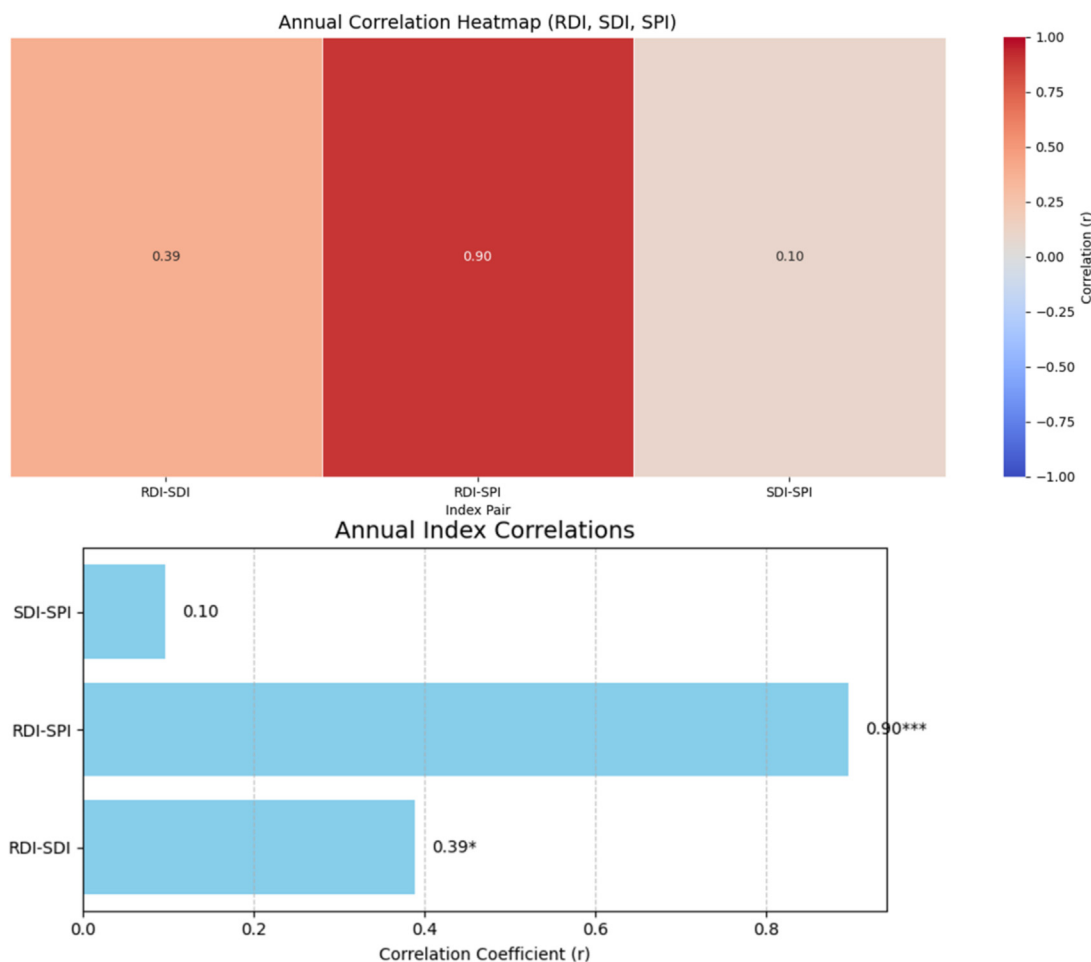


Fig. 7. The correlation chart between SPI, RDI, and SPI of annual time frames.

models over intricate topographies, such as the Ethiopian highlands.

There are numerous recent studies conducted in Ethiopia and sub-Saharan Africa that support this predicted decrease in streamflow. For instance, [Worku et al. \(2021\)](#) modeled the Upper Blue Nile Basin using the SWAT model and found that climate change would likely cause seasonal declines in streamflow, particularly during dry periods, due to decreased rainfall and higher temperatures. Similarly, [Orkodjo et al. \(2022\)](#) projected declining streamflow in northern Ethiopia under future climate scenarios (RCP 4.5 and 8.5), attributing it to both reduced rainfall and increased temperature extremes. [Beyene et al. \(2010\)](#), studying the broader Nile Basin, also forecasted reduced streamflow under various GCM outputs, further affirming the SARIMA-based results.

Across sub-Saharan Africa, [Dosio et al. \(2019\)](#) projected increasing temperature extremes and variable rainfall, especially in Eastern Africa, leading to a heightened risk of hydrological droughts. Similarly, [Haile et al. \(2020a,b\)](#) noted that many catchments in SSA are likely to experience greater hydrological stress, particularly in areas with high climate sensitivity and dependence on rain-fed systems.

However, some contrasting evidence should be acknowledged. For example, [Tesemma et al. \(2010\)](#) suggested that despite annual rainfall decreases, short-term streamflow might increase in certain regions due to more intense and concentrated rainfall events.

3.2.1. Prediction accuracy assessment

Three common performance metrics, namely RMSE, MAE, and MAPE, were used to evaluate the accuracy of the SARIMA-based forecasts. As presented in [Table 2](#), the findings showed that the temperature forecasts had the lowest errors, while the rainfall and streamflow estimates had the highest errors compared to temperature.

MAPE values of 5.99% and 13.9% in forecasting maximum and minimum temperature mean that the average difference between the forecasted value and the actual value is 5.99% and 13.9%, respectively ([Table 2](#)). With these metrics, the prediction model can be considered a very accurate model. Similarly, the RMSE and MAE values of temperature are very small; this is an indicator of the accuracy of the prediction model. This is expected, as temperature series are generally more stable and follow smoother seasonal trends compared to rainfall or streamflow. SARIMA models are well-suited for such stable time series, leading to better predictive performance. However, the rainfall and streamflow projections showed higher error values. Although SARIMA can capture seasonal patterns reasonably well for temperature, it is found to be inherently more variable and stochastic for rainfall and streamflow.

As indicated in the equation to compute MAPE, there is a division by the actual value. Both rainfall and streamflow often exhibit sharper peaks and greater variability, making it more difficult for

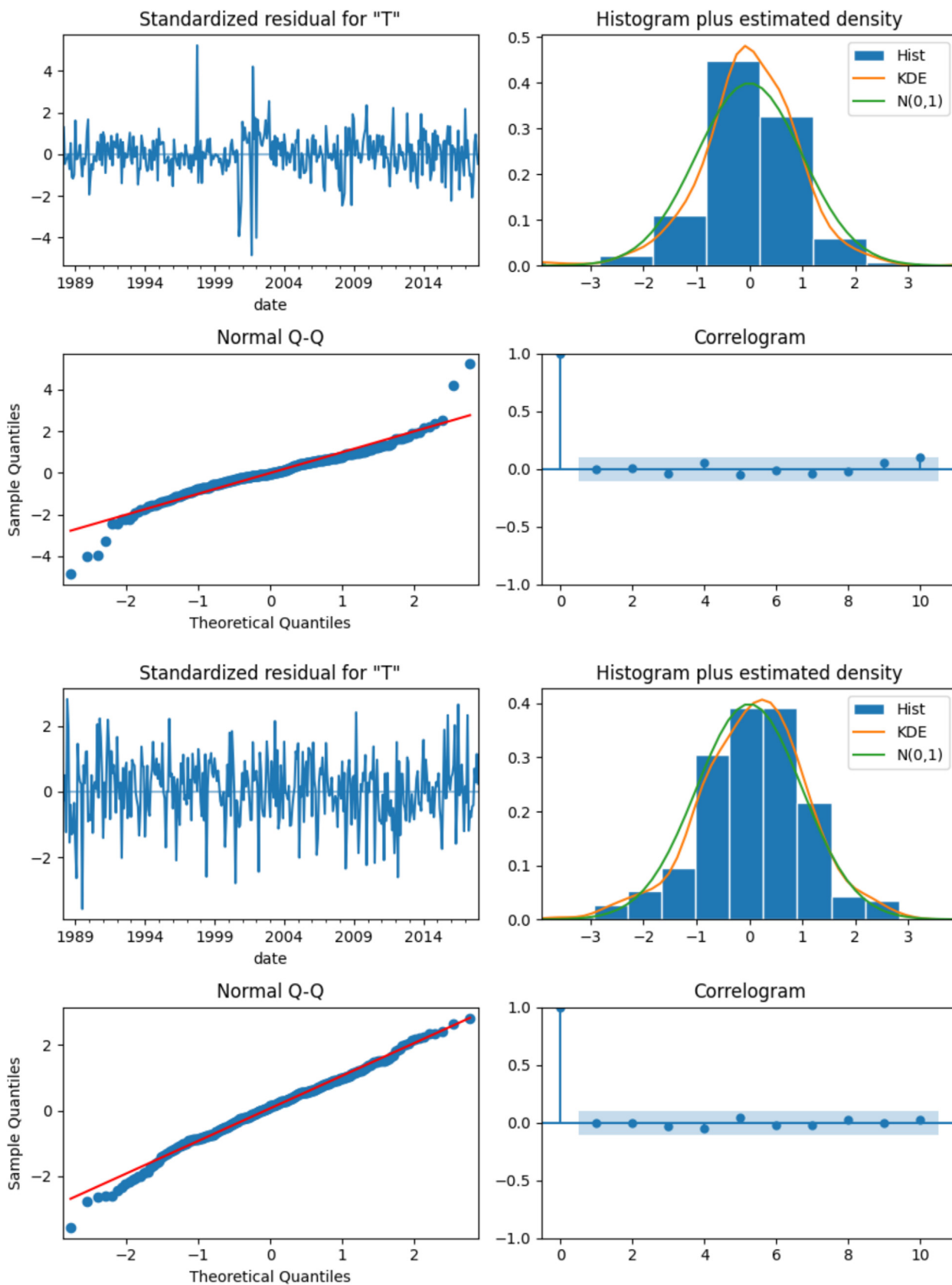


Fig. 8. Diagnostic test results of the minimum (in the top) and maximum (the bottom) temperatures.

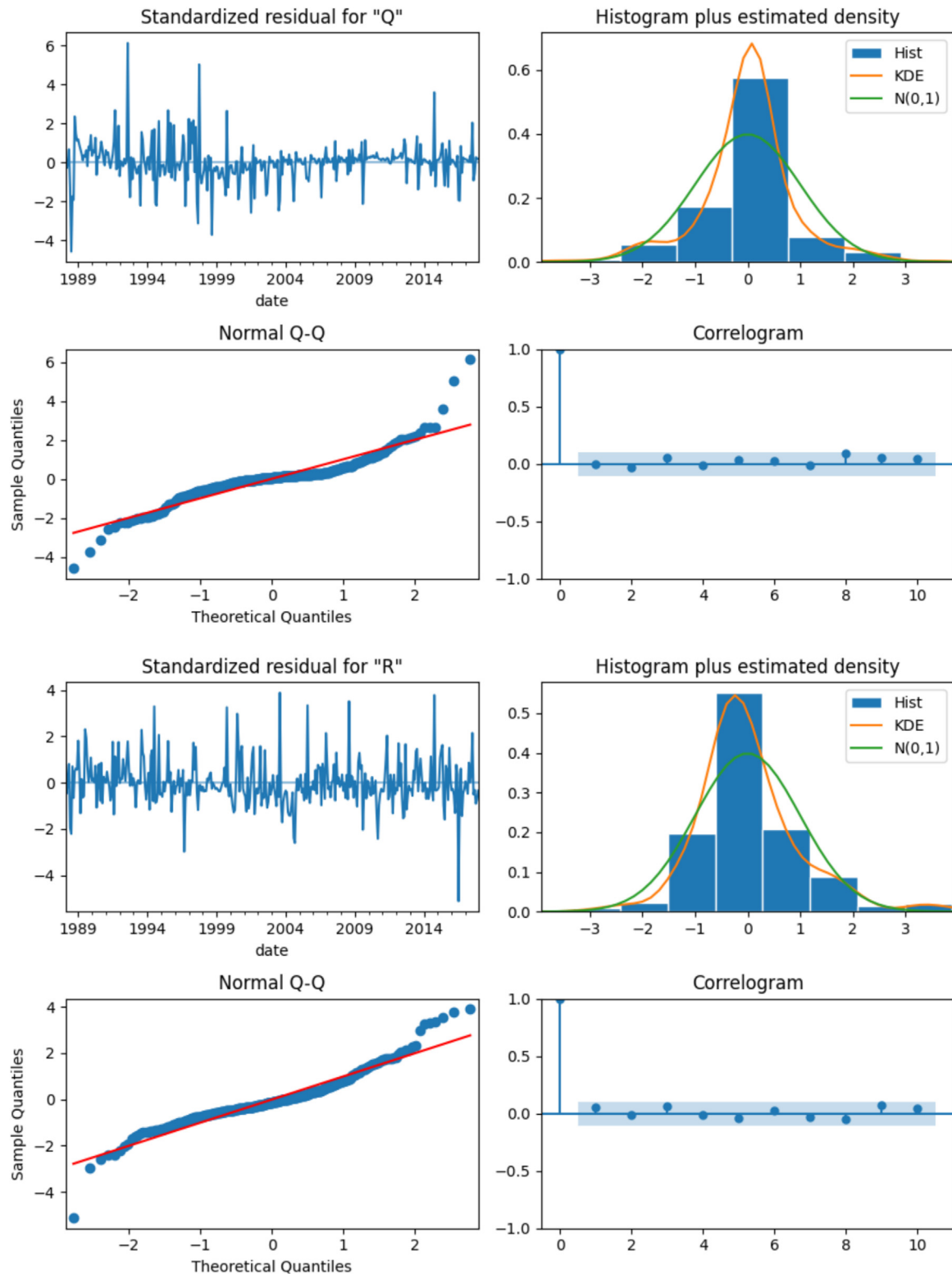


Fig. 9. Diagnostic test results of the streamflow (at the top) and rainfall (the bottom).

linear time series models like SARIMA to capture their dynamics accurately. In the case of rainfall, the variability over time of the convective rainfall events or the driest and wettest seasons of the watershed may cause extremely high or infinite error values. Behaviorally, the infinite value of MAPE is not only due to

the model's inability to project accurately, but may also result from nearly '0' values in the historical monthly rainfall data. If the data records contain very small values, the MAPE can be huge (Hyndman and George, 2014). Due to its advantages of scale-independence and interpretability, MAPE is one of the most widely

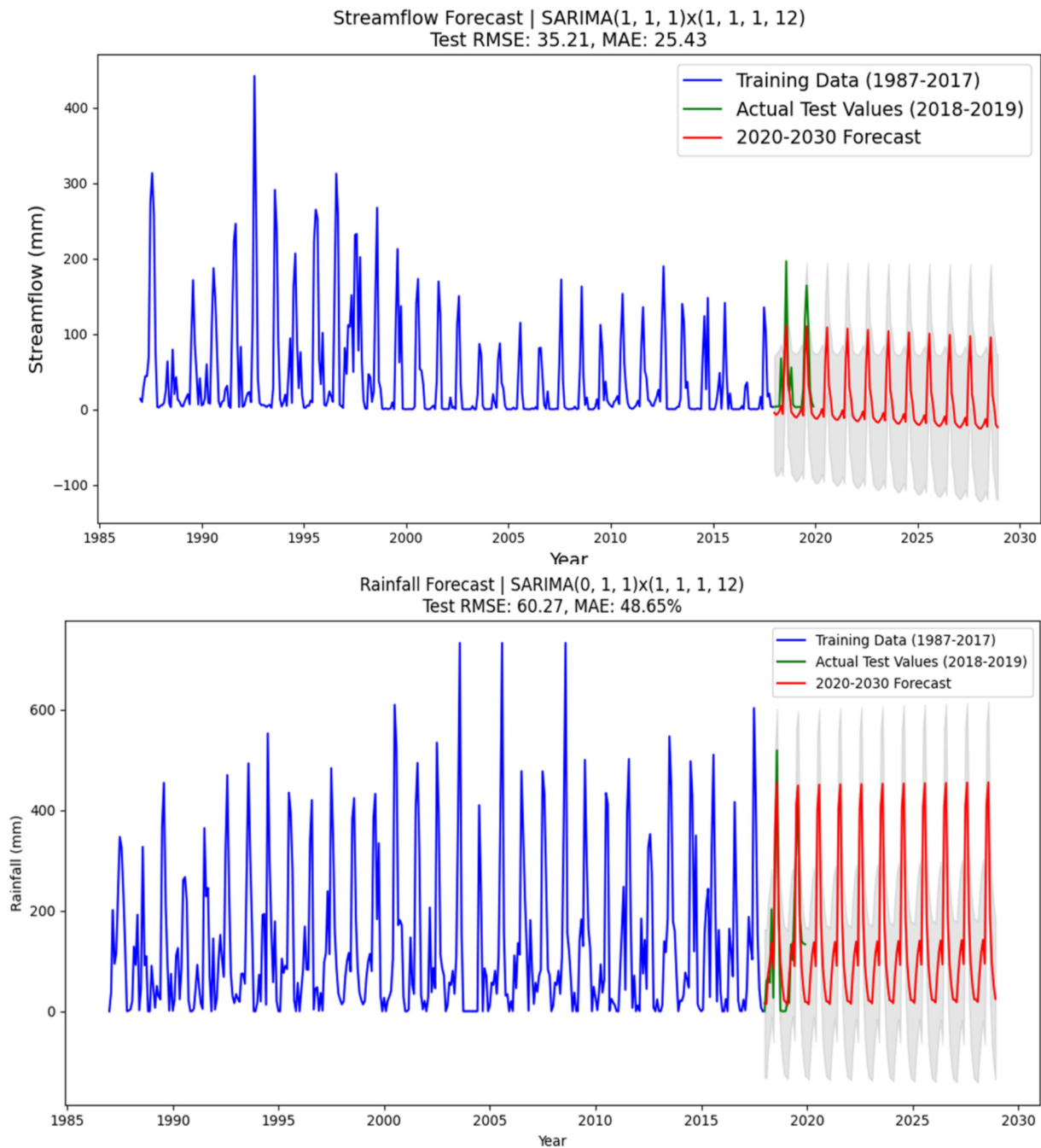


Fig. 10. Time series forecasts of streamflow and rainfall generated using the best-performing SARIMA model.

used measures of forecast accuracy, but it has a significant limitation in that it produces infinite or undefined values for zero or close-to-zero actual values. This makes the reader and analyzer confused whether the result is due to the inability of MAPE or due to the characteristics of the data.

4. Conclusion and recommendation

The sensitivity of streamflow to meteorological droughts was examined using 34 years of rainfall, temperature, and streamflow data from the Andit Tid watershed. SPI and RDI were employed to assess meteorological drought, while the SDI was used for hydrological drought evaluation. Data analysis was performed

using DrinC, R software, Python, and Microsoft Excel. The results indicated that both meteorological and hydrological droughts occurred in the watershed at various intervals (1, 3, 6, and 12 months). The drought analysis identified 1986, 2003, and 2015 as particularly dry years in the watershed. Correlation analysis of drought indices showed that meteorological drought indices exhibited stronger correlations among themselves. Furthermore, a significant correlation was found between hydrological and meteorological drought indices ($P < 0.05$). The correlation between SDI and RDI was higher than that between SPI and other indices, illustrating that streamflow responds more strongly to evapotranspiration than to actual temperature. Overall, drought indices showed better correlation during dry seasons than during wet seasons.

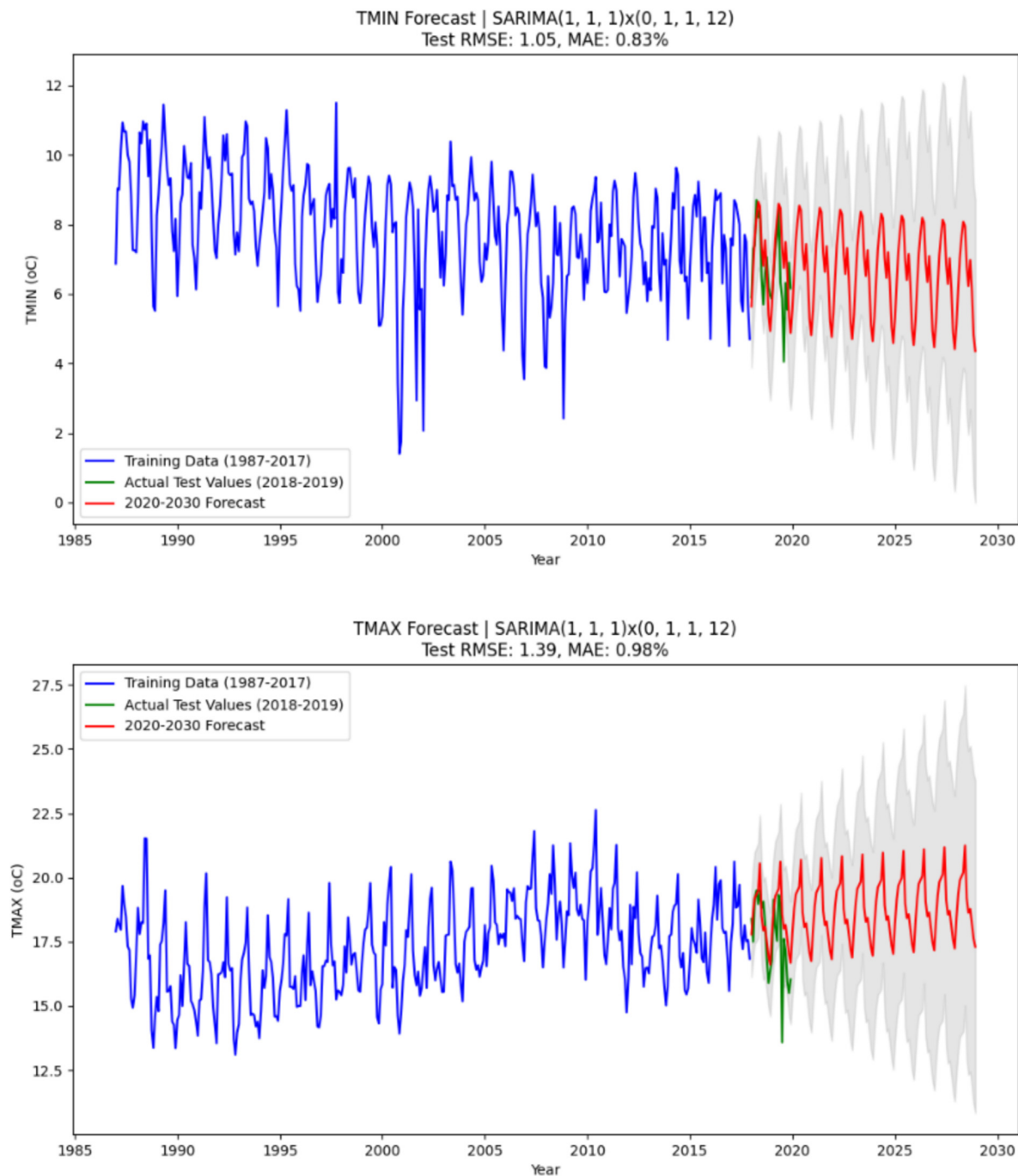


Fig. 11. Time series forecasts of minimum and maximum temperatures generated using the best-performing SARIMA model.

Table 2

Statistics measuring the forecasting accuracy of the SARIMA model.

Forecasted parameters	Forecasted years	RMSE	MAE	MAPE
Rainfall (mm)	10	60.27	48.6	∞
Streamflow (mm)	10	35.2	25.4	171.4
Minimum temperature (°C)	10	1.05	0.82	13.9
Maximum temperature (°C)	10	1.39	0.98	5.99

Taking into account the large and infinite values of MAPE during projection is the result of minimal values in rainfall and streamflow observations; streamflow, rainfall, and minimum temperature

are expected to fall slightly over the next few years, while maximum temperature is expected to rise slightly. However, further comprehensive analysis is required into the performance of the

SARIMA model and the suitability of the MAPE as an evaluation metric of climate variables and streamflow. Otherwise, this research advises the downstream community to implement water harvesting and management strategies to help mitigate the impacts of climate change on their water resource availability.

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CRediT authorship contribution statement

Ayele Desalegn Woldemariam: Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kebede Bekele Atlaw:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Tilahun Getachew Abebe:** Writing – review & editing, Visualization, Project administration. **Getacher Kassa Mitiku:** Writing – review & editing, Funding acquisition, Data curation.

Data availability

The data used in this research are in the hands of the corresponding author and can be readily available upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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