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Research

Spatiotemporal variability of streamflow under current and projected climate scenarios of Andit Tid watershed, central highland of Ethiopia

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Abstract

This study examined the impact of climate change on streamflow in the Andit Tid watershed using climate models of dynamically downscaled Ethiopia's CORDEX. The Arc SWAT and ArcGIS 10.5 software assessed the spatial and temporal distribution of streamflow, incorporating geospatial data like land use maps, digital elevation models, soil maps, and climate data. The SWAT model was calibrated and validated using SWAT-CUP with the SUFI-2 algorithm. The Canadian Centre for Climate Modeling and Analysis, Canada (CCCma (RCA4) model was selected for future projections after validation. From 1991 to 2021, the average streamflow rate was 0.0374 m³/s (247 mm), with R² values of 0.83 for calibration and 0.72 for validation. Hotspots with active gullies and slopes over 20% were identified mainly in cultivated lands. Future projections indicated a comparable streamflow rate to current conditions at 0.0322 m³/s (212.6 mm). A decline in streamflow is projected: 7.2% and 30.2% decreases in the near and far future under RCP 4.5, and 32.3% decreases and 5% increases under RCP 8.5 scenarios. These variations were attributed to differences in catchment characteristics and climate variability. Further research is needed to validate these findings by incorporating additional biophysical variables. This study provides insights into hydrological planning and management in the Andit Tid watershed and similar regions facing climate variability.

Keywords Arc GIS · Climate · CORDEX · Streamflow · SUFI-2

1 Introduction

Climate change involves alterations of climate variability that significantly impact natural systems across disciplinary issues [1]. According to Alexander [2], the climate system is influenced by both external forcing and internal processes, resulting in increased warm temperature extremes and decreased cold temperature extremes. The rising concentrations of greenhouse gases in the atmosphere is a major global concern [3]. Climate models predict a steady increase in temperatures and variable precipitation patterns [4]. The projects that global mean air temperature could rise by 1.4 to 4.8 °C by the end of the twenty-first century under various emission scenarios [5].

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The variability in climate significantly affects hydrological attributes within watersheds. Increased storm frequency and intensity due to climate change can lead to higher storm runoff, with soil infiltration capacity and rainfall intensity playing crucial roles in runoff formation [6]. Legesse et al. [7] found that runoff volume is highly sensitive to changes in rainfall and temperature, with increases in rainfall having a greater impact. A study on the Indus River found that climate change had a significantly greater impact on river runoff (97.47%) compared to land-use change (2.53%) [8].

Recent studies have further emphasized the impact of climate change on streamflow. For instance, an increase in temperature at 1.1 °C and 4.6 °C is expected to reduce annual streamflow rates by 2.4% and 11.9% respectively [9]. Runoff is projected to increase during rainy seasons and decrease during dry seasons due to changes in precipitation patterns [10]. Wale Worqlul et al. [11] found that streamflow could increase by up to 64% in dry seasons and decrease by 19% in wet seasons. Similarly the Ref. [12] projected that streamflow in the Tekeze Basin would increase due to the higher temperatures and precipitation under RCP 4.5 and RCP 8.5 climatic scenarios. Future climate change is expected to significantly impact national and regional hydrologic conditions, affecting runoff volume and chemical losses on a watershed scale [13]. The spatial and temporal variability of rainfall is the factor that leads to the increase and decrease of runoff [14]. The upper Blue Nile Basin, like many Ethiopian river basins, faces significant environmental stress due to a growing population's demand for natural resources [15].

More recent studies have highlighted the need for research on future climatic scenarios in Ethiopia. For example, Sitotaw et al. [16] found that future streamflow in the upper Blue Nile Basin could be significantly impacted by projected climate changes, emphasizing the need for adaptive management strategies. Similarly, Ademe et al. [17] indicated that changes in precipitation and temperature under future climate scenarios could lead to substantial variability in streamflow patterns in the Awash Basin. Recent research has focused on the regional implications of climate change on streamflow, emphasizing the importance of localized studies. For instance, Berhane et al. and Alemayehu and Bewket [18, 19] highlighted that in the central highlands of Ethiopia, changes in precipitation patterns and temperature significantly affect streamflow, necessitating region-specific adaptation strategies. Additionally, Gebremeskel and Kebede [20] and Kassaye et al. [21] emphasized the need for integrating local climate projections with hydrological models to better understand future water availability and manage resources effectively.

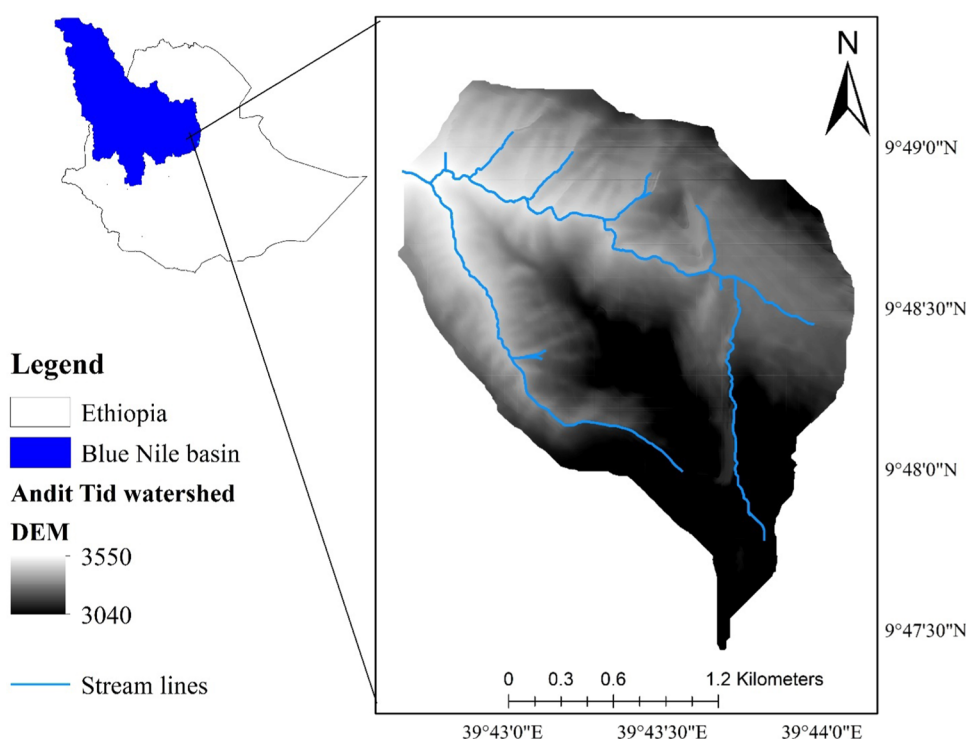
In Ethiopia, numerous studies have examined the effects of rainfall on streamflow, primarily focusing on present conditions and often neglecting potential future extremes in climatic and hydrologic variables. For instance, Daba et al. [22] projected that in the 2050s, runoff would rise while streamflow would fall. Even within the same basin, different models and emission scenarios can yield varying results [23, 24]. This indicates a need for further research to explore future climatic scenarios for all aspects of the Andit Tid watershed. This study examined temperature and rainfall trends and their impact on streamflow in the near (2022–2060) and far (2061–2098) future addressing gaps in existing studies. The findings will provide critical insights for hydrological planning and management in the Andit Tid watershed and similar regions facing climate variability challenges.

2 Methodology

2.1 Description of Andit Tid watershed

The Andit Tid watershed is a relatively small watershed that flows towards the Blue Nile (Abay River) in Ethiopia. Within this watershed, there are two primary rivers, the Wadiyat and the Gudi Bado. These rivers converge approximately 150 m upstream from the gauging station, merging to form the Hulet Wenz River. The watershed is situated about 180 km northeast of Addis Ababa, Ethiopia's capital, located at coordinates 39.6° N and 9.72° E in the central highlands of Ethiopia. This region is characterized by its highland terrain and plays a crucial role in the hydrology of the downstream. It is one of the model watersheds established by the Soil Conservation Research Project (SCRIP) in 1982 as a representative for the humid highland part of Ethiopia. The Water and Land Resource Center (WLRC) took control of the watershed and began SCRIP's initial monitoring of it in 2007. Currently, the Debre Brihan Agricultural Research Center (DBARC) controls and finances the watershed. According to Fig. 1, the watershed is a small tributary of the Blue Nile basin.

Fig. 1 Geographical location of Andit Tid watershed from Ethiopia and Blue Nile basin



2.2 Data sources and methods of data collection

2.2.1 Sources of geospatial data

A digital soil map developed by the Food and Agricultural Organization of the United Nations (FAO-UN) soil data was used for clipping the soil map of the study watershed. Therefore, the clipped soil map of the study watershed was used as an input for the model. The soil map with the resolution of 1 km has been derived from Harmonized World Soil Database (HWSD) v1.2 a database that combines existing regional and national soil information and information provided by the FAO soil map [25]. This information included soil texture, hydraulic conductivity, available soil water content, bulk density, soil depth, and soil drainage attributes. The office of the Water and Land Resource Center (WLRC) provided the Digital Elevation Model (DEM) of the watershed with a resolution of 2 m by 2 m. For this study, the land use land cover map was digitized and classified using Google Earth imagery and Arc GIS 10.5. Supervised classification was done for the identification of land use and land cover types of the study watershed. The land use of an area is one of the most important factors that affect surface erosion, runoff, and evapotranspiration in a watershed.

2.2.2 Sources of climate data

The climate station at the outlet of the watershed, which was managed by the Debre Brihan Agriculture Research Centre and Water and Land Resource Center (WLRC) was used to get the precipitation and minimum ($t_{\min}$) and maximum temperature ($T_{\max}$) data needed to run the SWAT model. Four rain gauge sites distributed in the watershed and 3 additional climatic stations (Mezezo, Debre Sina, and Gudoberet) outside of the watershed have been used for modeling. The data for the stations outside the watershed have been obtained from the Ethiopian Meteorological Institute (EMI).

Projected climate data was obtained from the Coordinated Regional Climate Downscaling Experiment (CORDEX) Ethiopia, which is dynamically downscaled from CORDEX African. CORDEX is experimentally developed specifically for climate impact studies in Ethiopia [26]. To give reasoned, predictable fluctuations in local climates and to assess any rationale for uncertainty in the projection, it was developed to make use of many RCMs. RCMs are being used to examine climate projections at the local level [27]. According to a previous study by Dosio et al. [28], RCMs can simulate the most accurate estimates of yearly and seasonal rainfall and air temperature. It also provides climate datasets with a higher spatial resolution and is suited for

impact research. The performance of CORDEX regional climate models (RCM) in simulating climate variables (rainfall and temperature) is good [29].

The four different representative concentration pathways (RCPs) including high emission scenario RCP8.5 (radiative forcing of 8.5 W/m^2 by 2100), 6.0 (radiative forcing of 6 W/m^2 stabilize after 2100), 4.5 (radiative forcing of 4.5 W/m^2 and stabilize after 2100), and 2.6 (radiative forcing of 3 W/m^2 and decline to 2.6 after 2100) [30]. Two RCP scenarios RCP 4.5 and RCP 8.5, the most widely used for hydrologic modeling, are employed in this study. By the year 2100, the radiative force of RCP 4.5 could reach 4.5 W/m^2 , and then be stabilized over various land uses. RCP8.5 is a worst-case scenario (the current trend) with rapid population growth, a slower pace of technological advancement, minimal effort to reduce emissions, and a large reliance on coal-fired power [30]. Thus, it is important to reduce forcing from RCP 8.5 in contrast to the other three RCP scenarios [31]. A detailed description of each RCPs can be found in [30]. Therefore, future climate data for this study have been obtained from Ethiopian CORDEX regional climate models. This CORDEX Ethiopia contains 11 models and these models were verified using station-based collected data.

2.2.3 Sources of streamflow data

This study obtained 2012–2018 monthly streamflow data from the Hulet Wenz River of the Andit Tid watershed. In this watershed, Manual River stage recording of the stage height is done every morning at 08:00. Then the streamflow volume is determined following Eqs. 1 and 2 [32]:

$$Q (H \leq 67) = 0.03 * H^{2.749}, \quad (1)$$

$$Q (67 < H \leq 250) = 10.846 * H^{1.35}, \quad (2)$$

where Q is the stream discharge in L/s and H is the true water level (stage) in cm.

2.2.4 Method of simulation of streamflow

Using the Soil and Water Assessment Tool (SWAT), streamflow simulations were performed. One of the most common watershed modeling tools in use currently is SWAT, which may be applied to a variety of water quantity and quality problems [33].

In the study of the Andit Tid watershed, land use maps, DEM, and soil maps were integrated into SWAT and ArcGIS analyses to model hydrological processes. Land use maps were classified, georeferenced, and imported into SWAT to assign land cover-specific parameters. The DEM was utilized for watershed delineation, slope and aspect calculation, stream network generation, and topographic modeling. Soil maps were classified, georeferenced, and imported into SWAT to define soil-specific parameters and Hydrological Response Units (HRUs). This integration enabled a comprehensive analysis of the spatiotemporal variability of streamflow under current and projected climate scenarios, providing valuable insights into the watershed's hydrological responses to climate change.

SWAT takes into account factors such as weather, surface runoff, evapotranspiration, irrigation, sediment transportation, groundwater flow, crop growth, nutrient yielding, pesticide yielding, and water routing, and also the long-term consequences of various agricultural management strategies [34]. In the hydrological component, the total streamflow for the watershed is calculated by routing the predicted streamflow separately for each sub-basin of the total watershed area. Using modified SCS-CN and Green-Ampt techniques, streamflow is calculated from daily rainfall (Eq. 3). The watershed is classified into sub-basins in the SWAT model, and these sub-basins are further subdivided into one or more homogeneous Hydrological Response Units (HRUs) with relatively unique combinations of land cover, soil, and topographic conditions. The model could produce summary statistics per sub-basins or HRUs as an output. Therefore, it was possible to identify major contributors' regions or sub-basins for streamflow using the output map.

$$SW_t = SW_0 + \sum_{t=1}^n (R - Q - ET - W_{seep} - Q_{gw}), \quad (3)$$

where SW_t is the final soil water content (mm), SW_0 is the initial soil water content (mm), t is time in days, R is precipitation (mm), Q is surface streamflow (mm), ET is the evapotranspiration (mm), W_{seep} is percolation (mm), and Q_{gw} is return flow (mm).

In this study, evapotranspiration was estimated using Hargreaves methods [35]. The Hargreaves method was employed to determine potential evapotranspiration because rainfall and minimum and maximum temperatures were the only climate data available.

$$ET = 0.0023 * 0.408 * R_a (T_{\text{mean}} + 17.8) (T_{\text{max}} - T_{\text{daily}})^{0.5}, \quad (4)$$

T_{mean} is the maximum air temperature (C), T_{daily} is the average air temperature (C), R_a is extraterrestrial radiation (MJ m^{-2}), and 0.408 is a factor to convert MJ m^{-2} to mm. R_a is an estimate of extraterrestrial radiation based on the location's latitude and the calendar day of the year.

SWAT employs two approaches based on the aforementioned assumption to estimate streamflow; the Green and Ampt infiltration method and the Soil Conservation Service curve number (SCS) method [36]. SCS is widely utilized due to its ability to employ daily input data. The surface flow in this study was evaluated using the Soil Conservation Service curve number (SCS) approach. Mathematically, surface flow has been estimated as Eq. 5:

$$Q_{\text{surf}} = \frac{(R_{\text{day}} - 0.2)^2}{(R_{\text{day}} + 0.8S)^2}, \quad (5)$$

where Q_{surf} is the accumulated streamflow (mm), R_{day} is the rainfall depth for the day (mm), and S is the retention parameter (mm) Eq. 6.

$$S = 25.4 * \left(\frac{100}{\text{CN}} - 10 \right). \quad (6)$$

2.3 Model sensitivity, calibration, and validation

The Sequential Uncertainty Fitting version 2 (SUFI-2) algorithm associated with SWAT-CUP 2012 has been used for a combined model sensitivity analysis, calibration, and validation procedures. The SUFI-2 algorithm considers both uncertainties of the conceptual model and uncertainties of the input data [37]. SUFI-2 employs a semi-automated approach that integrates both manual and automated calibration methods. This combination allows for more efficient and accurate model calibration by systematically adjusting model parameters and evaluating their impact on model outputs [38].

Coefficient of determination (R^2) [39], Nash–Sutcliffe efficiency (NSE) [40], percent bias (PBIAS) [41] and Kling–Gupta efficiency (KGE) [42] have been considered during the evaluation of the goodness of fit of the model [43].

The R^2 measures the proportion of variance in observed data (Eq. 7), with higher values implying less error variance. The R^2 value could indicate the model's performance as very good, good, satisfactory, and unsatisfactory with values of, $0.7 < R^2 \leq 1$, $0.6 < R^2 \leq 0.7$, $0.5 < R^2 \leq 0.6$, and $R^2 < 0.5$ respectively [43]. Equation 8 describes the NSE as a normalized statistic that evaluates the relative size of residual variance about observed data [40]. It also showed how well the 1:1 line follows in the plot of actual versus simulated data. NSE is the most common; emphasizes high flow; neglects the low flows and is a distance-based evaluation method [39, 44]. The model performance can be determined by the value of NSE, which can be $0.75 < \text{NSE} \leq 1$, $0.65 < \text{NSE} \leq 0.75$, $0.5 < \text{NSE} \leq 0.65$, $0.4 < \text{NSE} \leq 0.5$ and $\text{NSE} \leq 0.4$, with very good, good, satisfactory, acceptable, and unsatisfactory respectively [45].

$$R^2 = 1 - \frac{\sum [(Q_m - \bar{Q}_m)(Q_s - \bar{Q}_s)]^2}{\sum (Q_{mi} - \bar{Q}_m)^2 \sum (Q_s - \bar{Q}_s)^2}, \quad (7)$$

$$\text{NSE} = 1 - \frac{\sum (Q_m - Q_s)^2}{\sum (Q_m - \bar{Q}_m)^2}, \quad (8)$$

where Q_m is the measured discharge, Q_s is the simulated discharge, $\bar{Q}_m$ is the average measured discharge and $\bar{Q}_s$ is the average simulated discharge.

Percentage bias (PBIAS) is a measure of the average tendency of simulated data to differ from their actual counterparts by the given amount. It has an ideal value of 0, and low magnitude values indicate accurate model simulation. Positive values indicate underestimation bias in the model, whereas negative values suggest overestimation bias in the model [41]. PBIAS is monotony and cannot be used as a decision-making criterion alone, but in collaboration with other criteria statistics, it might determine the model as very good, good, satisfactory, and unsatisfactory with the value $\text{PBIAS} < \pm 10$, $\pm 10 < \text{PBIAS} < \pm 15$, $\pm 15 < \text{PBIAS} < \pm 25$ and $\text{PBIAS} > \pm 25$ respectively [46]. Mathematically PBIAS can be calculated as (Eq. 9):

$$\text{PBIAS} = \left[\frac{\sum_{i=1}^n (Q_{im} - Q_{is}) * 100}{\sum_{i=1}^n Q_{im}} \right]. \quad (9)$$

The KGE goodness-of-fit measure provides an analysis of the relative importance of different components (correlation, bias, and variability) in hydrologic simulations. KGE is calculated in Eqs. 10 and 11 [42].

$$\text{KGE} = 1 - \text{ED}, \quad (10)$$

$$\text{ED} = \sqrt{(r - 1)^2 + (\beta - 1)^2 + (\alpha - 1)^2}, \quad (11)$$

where ED is Euclidian distance from the ideal point, r is the Pearson product-moment correlation coefficient between the observed and the simulated, α is the standard deviation of the simulated over the standard deviation of the observed (measure of variability), and β is the mean of simulated over the mean of observed. KGE ranges from $-\infty$ to 1, where KGE of 1 is the optimal value and $\text{KGE} > 0.5$ is acceptable [42, 47]. The value of KGE and the performance of the model is if, $\text{KGE} \geq 0.75$, $0.75 > \text{KGE} \geq 0.5$, $0.5 > \text{KGE} > 0$, and $\text{KGE} \leq 0$ the simulation is then good, intermediate, poor, and very poor respectively [48].

2.3.1 Future climate data sources

The future changes in rainfall and minimum and maximum temperature have been projected for two time periods: the near future (2022–2060), and the far future (2061–2098). The projected climate data from 11 CORDEX regional climate models (Table 1) between 2022 and 2098 under two Representative Concentration Pathways, RCP 4.5 and RCP 8.5 were downloaded.

2.4 Climate model performance evaluation

Taylor diagram, a graphical evaluation technique, was used in this study. Taylor diagrams were used to visually show which of the climate models is the most accurate. The Pearson correlation coefficient, the root means square error, and the standard deviation are used to measure the degree of agreement between the modeled and observed. Simulated patterns that closely resemble observations have been located closest to the x-axis point labeled “observed”. Taylor’s diagram is used as a decision-making criterion for the confusing result of the statistical criteria [49]. This diagram provides a way of plotting three statistics on a 2-D graph that indicates how closely a pattern matches observations [49]. In this study, the Taylor diagram was plotted using the R programming language within the RStudio version 3 environment.

2.4.1 Climate model performance evaluation result

To select the most suitable climate model from CORDEX for future projections, the study employed a Climate Model Performance Evaluation assessment based on three main criteria: correlation with observed data, standard deviation, and overall consistency in predicting key climate variables (maximum temperature, minimum temperature, and rainfall) similar to [50, 51].

i. Correlation with observed data:

The models MPI (CRCM5), MPI (RCA4), and CNRM-CERFACS-CNRM-CM5 were considered as they had a high correlation ($r = 0.8$) with observed maximum temperatures, indicating a strong agreement with the actual

Table 1 List of climate models; their global climate model name, regional climate model name, and realization

No	Modeling centre	GCM name	RCM name	Ensemble
1	Canadian Centre for Climate Modeling and Analysis, Canada	CCCma-CanESM2	CRCM4	r1i1p1
2	Canadian Centre for Climate Modeling and Analysis, Canada	CCCma-CanESM2	RCA4	r1i1p1
3	The Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan	MIROC-MIROC5	RCA4	r1i1p1
4	Bjerknes Centre for Climate Research, Norwegian Meteorological Institute, Norway	NCC-NorESM1-M	RCA4	r1i1p1
5	Max Planck Institute for Meteorology, Germany	M-MPI-ESM-LR	RCA4	r1i1p1
6	Max Planck Institute for Meteorology, Germany	MPI-M-MPI-ESM-LR	CFCM5	r1i1p1
7	Centre National de Recherches Météorologiques, Centre Européen de Recherche et de Formation Avancée en Calcul Scientifique France	CNRM-CERFACS-CNRM-CM5	RCA4	r1i1p1
8	Geophysical Fluid Dynamics Laboratory, USA	NOAA-GFDL-GFDL-ESM2M	RCA4	r1i1p1
9	Irish Centre for High-End Computing Ireland European Centre Earth global climate model system	ICHEC-EC-EARTH	HIRHAM5	r3i1p1
10	Irish Centre for High-End Computing Ireland European Centre Earth global climate model system	ICHEC-EC-EARTH	RACMO22T	r1i1p1
11	Irish Centre for High-End Computing Ireland European Centre Earth global climate model system	ICHEC-EC-EARTH	RCA4	r1i1p1

Fig. 2 Pattern statistical comparison between the observed maximum temperature and eleven model estimates

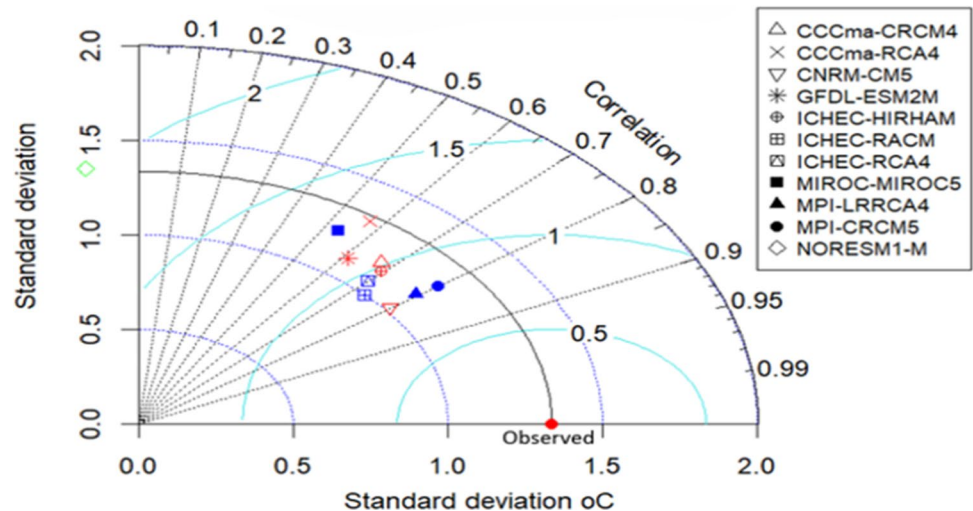
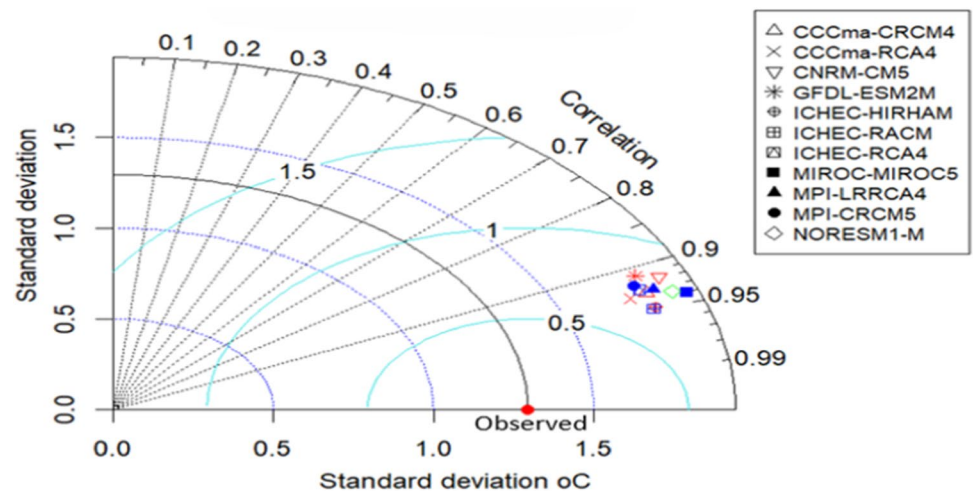


Fig. 3 Pattern statistical comparison between the observed minimum temperature and eleven model estimates



temperature patterns. In contrast, NorESM1-M was identified as less accurate due to its low pattern correlation with observed maximum temperatures as presented in Fig. 2.

All the evaluated climate models showed a strong correlation ($r > 0.9$) with observed minimum temperatures, demonstrating their reliability in predicting future minimum temperatures (Fig. 3).

MPI-CRCM5 and ICHEC-HIRHAM stood out as the best models for rainfall projection, with a high correlation ($r \approx 0.8$) with observed rainfall. This high correlation implies, that these models closely match the actual rainfall patterns in the study area. NorESM1-M showed a lower correlation ($r < 0.5$) with observed rainfall, indicating less reliability in predicting rainfall (Fig. 4).

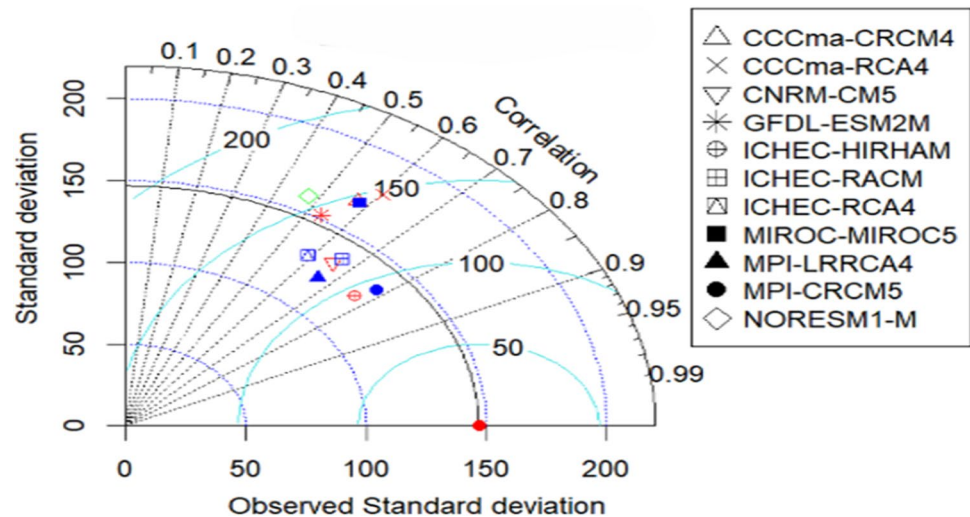
ii. Standard deviation:

Standard deviation is a measure of the spread of the model predictions around the mean, it helps in understanding the model's ability to capture variability and extremes. The CCCma (RCA4) model exhibited a relatively lower standard deviation in minimum temperature predictions and matched the observed standard deviation for both rainfall (Fig. 4) and maximum temperature projections. This indicates a better fit to the observed data and suggests reliable predictions.

2.5 Bias correction for climate data

The future periods of rainfall and temperature of 2022 to 2098 were simulated against the 1991 to 2010 baseline era using Climate Model data for hydrologic modeling (Cmhyd) as recommended by Mohammed et al. [52] and used by

Fig. 4 The Taylor diagram for comparing the rainfall pattern between the observed and RCMs



Zhang et al. [36]. Local intensity scaling (LOCI) was used in precipitation bias correction and Distribution Mapping was used for the correction of the temperature [36]. Then, SWAT was run with bias-corrected projected climate data from the two models for the near future (2022–2060) and the far future (2061–2098). The impact of climate conditions with both RCPs (RCP 4.5 and RCP 8.5) on streamflow was then determined by comparing the current with projected outputs. In all scenarios, the spatial distribution and hot spot area mapping were done using Arc GIS 10.5.

2.6 Innovative trend analysis (ITA)

The innovative trend analysis method is a very crucial method for detecting the trends in rainfall time series data due to its potential to present the results in graphical format as well [53]. Şen [54] introduced the ITA approach, which splits a hydrometeorological time series into half equal parts and arranges both sub-series in ascending order. As illustrated in Fig. 12, the Cartesian coordinate system has the first half series (x_i) on the horizontal axis and the second half series (y_i) on the vertical axis. The coordinate system's 1:1 line, which divides upward and downward trends, is referred to as the no-trend line. The time series shows a monotonic increasing or decreasing trend if the scatter points lie above or below the 1:1 line. The straight-line trend slope (s) that the ITA plotted can be determined using the formula in Eq. 12 [55]. This study utilized Microsoft Excel 2020 to apply the equation and draw the one-to-one line.

$$S = \frac{2(y_2\text{bar} - y_1\text{bar})}{n}, \quad (12)$$

where $y_1\text{bar}$ and $y_2\text{bar}$ are the arithmetic averages of the near future and far future streamflow, and n is the total number of years projected.

3 Results

3.1 Estimation and hotspot area mapping of streamflow

The long-term average streamflow discharge of the watershed has been determined that $0.0373 \text{ m}^3/\text{s}$, or $1,176,293 \text{ m}^3$ annually. The lowest discharge occurs in sub-basin 10, which is followed by sub-basins 1 and 23, both of which have flow rates of less than $0.002 \text{ m}^3/\text{s}$. The sub-basins that contributed the most runoff to the stream were sub-basins 3, 4, 5, 9, 11, 12, and 15 (Fig. 5). Sub-basins 4 and 5 in particular are situated quite near the watershed's outlet.

The analysis of the temporal variability of the streamflow showed that the annual streamflow ranged from $0.004 \text{ m}^3/\text{s}$ (26.12 mm) to $0.129 \text{ m}^3/\text{s}$ (849.8 mm) in 2005 and 2017, respectively (Fig. 6). The result confirmed that a severe drought occurred in Ethiopia in 2005 (1997 by the Ethiopian calendar). The trend line in the chart (Fig. 6) shows there is a slightly increasing trend of streamflow in the watershed.

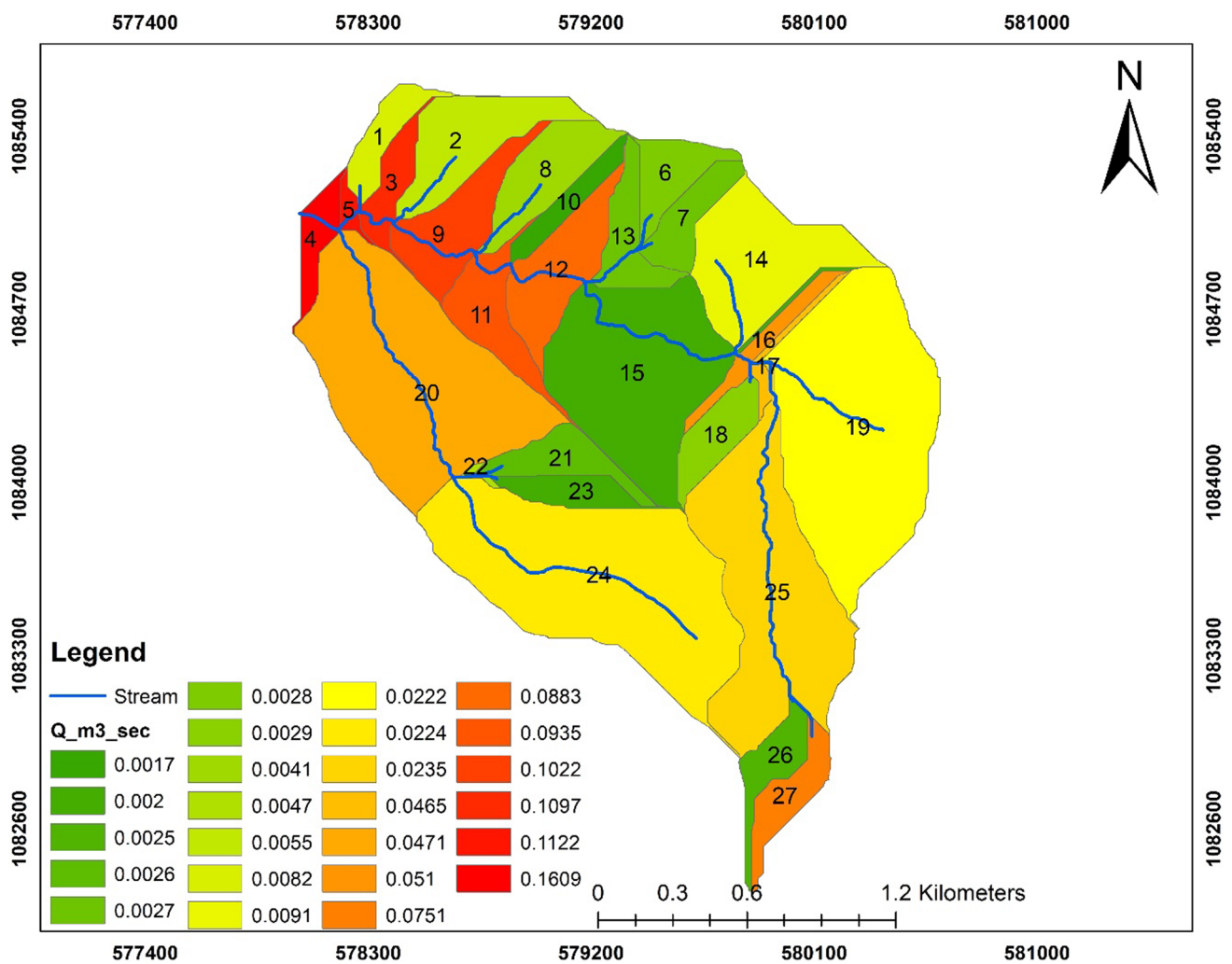
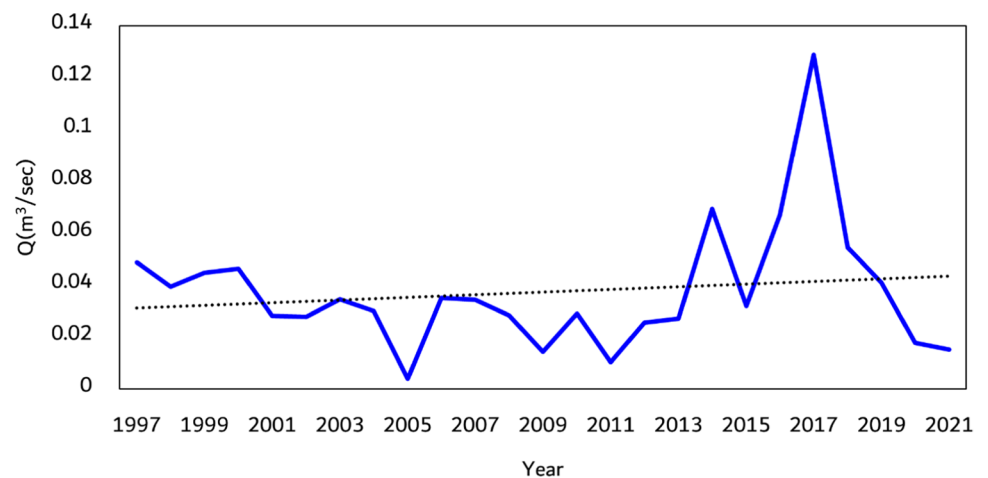


Fig. 5 The estimated streamflow discharge of Andit Tid watershed per sub-basins (the red shaded contribute more runoff while the green shaded are fewer contributing sub-basins)

Fig. 6 The temporal variability of streamflow of the Andit Tid watershed as simulated by SWAT



3.2 Sensitive parameters during streamflow simulation

The sensitive parameters during the calibration of streamflow discharge were ranked in (Table 2). From all listed parameters, ALPHA_BF.gw, CH-K2.rte, GW_Revap.gw, and CN2.mgt were the most sensitive parameters for the simulation of streamflow discharge in the Andit Tid watershed at ($P < 0.05$) level of significance. The baseflow recession constant (ALPHA_BF), which was calibrated with values of 0.78, showed a modest sensitivity of groundwater flow to variations in recharge when it was varied from 0 to 1. Groundwater “revap” coefficient (GW-REVAP) was fitted with 0.094 and calibrated between 0.02 and 0.2. The calibrated value showed that groundwater was moving from the shallow aquifer to the unsaturated zone above at a modest pace. The moisture condition of the initial SCS curve number (CN2.mgt) value was calibrated between 35 and 198, it was fitted at 129.53, which indicates peak flow and discharge could be increased. The sensitivity of CN2 indicates rapid variations in land use classes. The sensitivity of Manning’s roughness coefficient in the model indicates the significance of the streamflow channel material in the watershed. The parameter ‘effective hydraulic conductivity in the main channel alluvium (CH_K2) was calibrated within -0.01 to 500 mm/h, and it was fitted with 192.48 mm/h. The calibrated value indicates the ‘very high loss rate’ of alluvium material.

The 95 percent prediction uncertainty in SUFI2 expresses the prediction uncertainty and is shown in Fig. 7 the green-colored zone for the calibration and validation processes, respectively. The calculated p-value implied that 46% and 44% of the observed discharge were enveloped by the 95PPU during the calibration and validation periods, respectively. As indicated in Fig. 7, calibration and validation processes especially in rainy seasons of the observed streamflow were found higher than the simulated streamflow.

The performance indicators in calibration and validation times ($KGE > 50\%$), (R^2 and $ENS > 0.71$, and ($PBIAS \leq \pm 25$ for streamflow discharge) are in an acceptable range (Table 3). The following findings from this study were attained based on this assessment criterion.

The R^2 value between the simulated and actual streamflow was 0.83 and 0.73, respectively, in the calibration and validation processes (Table 3). According to numerous academic studies, R^2 greater than 0.5 is an indicator that a simulation model is good [47, 56–59]. The NSE, which was determined to be 0.72 and 0.65, is another reliable sign that the model outcome is satisfactory. The PBIAS (23.8 and 21.7 in calibration and validation) indicates that the models underestimated the streamflow by 23.8% during calibration and by 21.7% during validation. The KGE was also found as 0.53 and 0.59 during calibration and validation, respectively. Based on the statistical indicators, there was good agreement between the observed and simulated streamflow and the model was generally suitable to simulate streamflow at current and future times.

3.2.1 Relationship between the observed and simulated streamflow

After the streamflow discharge was calibrated and validated, it was essential to investigate the correlation between the simulated and observed streamflow discharge. As shown in Fig. 8, the simulated and observed streamflow discharge were found to have a significant correlation ($r = 0.89$) at the ($P < 0.05$) level of significance.

3.3 Projected climatic variables

With 1158.2 mm of historical average rainfall, this climate model was the wettest of the 11 regional climate models. In 2098, this model predicted that the average yearly rainfall of Andit Tid watershed will be 1451.7 mm, with a range from 468.3 to 3812.1 mm in RCP 4.5 and 1561.5 mm, with a range from 563.2 to 4541.1 mm in RCP 8.5, respectively.

The average rainfall in the near future (2022–2060) would be 1572.05 mm and 1352.4 mm in RCP 4.5 and RCP 8.5, respectively. The annual rainfall could then drop by 247.78 mm to 1328.27 mm in RCP 4.5 and rise by 432.63 mm to 1776.03 mm in RCP 8.5 in the far future (2061–2098). Therefore, as RCP 4.5 projects, the annual rainfall in the mid-century will be greater than the annual rainfall in the late century, while as RCP 8.5 projects the rainfall will continuously be increased up to 2098.

According to RCP 4.5, the driest and wettest years were 2050 and 2043, respectively. Furthermore, RCP 8.5 predicted that 2047 could be the driest year and 2073 the wettest. Figure 9 displays the projected future rainfall pattern of Andit Tid watersheds for both RCP 4.5 and RCP 8.5 scenarios.

In regards to temperature, the study watershed’s projected levels under RCP 4.5 and RCP 8.5 might be 19.3°C and 20.5°C , respectively. The temperature of the study watershed showed an increase over time in both RCPs, as

Table 2 Parameter sensitivity test, method of a parameter change, initial intervals, and fitted values

Parameters	Descriptions	t-Stat	P-value	Fitted-value	Min-value	Max-value	Rank
R__ALPHA_BF.gw	Baseflow alpha factor (days)	5.39	0.0001	0.78	0	1	1
V__CH_K2.rte	Effective hydraulic conductivity in main channel alluvium	-2.98	0.011	192.48	-0.01	500	2
R__GW_REVAP.gw	Groundwater "revap" coefficient	2.23	0.04	0.094	0.02	0.2	3
R__CN2.mgt	Moisture condition of initial SCS runoff curve number	1.88	0.048	64.78	35	98	4
R__SLSUBBSN.hru	Average slope length	1.466	0.168	64.93	10	150	5
R__GW_DELAY.gw	Groundwater delay (days)	1.09	0.29	288.99	0	500	6
V__CH_N2.rte	Manning's "n" value for the main channel	-1.09	0.29	0.2318	-0.01	0.3	7
A__REVAPMN.gw	Depth from the soil surface to the bottom of the layer	0.71	0.48	208.3	0	500	8
R__SOL_BD(.).sol	Moist bulk density	-0.61	0.55	0.92	0.9	2.5	9
R__HRU_SLP.hru	Average slope steepness	-0.579	0.57	0.054	0	1	10
V__SURLAG.bsn	Surface runoff lag time	-0.052	0.96	22.48	0.05	24	11
R__GWQMN.gw	The acceptable depth of shallow aquifer for return flow to occur (mm)	-0.019	0.98	1069.18	0	5000	12

V_ means the existing parameter value is to be replaced by the given value

A_ means that the given value is added to the existing parameter value

R_ means that the value of the existing parameter is multiplied by (1 + a given value)

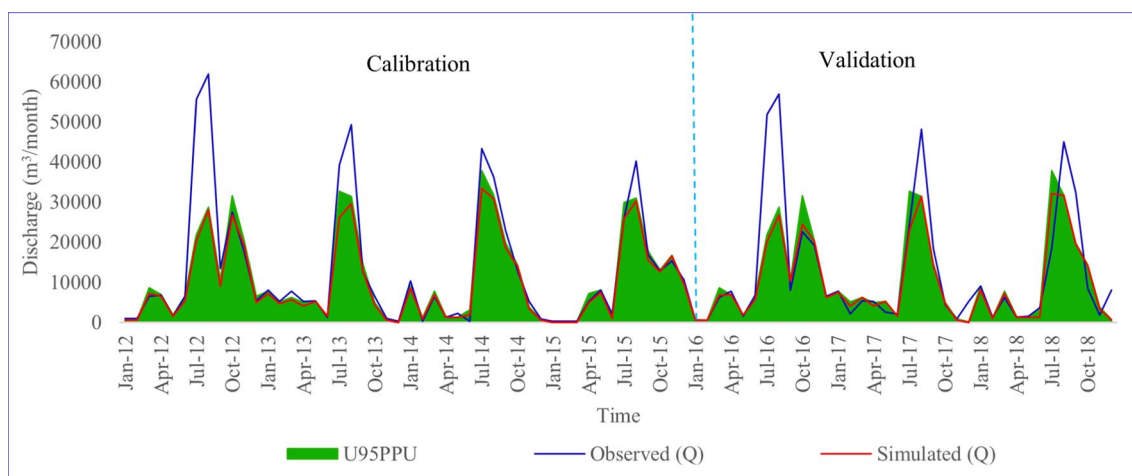


Fig. 7 Comparison of measured and simulated monthly streamflow during the calibration (2012–2015) and validation (2016–2018)

Table 3 Summary statistics for calibration and validation of streamflow in the outlet of the Andit Tid watershed

Variable	Tests	Objective functions				
		R ²	PBIAS	NSE	p-factor	KGE
Streamflow discharge	Calibration	0.83	23.8	0.72	0.46	0.53
	Validation	0.73	21.7	0.65	0.44	0.59

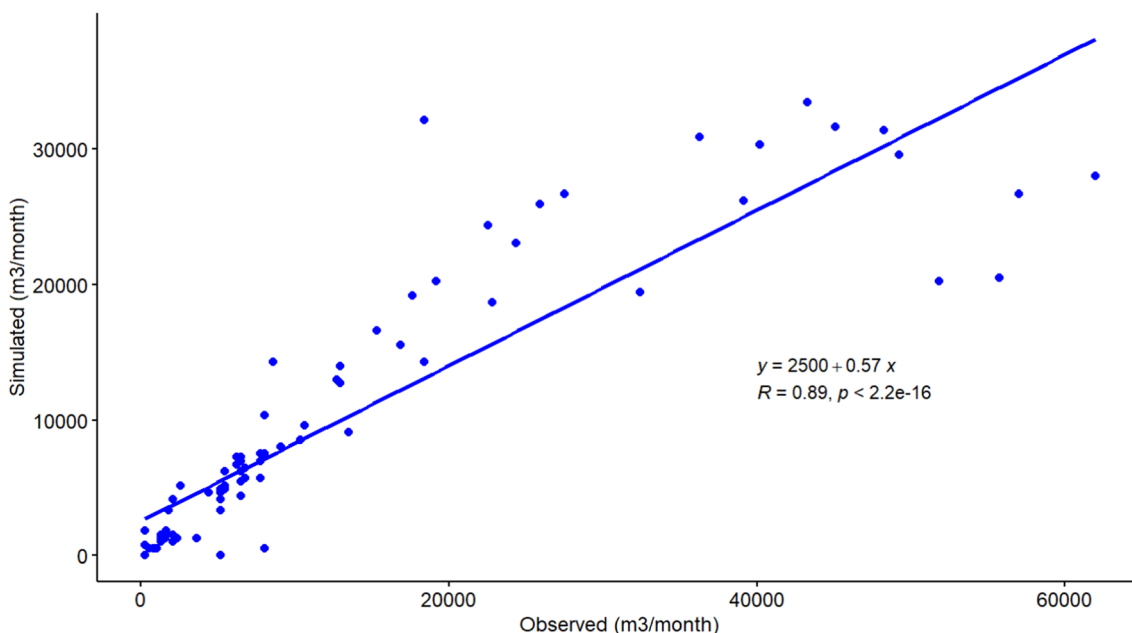


Fig. 8 The regression chart between simulated and actual streamflow

presented in Fig. 10. RCP 4.5 and RCP 8.5 project that shortly (2022–2060), the average temperature may be 19 °C and 19.6 °C, respectively. In the long periods (2061–2098), it is projected that the temperature will increase by 0.7 °C and 1.8 °C, respectively, for RCP 4.5 and RCP 8.5. The coldest years were determined to be 2026 and 2028, with an annual average temperature of 18.4 °C in both RCPs. The hottest years would be 2086 and 2094, with annual temperatures of 20.1 °C and 22.5 °C in RCP 4.5 and RCP 8.5, respectively. The time series of the model's projected annual average temperature is shown in Fig. 10.

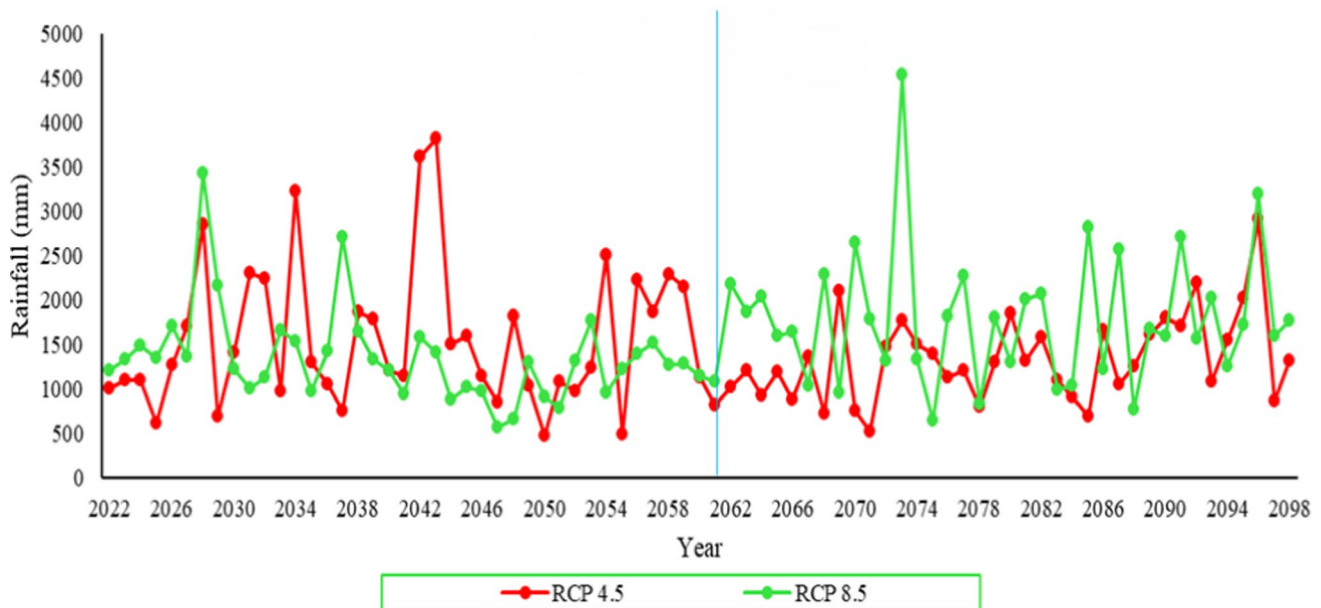


Fig. 9 The projected near and far future rainfall of the Andit Tid watershed

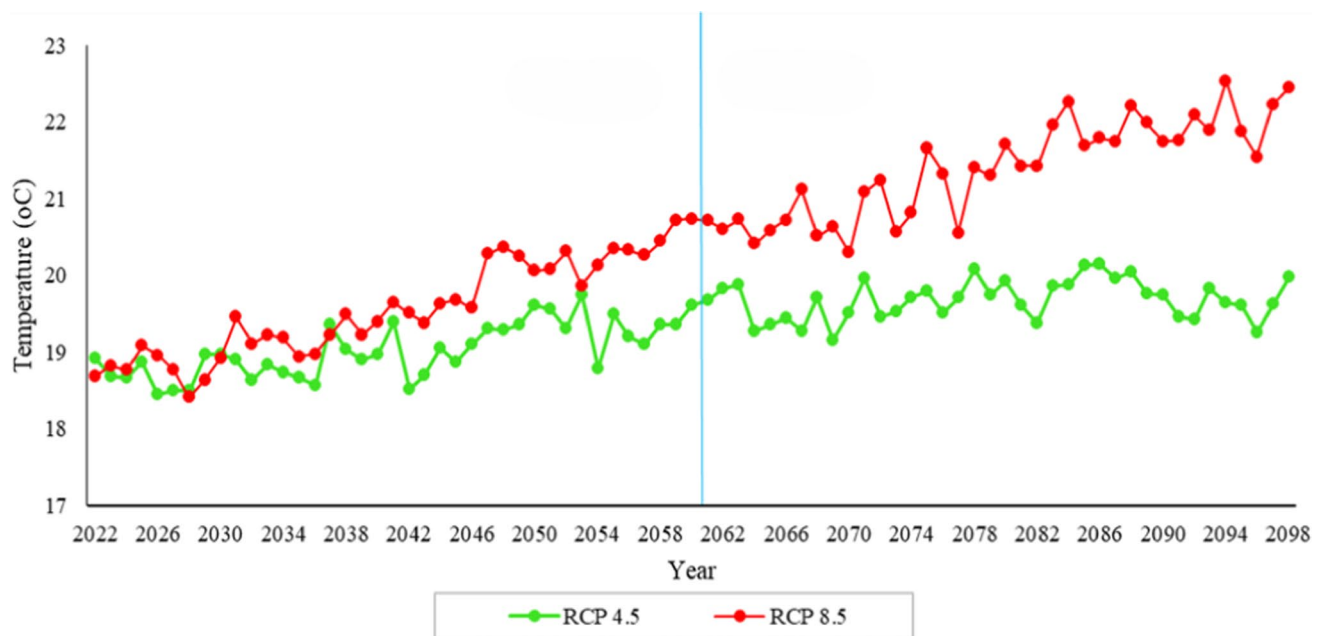


Fig. 10 The projected near and far future temperature of the study watershed in both scenarios

3.3.1 Temporal analysis of projected streamflow

The temporal distribution of streamflow discharge of the watershed is displayed in Fig. 11. The simulated streamflow in 2098 was estimated to be $0.0304 \text{ m}^3/\text{s}$ (200.73 mm) in RCP 4.5. The near future average streamflow discharge was estimated to be $0.035 \text{ m}^3/\text{sec}$ and decreased to $0.026 \text{ m}^3/\text{s}$ in the far future. The streamflow was determined as $0.112 \text{ m}^3/\text{s}$ at its peak in 2043 and $0.0027 \text{ m}^3/\text{s}$ at its lowest point in 2050. It revealed the streamflow discharge in 2043 was determined as 42 times greater than compared to 2050 (the dry year).

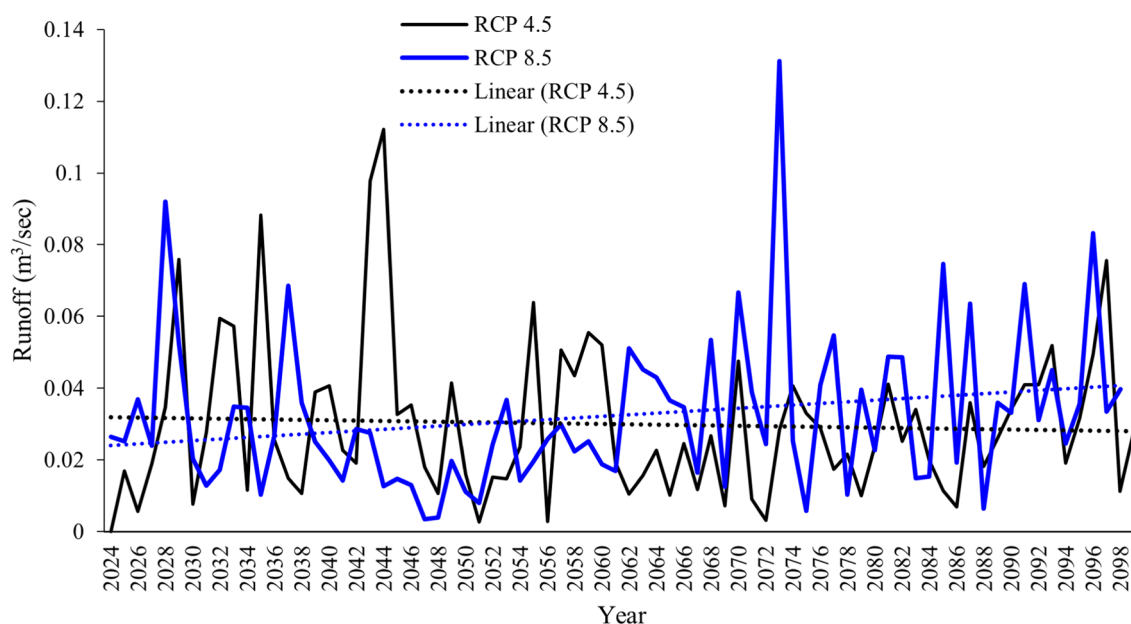


Fig. 11 Projected temporal variability of streamflow from the projected rainfall and temperature and simulated using SWAT

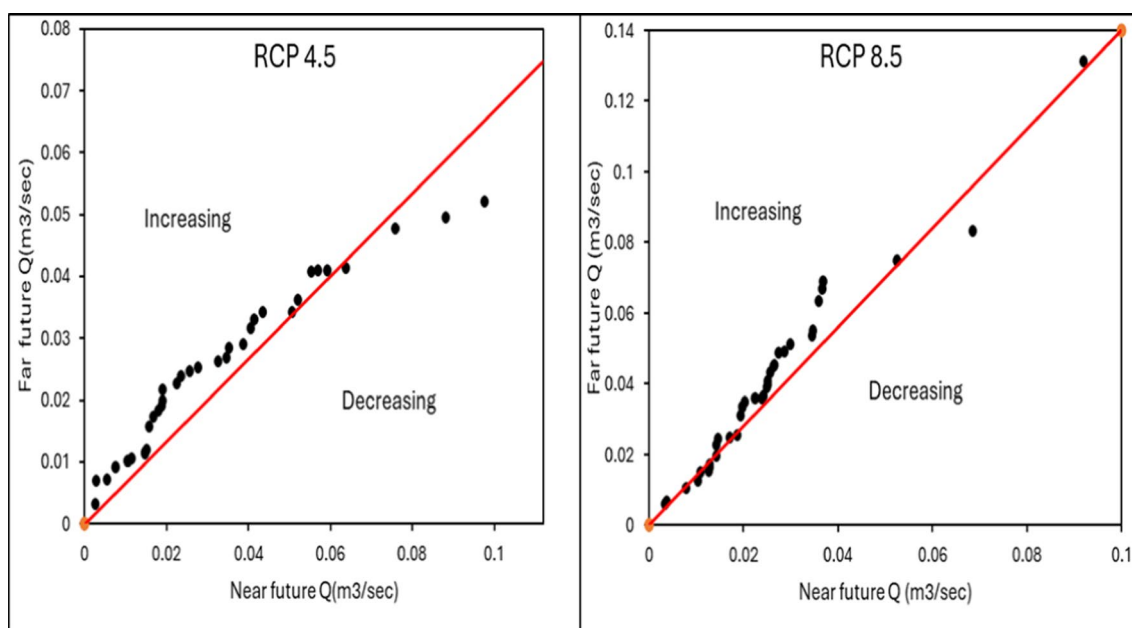


Fig. 12 The innovative trend analysis for the near (2022–2060) and far (2061–2098) future streamflow of the Andit Tid watershed

3.4 Innovative trend analysis

The innovative trend analysis of the predicted streamflow verified that, under the RCP 4.5 (stabilization) climate scenario, there is an increasing trend in the near future (2022–2060) and a decreasing trend in far periods (2061–2098). Conversely, though, the RCP 8.5 (emission) climatic scenario exhibits a continuous upward trend of streamflow in both the near and far futures. In Fig. 12, the scatter points falling above the 1:1 line mean the time series exhibits a monotonic increase while the scatter point below the 1:1 line indicates a decreasing trend.

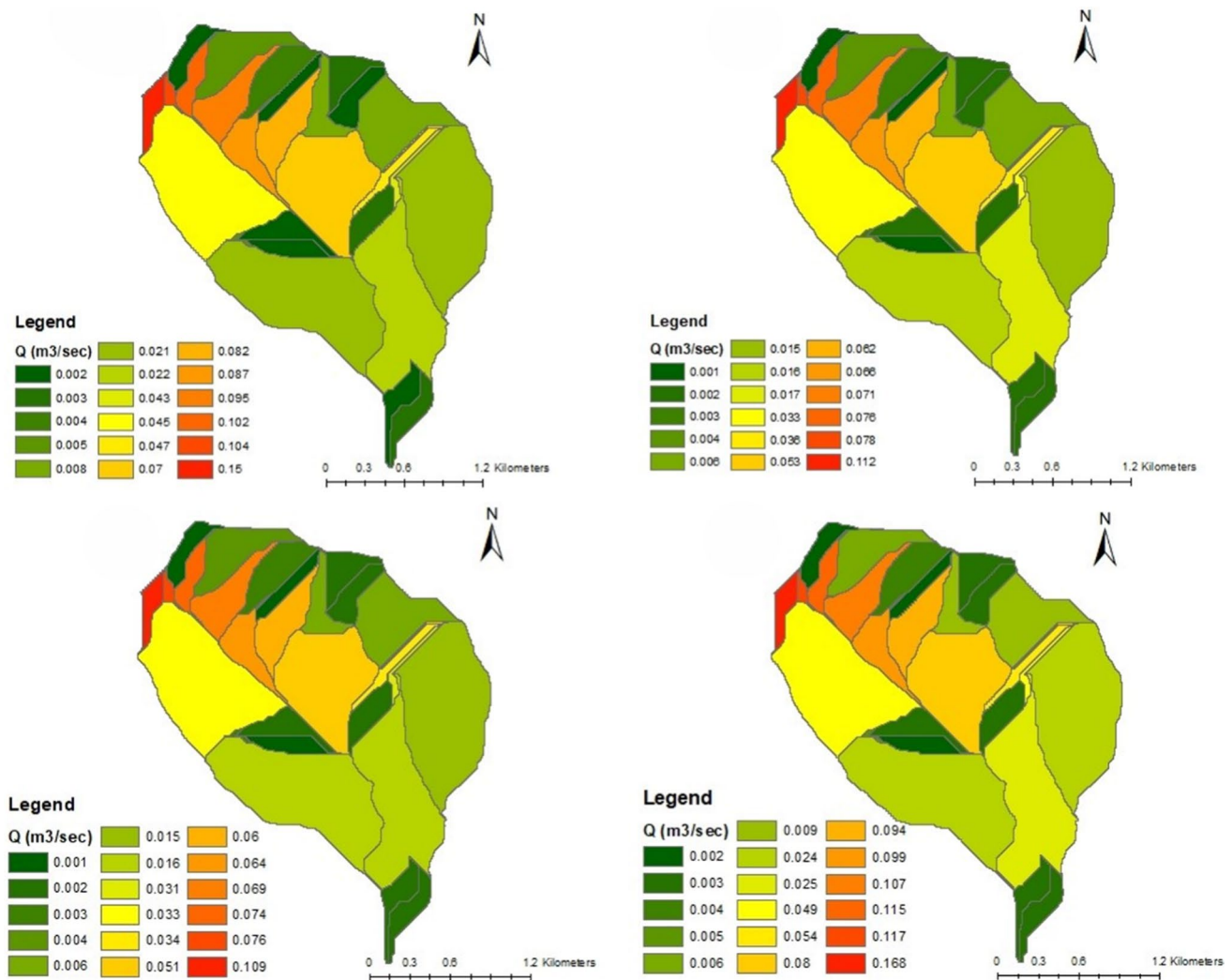


Fig. 13 The spatial distributions of stream flow discharge are shown in the following figures: the first left-sided figure represents the near future under RCP 4.5, the first right-sided figure depicts the far future under RCP 4.5, the second left-sided figure illustrates the near future under RCP 8.5, and the second right-sided figure shows the far future under RCP 8.5. These simulations are derived from projected rainfall and temperature and SWAT models

3.4.1 Spatial analysis of projected streamflow

The spatial variability of streamflow of both RCPs is illustrated in Fig. 13. The projected streamflow in the watershed spatially varied from 0.001 to 0.15 m³/s in RCP 4.5. The near future streamflow discharge varies spatially between 0.001 and 0.109 m³/s and the far future ranged between 0.002 and 0.168 m³/s in RCP 8.5. Less streamflow occurs in the sub-basins with green shading, and high streamflow occurs in the sub-basins with red shading. In light of this, the sub-basins 3, 4, 5, 9, and 11 were identified as having high streamflow, whereas 1, 6, 7, 10, 18, 21, 23, and 26 were identified as having low streamflow.

Despite a significant difference in streamflow discharge between time frames, sub-basins 1 and 4 are the lowest and largest streamflow-contributing sub-basins, respectively in the near and distant future. Overall, the streamflow discharge trended downward in RCP 4.5 and upward in RCP 8.5 from the near to far future. The highest streamflow discharge in the watershed was typically found in the northern, northwestern, and central sub-basins, while the lowest streamflow discharge was found in the northeastern, eastern, and southern sub-basins (Fig. 13).

4 Discussion

The analysis of both the stabilisation and emission climate change scenarios reveals a definite rise in temperature together with an unclear trend in rainfall. Their impact indicated that, the streamflow in the study watershed showed a reduction as compared to the current rate. Comparable to the current rate of discharge, it was discovered that streamflow in this scenario would've been decreased by more than half. It is anticipated that the projected decrease in streamflow will be related to the anticipated reduction in rainfall. Climate change may cause a consistent decrease in surface runoff and total water yield and an increase in evapotranspiration. A similar study in the upper Blue Nile Basin's Jemma sub-basin reported that climate change may cause a consistent decrease in surface runoff and total water yield and an increase in evapotranspiration under all climate scenarios [60]. Since precipitation is predicted to decline in the future, streamflow to the Geba reservoir is likely to decline throughout the rainy seasons [61].

The finding stated that in comparison to the baseline period, climate change is predicted to increase average annual runoff by 15% to 38% [62]. The research conducted in Addis Ababa's Legedadi watershed also found that the runoff magnitude could increase by 2050 [63]. Research carried out in the upper Blue Nile Basin's headwater catchments projects that by the end of the century, streamflow will increase by up to 64% during the dry seasons and fall by 19% during the rainy seasons [11]. Climate change has increased the regions at high risk of soil erosion because of the increases in rainfall intensity in a pan-Africa convection-permitting climate model simulation (CP4A) [64]. For 2020, 2050, and 2080s, respectively, the increases in climate variables are predicted to increase mean annual streamflow by 8%, 13%, and 15% for the RCP2.6 scenario, 17%, 24%, and 31% for the RCP4.5 scenario, and 14%, 24% and 35% for the RCP8.5 scenario [65].

During the transition period from 1994 to 2017, streamflow experienced a decrease of 20.48 mm (equivalent to 13.59%) compared to the reference period spanning from 1958 to 1993 [66]. Climate change exerted significant effects on watershed hydrology, manifesting in increased potential evapotranspiration (PET) by 4.4% to 17.3%, alongside reductions in streamflow and soil water ranging from 48.8% to 95.6% and 12.7% to 76.8%, respectively [67]. Furthermore, under different Representative Concentration Pathways (RCPs) scenarios, the average monthly variation of streamflow fluctuated from −16.47 to 6.58% under RCP4.5 and from −3.6 to 8.27% under RCP8.5, spanning the period from 2022 to 2080 [68]. A rise of 1.5 °C in temperature led to a 6% escalation in potential evapotranspiration while inducing a 13% reduction in streamflow [69]. Moreover, there's a discernible trend toward decreased precipitation over the studied region in the forthcoming century as a consequence of rising temperatures. This shift, coupled with temperature increases, is anticipated to lead to diminished mean discharge [70].

Projections indicate a decline in runoff, groundwater, and water yield by approximately 11.24%, 12.54%, and 11.54% respectively due to combined climate and land use/land cover (LULC) changes [71]. However, potential and actual evapotranspiration are forecasted to rise by 19% and 14.7% respectively. These climate shifts are anticipated to boost mean annual streamflow by varying degrees across different scenarios and time frames. For instance, under the RCP2.6 scenario, streamflow is expected to increase by 8%, 13%, and 15% for the 2020s, 2050s, and 2080s respectively [65]. The RCP4.5 scenario predicts even higher increases of 17%, 24%, and 31%, while the RCP8.5 scenario anticipates increments of 14%, 24%, and 35% for the same time intervals [65]. However, towards the latter part of the century, a significant decrease in surface flow is projected, ranging from 9% in some regions to 22% in others [72].

Looking at more specific time frames, for the periods 2021–2040 and 2041–2060, streamflow is expected to rise by 40.1% and 29.4% respectively under the RCP4.5 scenario, and by 16.9% and 18.5% respectively under the RCP8.5 scenario [73]. Over the longer term, from 2010 to 2040, a decrease in flow volume ranging from −40 to 50% is foreseen due to climate change, though this trend may reverse dramatically, potentially doubling or more, by 2070–2100 [74]. Notably, while streamflow is predicted to increase across all scenarios over extended periods, there's a decrease of 6.68 m³/s projected under the RCP 8.5 scenario in the near and mid-future [75].

According to Tariku et al. [76], projections suggest a decrease in UBN streamflow of 7.6% by the 2050s, ranging from −19.7 to 17.7%, and by 12.7% by the 2080s, ranging from −26.8 to 31.6%. Runoff discharge exhibited a downward trend across all timeframes for both A2a and B2a scenarios [61]. Projected runoff reductions of 4.29%, 10.62%, and 18.07% for the 2020s, 2050s, and 2080s, respectively, were noted for both A2a and B2a emissions scenarios [77]. Gurara et al. [78] found a decrease in mean seasonal streamflow during the Belg season by −10.91% and an increase during the Kiremt season by 17.4%. Woldemariam et al. and Hirpa et al. [79, 80] indicated significant reductions in streamflow, including seasonal, long-term mean, and extreme events, for major rivers in Ethiopia, with increases in equatorial regions by the century's end. Liemohn et al. [81] observed an increase in annual streamflow of 5.8%, 2.8%, and 9.5% for the A1F1, A2, and B1 emission scenarios, respectively, during 2040–2069.

5 Conclusion and recommendation

Using hydrological simulations carried out with SWAT and ArcGIS 10.5 software, as well as climate models from the 11 Ethiopia CORDEX, this study thoroughly examined the effects of climate change on streamflow in the Andit Tid watershed. Significant temporal and spatial changes in streamflow resulting from climate change were observed by the analysis, and future streamflow rates were predicted to decline under RCP 4.5 and RCP 8.5 scenarios. The SWAT model performed satisfactorily during calibration and validation, with R^2 values of 0.83 and 0.72, respectively. According to the findings, streamflow is mostly contributed by the watershed's northern and middle parts, both currently and in the future. Steep slopes and active gullies were shown to be hotspot areas, indicating areas susceptible to major hydrological changes. Overall, the study emphasizes how crucial it is to take watershed characteristics and climate variability into account when planning and managing hydrological systems.

In the Andit Tid watershed, climate and hydrological factors must be regularly monitored to improve prediction accuracy and model calibration. To enhance water resource management and climate adaptation in the Andit Tid watershed, it is recommended to conduct detailed studies assessing the socio-economic impacts of changing streamflow patterns on local communities and agriculture and to develop frameworks for involving local stakeholders in planning processes. Additionally, employing higher-resolution regional climate models and ensemble approaches will improve the accuracy and robustness of future streamflow predictions, which is crucial for sustainable watershed management.

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Data availability The data used in this manuscript can be sent by requesting the corresponding author.

Declarations

Competing interests The authors declare no competing interests.

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