Hydrological response to climate change in Baro basin, Ethiopia, using representative concentration pathway scenarios

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Abstract

Droughts and floods are common in the Baro basin and climate change may exacerbate them. This study aimed to investigate the hydrological response to climate change's impact in the Baro River basin. Four climate models namely, Hadley Centre Global Environmental Model, version 2 (HadGEM2-ES), Max Planck Institute Earth System Model—Low Resolution (MPI-ESM-LR), Coupled Model Version 5, Medium Resolution (CM5A-MR) and European Community Earth System Model (EC-Earth) dynamically downscaled outputs were obtained from Africa coordinated regional downscaling experiment program. The four climate models were evaluated using a suite of statistical measures such as bias, Root Mean Squared Error, and Coefficient of Variation. The bias of the simulated rainfall varies between − 4.20% and − 25.39% suggesting underestimation. The performance of the models differs subject to the performance measures used for evaluation. Before being used in the climate impact analysis, the climate model data was heavily skewed and needed correction. In terms of bias, HadGEM2-ES performed the worst while EC-Earth performed the best. MPI-ESM-LR was the worst performer in terms of RMSE and CM5A-MR was the best. Changes in the hydrological response to climate change were compared to the baseline scenario (1971–2000) under the Representative Concentration Pathway Scenarios (RCP 4.5) for the medium term (2041–2070). The GCM predictions for the RCP 4.5 scenarios suggested that, in the medium period (2041–2070) the maximum temperature in the Baro River basin will probably rise by 2.1 °C for MPI-ESM-LR and 2.49 °C for CM5A-MR, while the minimum temperature would likely climb by 1.7 °C to EC-Earth and 2.8 °C for HadGEM2-ES. Annual rainfall is expected to fall by 7.02% for CM5A-MR and 17.01% for HadGEM2-ES, while annual evapotranspiration potential is likely to rise. Except from March to May CM5A-MR consistently generated the greatest amount of streamflow change, while MPI-ESM-LR consistently generated the highest magnitude of streamflow change. The annual streamflow reduction is consistent with the annual precipitation reduction and increased annual potential evapotranspiration. Generally, climate change is predicted to have a significant impact on the hydrological response in the Baro River basin under the RCP 4.5 scenario.

Keywords Baro River Basin, Climate change, Extreme flows, RCP

Introduction

According to the most recent International Panel Climate Change (IPCC) scenarios Assessment Report Fifth (AR5), global temperatures will rise by 1.4–5.8 °C by 2100. This caused changes in temperature and rainfall at the regional and sub-basin levels. Changes in local climate may affect the frequency and intensity of extreme weather events, having a significant impact on natural

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and human systems (Sheridan and Allen 2015). Climate Change is a serious threat to our planet's ecology, human well-being, environment, social, economic, and future development that we face today (Fentaw 2018). It is the study of how the weather system changes over decades or longer periods because of natural and human influences. Climate change is a global issue, and its influence on hydrological variables and water resource availability cannot be overstated.

Climate change can change the hydrologic regime of river basins, including low, high, and medium stream flows (Alodah and Seidou 2019). These changes affect power generation, water supply systems, sediment transport, deposition, and ecosystem conservation. Because water resources are so important to society, it is critical to study their effects. Because all-natural and socioeconomic systems rely heavily on the effects of climate change hydrological variables and water resource availability are critical. Climate change has the potential to have a direct impact on water resources availability and hydrological extreme events like droughts and floods, as well as indirect effects on food and energy production, agriculture, and overall water infrastructure (Mekonnen and Disse 2016).

Many factors, including climatological, environmental, and social factors, have a significant impact on water resources. As a result, making the best use of available water requires understanding and mitigating these factors. In this study, assessing the impact of climate change on stream flow and evaluating the future trend of climate variables would provide a clue direction for water resource problems and would help to develop mitigation and adaptation strategies to overcome the problems that have emerged. The study's findings serve as a guide for planners, decision-makers, and concerned individuals to integrate their duties with climate change in their roles as protectors of current and future water development projects and activities such as navigation, fishery, irrigation, hydropower, water supply and different infrastructures, to incorporate the effects of climate change into their water planning, implementation, and management. The study's main significance is that it will be used to support sustainable development and the effects of climate change on various water resource projects within and around the catchment.

Climate change is mostly altered by human beings and the change in climate poses risks for humanity (IPCC 2014). Climate change will exacerbate the periodic and chronic water shortage (Du et al. 2021). Because of their low economic structure and reliance on agriculture, developing countries such as Ethiopia are the most exposed to climate change and variability (NMA 2001). This is fundamentally, due to their socio-economic

systems' high sensitivity and low adaptive capacity. Gambela has been severely impacted by repeated floods, droughts, and famines (Haile et al. 2013). Agricultural activities in the country's semi-arid and arid regions are heavily reliant on rainfall. It is critical to gain better acceptance of the hydrological features of the various watersheds of the Baro River Basin, because of its high potential for socio-economic development such as for irrigation purposes, domestic water supply, and livestock. Yet, sustainable development requires consideration of emerging problems like climate change. However, limited studies were conducted to evaluate climate change's impact on the Baro River basin using RCP scenarios (Kebede 2013). Previous studies focused on Coupled Model Intercomparison Project Phase (CMIP3) and (CMIP5) scenarios for large river basins, but the heightened risk of local climate changes poses a significant threat to smaller basins, notably affecting crops. This study assesses the impact of climate change on the hydrology of Ethiopia's Baro River basin using four climate models in Ethiopia's Baro Basin.

It is suggested that the Global Climate Model and the old climate scenario SRES temperature in the basin is projected to increase and rainfall does not show a logical decrease or increase. To properly evaluate forthcoming projections, the author proposed extra investigation using additional climate models. The Baro River basin studies conducted previously solely utilized the Global Climate Model finding for the SRES scenario. In contrast, regional climate model (RCM) outputs for the new representative concentration pathway scenarios are freely available and must be estimated for the Baro River basin (Kassa 2013).

In addition, the previous studies used the SRES climate scenario while very few studies used the newly developed representative concentration pathway scenario (Haile et al. 2017), (Kassa 2013), (Mengesha 2016), (Feyissa et al. 2018). Representative concentration pathway scenarios (RCP) allow the modeling of the climate system response to human activities and they include information on a range of long-lived GHGs, including emissions of radiatively active gases and aerosols, land use, and socioeconomic conditions (Neitsch et al. 2011; Vuuren et al. 2011). Previous studies used single or very few climate models which makes it difficult to be conclusive. Therefore, additional studies using the outputs of multiple climate models are needed to understand the uncertainties of climate change projections.

This study used the Representative Concentration Pathway scenarios (RCP) 4.5 to evaluate the hydrological climate change impacts, specific changes in temperature and precipitation, on the availability of water resources in the Baro River basin in western Ethiopia. The Baro River

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basin is White Nile's major perennial tributary. Gambela is one of Ethiopia's most exposed regions to the adverse effects of climate change, as its livelihood- is based on livestock keeping and farming (Mekonnen et al. 2016). The study's findings are expected to assist with the future management of water resources in the area, as well as contributions to the scientific research on global warming impact studies, will be studied. Changes in climate variables such as precipitation, evapotranspiration, and temperature have influenced the availability and distribution of water resources in time and space by causing changes in the hydrological cycle. The objective of this study was to investigate the hydrological response to climate change in the Baro River basin under representative concentration pathways scenarios (RCP) 4.5 using the HBV-96 model software.

Materials and methods
Study area description
Baro River basin is located in Ethiopia's southwestern region between the longitude of 34° 31′ 48"E–36° 17′ 00"E and the latitude of 7° 26′ 24"N to 9° 24′ 00"N and span over 23461 km^2 (Fig. 1) (Kassaye et al. 2024a). Elevation of the Baro River basin varies from 390 m up to 3266 m above mean sea level (AMSL) and is processed from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) https://www.earthdata.nasa.gov/sensors/srtm (Accessed on 15 October 2023) in this study. The confluence of Geba and Birbir tributaries Rivers east of Mattu in the Oromia Region's Illubabor Zone forms the Baro River catchment.

From June to November, the hydrology of the Baro basin at Gambela River varies by high runoff generation (Haile et.al 2013). The climate of the area depends on tropical monsoons from the Indian Ocean, which has great rainfall during the rainy period from May to October and slight rainfall during the dry period from November to April (Adeba et al. 2016; Alemayehu and Nedaw 2016; Kebede et al. 2017; Kassaye et al. 2024b). December is typically the coldest month and May April and March, are the warmest (Kassa 2013).

Data sources, collection, and analysis
The HBV-96 software conceptual hydrological model was used in this study to evaluate climate change's impact on streamflow in the Baro Basin River. The datasets for this study area were obtained from appropriate sources such as streamflow, Digital Elevation Model (DEM), Meteorological, land use map, and soil map information, are among the data. Fluvisols are a type of soil that includes both dystric and eutrophic soils. This is the most common type of soil in the area. Soils of the Baro River basin are a result of the interaction of five soil formation factors: geology, primary fine-grained soils, secondary fine-grained soils, coarse-grained soils, climate, topography, Vertisols, and red soils. Land use/cover includes cultivated land, woodland, wetland, grassland, forest, and non-forest because other land use/cover such as glaciers and lakes are almost non-existent in the elevation zones of the current study. During simulation, land use influences climate change and hydrological responses by influencing surface erosion, evapotranspiration, and runoff in the sub-basin (Neitsch et al. 2011). It is an input to the HBV-96 model software used in this study area.

As shown in Table 1 and Fig. 2, the land use is predominantly covered by forest (66.09%). The remaining areas are covered by cropland (28.30%), woodland and grassland (2.42%), shrubland (2.07%), wetland (0.05%), water bodies (0.13%), settlements (0.12%), bare soil (0.02%), rock outcrop (0.78%), and lava flow (0.02%).
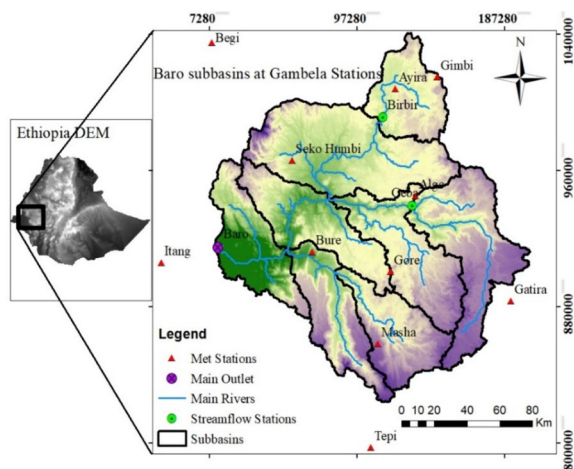

Fig. 1 Baro River Basin study area map

Table 1 Summary of Land use/cover classes in the Baro River basin

Land use/cover	Area (Km2) %	Land use/cover
Forest	15470.51	66.09
Grassland and woodland	567.64	2.42
Shrub land	485.67	2.07
Cropland	6624.75	28.30
Wetland	11.75	0.05
Water Body	30.81	0.13
Settlement	26.94	0.12
Bare soil	5.29	0.02
Rock Outcrop	182.05	0.78
Lava Flow	3.75	0.02
Salt Span	0.04	0.00
Total	23,409.17	100.00

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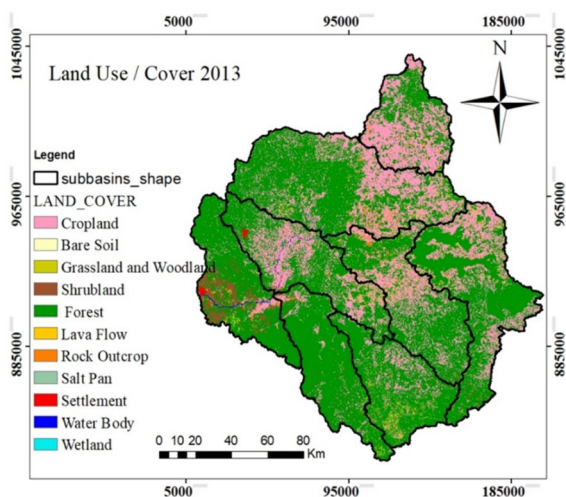
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Fig. 2 Baro River Basin land use/land cover

Table 2 Relevant Data and Data Source

Relevant data	Temporal scale	Time period	Data sources
Meteorological	Daily	1985–2016	NMA
Temperature min & max	Daily	1985–2016	NMA
Stream flow	Daily	1990–2006	MoWIE
Soil	–	2008	MoWIE
LULC	–	2013	EMA
DEM	–	––	USGS
Climate simulated data	Daily	1971–2071	CORDEX Africa

Rainfall, minimum and maximum temperatures, and other meteorological data were collected from Ethiopia's national meteorological agency. Ethiopia's Ministry of Water, Irrigation, and Energy provides the streamflow data. Meteorological and streamflow data were collected from available time sequences for analysis of the HBV-96 software model. The website of the United States Geological Survey (USGS) was used to obtain a Digital Elevation Model. The Shuttle Radar Topography Mission (SRTM) acquired Digital Elevation Model used in this study, which has a resolution of 30 m×30 m. The land use/ land cover map of the study was achieved from Ethiopia's mapping agency https://data.apps.fao.org/ (Accessed on 15 October 2023) for the current study. Table 2. Shows the general description of the climate and all meteorological data, which were collected from relevant offices.

Data quality analysis
To fill in missing data for minimum and maximum temperature and rainfall, inverse distance weighted (IDW) interpolation was used in this work to change rainfall station amount into Baro Sub-basin River. Inverse Distance

weighting, the observed amounts are weighted based on their distance from the interpolation station and the interpolated amount is the weighted mean of observations. After missing data rainfall was filled in, point data rainfall from numerous stations was changed to watershed mean rainfall using the Thiessen polygon method. Because the catchment limits must be precisely defined to have a solid theoretical foundation and the accessibility of computational tools. The technique is reliant on a well-connected network of typical rain gauges for the area. Daily rainfall area was considered from the sub-basin's rainfall point measurements. The amount of rainfall at each station is multiplied by the area influence of the station with the entire area of the basin. Some precipitation stations may have short gaps in their records due to observer absence or instrument failure. Missed data results from a lack of appropriate records, shifting of station location, and processing may contradict the actual condition. This missing record must frequently be estimated. Geographically Weighted Regression (GWR) is a type of local linear regression used to model spatially varying relationships. It is not possible to predict another dataset or generate raster coefficient outputs. Thiessen polygon method was selected arbitrarily as there was no solid reason to select other methods. However, the method requires representative rain gauge distribution in the study area. The Thiessen polygon approach gives weight to station data in proportion to the space between the stations and can easily create a polygon from a point. This method assigns weights for each station by drawing the perpendicular lines that cross the line that connects adjacent stations using ArcGIS 10.3.

Climate model rainfall simulation accuracy
Rain gauge data is used to evaluate rainfall simulations from various climate models. After converting point rainfall data to catchment average values, the evaluation was performed for the entire Baro River catchment. Four models were analyzed and selected based on statistical criteria like BIAS, NSE, R^2, RSR, and RMSE. Models project climate changes for near (2011–2040), mid (2041–2070), and far-future (2071–2100) periods against a baseline (1971–2000), investigating spatiotemporal variations in rainfall, temperature, and streamflow in the region. The accuracy of the rainfall from the models was estimated using both graphical methods and statistical methods. To compare simulated and observed rainfall data, line plots, and cumulative plots were used. Root Mean Squared Error (RMSE), Bias, and Coefficient Variation (CV) are statistically based performance measures.

The error in averaged rainfall amount over a long period is referred to as bias. A zero value indicates that no systematic difference exists between simulated rainfall

and observed rainfall amounts, whereas a big bias indicates that the RCM amount of rainfall deviates significantly from the rainfall observed amount. Positive bias represents overestimation and negative bias represents underestimation. Root Mean Square Error is easy to interpret because it has the same unit as the observed variable. The fraction of the total sum of squares corresponds to the difference between predictions and observations (residual sum of squares). The standard deviation of observations was used to normalize the RMSE. The measured data's Root mean square error observation standard deviation ratio (RSR) (Tilahun et al. 2023; Yuemei et al. 2008).

$$RSR = \frac{\text{RMSE}}{\text{STDEVobs}} = \frac{\sqrt{\sum_{i=1}^{n}\left(Q_{obs,i} - Q_{sim,i,}\right)2}}{\sqrt{\sum_{i=1}^{n}\left(Qobs,i - \overline{Qmean}\right)^2}} \tag{1}$$

Qsim = simulated discharge, Qobs = observed discharge, i time index, n = number of days, (Q̄ mean) = mean discharge.

RSR values range from zero to a large positive value, indicating that there is no RMSE and the model is perfectly simulated. Lower RSR values indicate lower RMSE values and better model simulation performance and high values indicate poor performance.

RMSE offers a new accurate evaluation of the error between models and observations. However, bias, in addition to giving the error value, is less accurate than the RMSE. The root mean square error is a measure of the variance between two variables that measures the mean magnitude of the evaluation error. The lower the RMSE value, the larger the central tendencies and the lesser the extreme error. Coefficient Variation is considered by dividing the standard deviation by the average rainfall total. Coefficient Variation was used to assess how fine RCMs capture and signify the rainfall variability at the station's network. The medium of each RCM grid cell's CV values measures according to (Krause and Boyle 2005; Chai and Draxler 2014; Haile and Rientjes 2015) as follows:

$$\text{Bias} = 100 * \frac{\overline{Rrcm - Robs}}{\overline{Robs}} \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{N}\left(Rrcm - Robs\right)^2}{N}} \tag{3}$$

$$Cv = 100 * \frac{\sigma Rrcm}{\sigma Robs} \tag{4}$$

Coefficient Variation (CV), Root Mean Squared Error (RMSE), i = time index, N = investigation period, $\overline{Robs}$ = mean rainfall basin amount, $\overline{Rrcm}$ = rainfall amount gained from RCM simulation, σRrcm = standard deviation of RCM statistics projected, σRobs = standard deviation of observed rainfall data or Gauge basin rainfall amount.

Bias correction

Bias correction is the identification and adjustment of biases in simulated climate variables using observed data as a reference. The Representative Concentration Pathways (RCP) 4.5 scenario represents a moderate mitigation scenario, whereas the others represent a higher stabilization pathway with a wider range of radiative forcing across (RCP) 4.5 extensions. As a result, RCP 4.5 is required for planning adaptation and mitigation options for river flow responses to changing climates. Due to this reason, Representative Concentration Pathways (RCP) 4.5 scenarios were selected. For Representative Concentration Pathways (RCP) 4.5 scenarios, the daily-downscaled climate variables are precipitation, temperature maximum, and minimum from regional climate models, with biasing corrected using power transformation. The bias-corrected data are fed into the hydrological model, which simulates the future. A power transformation nonlinearly corrects for both the precipitation mean and the coefficient of variance. In addition to the original Regional Climate Model (RCM) output data, the following, bias correction procedures were used to adjust RCM simulations (Driessen et al. 2010).

Precipitation correction

The statistics of the simulated and observed variables can be used to compute correction factors. The basic idea behind this method is average and standard deviation of rainfall data become equal to the average and standard deviation of observed data. (Lafon et al. 2013). Each rainfall daily total P is transformed to a corrected P* using a nonlinear correction method.

$$P^* = aP^b \tag{5}$$

P* denotes bias-corrected daily precipitation, P denotes uncorrected daily precipitation, and a and b denote transformation coefficients.

The b parameter is iteratively determined until the coefficient of variation of the corrected RCM daily rainfall time series matches the coefficient of variation of the observed rainfall time series for each area of each grid box in each month. When the mean of the transformed daily values matches the observed mean, the parameter a is determined.

Temperature correction

Temperature bias correction differs from precipitation bias correction. Temperature correction is simply scaling and shifting to adjust the variance and mean (Terink et al. 2009) calculated by

$$T^* = \overline{T} + \frac{\sigma(T_o)}{\sigma(\overline{T}_R)}\left(T_R - \overline{T}_o\right) + \left(\overline{T}_o - \overline{T}_R\right) \tag{6}$$

T^* = corrected temperature, TR = RCM uncorrected daily temperature, $\overline{T}_o$ = observed average temperature; and $\overline{T}_R$ = RCM mean temperature. Over-bar denotes the mean and standard deviation of the measured period.

Hydrological model selection criteria

HBV-96 model software, a catchment is subdivided into sub-catchments, which are additional sub-divided into elevation and land use zones. To calibrate the model rainfall, temperature, mean monthly potential evapotranspiration, landscape characteristics, and observed runoff data are used. The Digital Elevation Model (DEM) was created using Arc GIS 10.3 software. This processing helps to delineate the boundary of the Baro River sub-basin, extract its drainage network, and divide the area into multiple sub-basins, elevations, and vegetation zones. By dividing the basin into several smaller sub-basins, semi-distributed models allow parameters to vary in space. Because of the large size of the watershed and the availability and spatial distribution of meteorological stations, the Baro River basin was divided into sub-basins.

In this study, a two-year warm-up period (January 1, 1994–December 31, 1995) was specified before the actual simulation period rainfall data from the total period of model development for model initialization. This ensures that at the start of the simulation, the model storage is similar to catchment storage. Model calibration based on available time series (January 1, 1996–December 31, 2002) is the systematic procedure for adjusting model parameters until model results satisfactorily match observed data. The process of calibration determines which parameter values are optimal for minimizing the objective function. Calibration involves trial and error changes to one or two parameters at a time within the acceptable ranges. The objective function is chosen based on the requirement.

Model validation based on available time series (January 1, 2003–December 31, 2005) is the process of determining a model's ability to accurately simulate observed data other than that used for calibration. This process does not affect the calibrated model parameters; their values remain constant. The process of testing model performance against an independent set of observed data using calibrated model parameters is known as

validation. Volume parameters, soil parameters, snow parameters, and response parameters were used as calibration parameters in the HBV-96 software. Because there is no snow in the area, the snow parameter is ignored in this study. The soil parameter is determined by three empirical parameters (BETA, FC, and LP), the volume parameter (Rfcf), and calibration-derived response parameters (K4, Perc. Khq, Hq, and alpha).

$$Hq = \frac{\sqrt{MQ*MHQ}*86.4}{A} \tag{7}$$

MQ = mean observed discharge, and MHQ = mean annual peak flow. A = catchment area.

In this study, the model's performance was assessed using Relative volume error (RVE) and Nash and Sutcliffe efficiency (NSE). The difference between the observed and simulated discharge is the Relative Volumetric Error (RVE).

$$RVE = \left[\frac{\sum_{i=1}^{n}(Qsim, i - Qobs, i)}{\sum_{i=1}^{n} Qobs, i}\right] * 100\% \tag{8}$$

Qsim = simulated discharge, Qobs = observed discharge, i = time, and n = days in the simulation period. RVE values among -5.0% and 5.0% indicate a very good performance model and -10.0% to -5.0% and 5.0% to 10.0% indicate satisfactory performance.

Nash–Sutcliffe efficiency a is popular and greatly consistent method for assessing the performance of a hydrological model.

$$NSE = 1 - \left(\frac{\sum_{i=1}^{n}\left(Q_{obs,i} - Q_{sim,i,}\right)2}{\sum_{i=1}^{n}\left(Qobs, i - \overline{Qobs}\right)^2}\right) \tag{9}$$

Qsim = simulated discharge, Qobs = observed discharge, i = time, and n = days in simulation discharge period, $\overline{Qobs}$ = average discharge. NSE = 1 shows that the simulated discharge perfectly matches the observed data. It can range between-∞ to 1.

Climate change impact analysis

Climate change's influence on the flow of the Baro River basin was investigated for changes in flow statistics. To estimate the variation of streamflow, the comparative change in seasonal, monthly annual stream-flow was used. The following is an analysis of the relative change.

$$\text{Relative change} = \left(\frac{Q - Qbasline}{Qbasline}\right)*100\% \tag{10}$$

where: Q is the flow statistics projected (high, low, and medium flow) that was estimated from 30 years of period-simulated data for the future and Qbaseline is the

portion of the streamflow that is sustained between precipitation events, fed to streams by delayed pathways.

Q10 high flows and discharge are exceeded only 10% of the time. Downward style Q10 indicates a reduction of flood risk, while an upward style indicates an increase (Aich et al. 2014). The Q90 low flows and discharge exceeded 90% of the time. River droughts are likely because of Q90's downward style. A Q50 medium flow indicates that 50% of the time worth has been exceeded, potentially increasing flood risk. HBV-96 model software was used to simulate baseline and future stream flow using bias-corrected downscaled RCM model input. Climate change impact on river flow was assessed in three periods: baseline (1971–2000), the mid-term 2050s (2041–2070), and the long-term 2080s (2071–2100). The medium-term period is the focus here because it is closest to the current period, but results for long-term periods in the future are also addressed.

Eco-hydrological analysis

The RCP4.5 Eco-hydrologic analysis of the Baro River basin shows how the catchment uses energy and water as temperature and precipitation change. When considering the impact of climate change, precipitation or potential evapotranspiration results in a change in relative excess water and energy calculated from annual average rainfall, potential evapotranspiration, and actual evapotranspiration for the reference period (1971–2000) and the midterm period (2041–2070). Potential evapotranspiration, actual evapotranspiration, and Water information for the Baro River basin are available, allowing water and energy budgets to be combined. This method (Milne et al. 2002) evaluates the effectiveness, where water and energy are used by an ecosystem, which is well-defined as the vegetation within the catchment. The percentage and time of available water, potential evapotranspiration, and type and condition of vegetation all influence actual evapotranspiration. Plotting Pex against Eex ensures that climate change's impact on catchment hydrology is fully captured in this study area. The method is appropriate for showing the effects of climate change on catchment hydrology.

$$Pex = \frac{P - ETa}{P} \qquad (11)$$

$$Eex = \frac{PET - ETa}{PET} \qquad (12)$$

P = precipitation,   ETa = actual   evapotranspiration, Pex = percentage water available, Eex = available energy, and PET = potential evapotranspiration.

Results and discussions

The HBV-96 software was calibrated manually by changing one model parameter at a time until the model accurately simulated the observed stream flow, at which point the best-fit parameter sets were chosen. The observed discharge period is divided into three zones in the streamflow simulation: warming up, calibration, and validation. The calibration period was chosen because it included both normal and wet conditions and was accepted by correcting only one model parameter and leaving the others constant. First, by minimizing volume error, the total volume, the base flow, and the peak flow were calibrated. To better capture observed peak flows, the model's parameters were adjusted following the study's goal.

The parameters used for calibration in the HBV-96 model software are separated into two groups: response function routine and soil moisture routine. Three parameters FC, LP, and BETA govern the HBV-96 model's software water balance and are directly related to base flow. The soil moisture routine parameters are calibrated first because adjusting the base flow is easier than adjusting the quick flow. The parameters Khq, HQ, and alpha affect the form of the hydrograph and peak discharge. The best values for the response function routine parameters were obtained by combining Khq and alpha. To be physically meaningful, the model parameters must be calibrated within a reasonable range.

Finally, quick runoff increases as LP and base flow decrease (LP decreases, base flow decreases). FC and discharge volume are inversely proportional (as FC increases, so does discharge volume). As the temperature rises, less water percolates through the soil, resulting in more runoff. The Perc parameter was used to modify the base flow, and the k4 parameter was used to modify the recession of the base flow. Perc and base flow are directly proportional (as perc increases, so does base flow). The hydrograph's peak was adjusted using Khq parameters.

Many researchers have used the HBV-96 model software to evaluate the effect of climate change on the availability of water (Abdo 2009), (WaleWorqlul et al. 2018), (Gebre 2015), (Haile et al. 2013), (Haile et al. 2017), (Nigatu et al. 2016) and they can use catchment-specific HBV-96 model software parameters such as FC, Khq beta, Perc, K4, Alfa and LP. Table 3 shows that the parameter Hq was calculated by averaging the observed discharge over the entire period and the annual peak flows. Because Hq was not calibrated here, its value was estimated for the entire basin as well as the Baro basin sub-basin. In this study, the calculated Hq value of Baro @Gambela is 8.73 mm/day. The HBV-96 model's software performance was objectively evaluated using two objective functions (NSE and RVE). Visual inspection of

Table 3 The optimal calibration parameters

Parameters	Calibrated values	Range of Values
Alpha	0.5	0.5–1.1
Beta	1.35	1–4
FC	900	100–1500
K4	0.012	0.001–0.1
Khq	0.05	0.005–0.2
Lp	0.98	≤ 1
Perc	0.72	0.01–6
Calibration	NSE = 0.91 RVE = − 6.76%	
Validation	NSE = 0.72 RVE = 9.78%	

hydrographs and objective evaluation revealed HBV-96 model software study area done well during the calibration and validation period. The calibration procedure's goal is to adjust model parameters to reduce differences between observed and simulated discharge over a given period (Aich et al. 2014). Because the resulting relative volume error RVE-values would be inaccurate, the objective function is not evaluated during the model warm-up.

The Baro at Gambela outlet's two objective function (NSE and RVE) values are 0.91 and − 6.76%, indicating that the model performed exceptionally well during the calibration period. Throughout the years, an independent set of flow data was used to validate the calibrated parameter. The general efficiency of the model as measured by Nash and Sutcliffe efficiency and relative volume error was Baro at Gambela outlet were 0.72 and 9.78%, respectively, during the validation period. The values indicate that the model results are suitable for this study. The NSE criteria are used to assess the model's accuracy in terms

of accurately representing the observed hydrograph arrangement. NSE values ranging from 0.9 to 1 suggest that the model performs exceedingly well, while values varying from 0.6 to 0.8 indicate that the model performs moderately well (Rientjes and Haile 2011), (WaleWorqlul et al. 2018).

RVE ranges from − ∞ to + ∞, with − 5% and + 5% being considered good model RVE, and values ranging from − 10% to − 5% and + 5% to + 10% being considered a reasonably well-performing model. During the calibration period, the two objective function values of the Baro Gambela outlet were 0.91 and − 6.76%. These values show that the model performs admirably in this study. When validated for data collected outside of the calibration period, the estimated NSE and RVE values are 0.72 and 9.78%, respectively. This indicates that the model's performance has deteriorated when evaluated for an independent period, but it is still acceptable (Heyi et al. 2022), (Muleta and Marcell 2023). Table 3 shows that the calibrated and allowable range values of the HBV-96 model parameters.

Because of this, scatter plots of the observed flow versus stream flow simulated are generated. To approximate it, a regression line diagram with a slope of about 45^0 i.e. a regression coefficient of 0.93, can be used. The precise values for the slopes and R^2 values listed in the panels of Fig. 3 show that the agreement between simulated and observed stream flow is even slightly better during the calibration period. As a result HBV-96 simulation results also suggest that River flow highly complies with the seasonal rainfall pattern and is found to be very sensitive to variations in both precipitation and temperature changes (Abraham et al. 2018; Fentaw 2018).
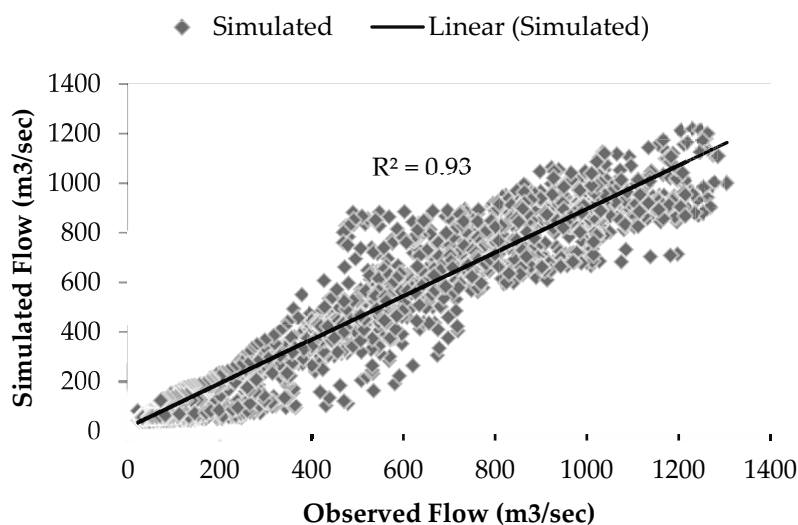

Fig. 3 Monthly-simulated vs stream flow at the Baro River basin

Evaluating the accuracy of climate model simulations

The annual rainfall and dynamically downscaled model simulation captured the annual gauged rainfall for the HadGEM2-ES, MPI-ESM-LR, and EC_EARTH models in this study. To evaluate climate change impact, the accuracy of climate models must be evaluated. The model's ability to reproduce the annual rainfall cycle was assessed using arithmetical trials like bias, Root Mean Squared Error, and Coefficient of Variation. Table 4 shows, the climate model simulations underestimated the observed annual rainfall. The accuracy of the climate models is not equal in representing the rainfall over the Baro basin receives 1710.2 mm of rain per annum on average. The climate model downscaled monthly rainfall results display that there is no good arrangement between observed and simulated rainfall.

All climate models (EC-Earth, MPI-ESM-LR, and HadGEM2-ES) underestimate the observed rainfall. This means that the climate models' accuracy in signifying rainfall in the study area is not equal. In terms of bias, EC-Earth performing best (Bias = − 3.4%) and MPI-ESM-LR performing worst (Bias = − 12.3%). The CV values for Observed, EC-Earth, MPI-ESM-LR, and HadGEM2-ES capture the observed inter-annual variability (70, 61, 73, and 83 respectively). Rainfall over the Sub-basin exhibits a large bias in terms of RMSE, with HadGEM2-ES performing worst (RMSE = 29 mm per year) and EC-Earth performing best (RMSE = 49 mm per year). These values show that for all climate models, the simulated rainfall over the Sub-basin is not in good agreement with the observed rainfall. Generally, the variance between observed and forecast rainfall values is too large to ignore. As a result, before using it for stream flow simulation, the bias should be corrected.

Bias correction of climate model rainfall estimates

After bias adjustment, the climate model simulations roughly replicated a measured annual rainfall over the Baro River basin in Fig. 4. The observed annual rainfall cycle's magnitude and pattern are well captured. As a result, rainfall data from the study area can be used to evaluate the effects of climate change.

Monthly and seasonal climate projections for the Baro Basin

Monthly and seasonal analyses were conducted for three seasons, Kiremt (June–September), Belg (February–May), and Bega (October–January). The simulation of the climate models shows a mixed monthly rainfall variation signal between the baseline 1971–2000 and future periods (2041–2070). The analysis was performed for the RCP4.5 scenario for the 30-year periods classified as medium-term in the 2050s (2041–2070), and there is a mixed indication of the direction of annual and seasonal

Table 4 Accuracy of dynamically downscaled rainfall from multiple GCM models

	Observed	EC-Earth	MPI	HadGEM2	CM5A	Ensemble
Rainfall (mm)	1724.5	1652.08	1441.90	1286.64	1388.25	1442.22
Bias (%)	–	− 4.20	− 16.39	− 25.39	− 19.50	− 16.37
RMSE (mm)	–	49.25	40.74	51.06	61.24	31.74
CV (%)	69.53	60.87	73.12	83.00	113.89	76.22
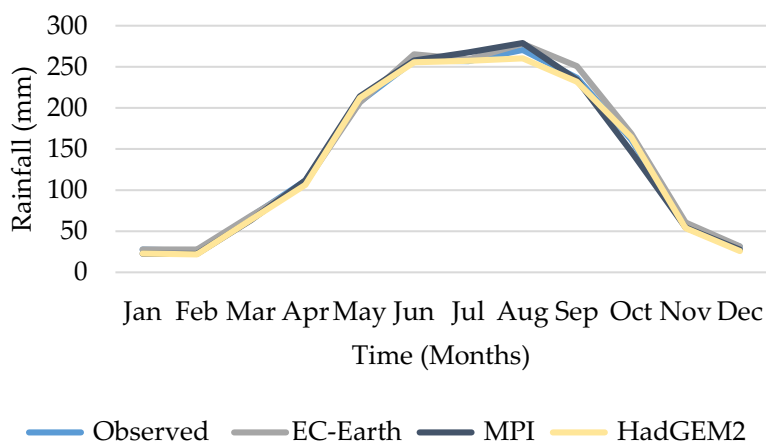
Fig. 4 Annual rainfall cycle bias-corrected GCM-RCM models

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rainfall change. Range of projected precipitation changes for the three seasons, simulations climate models precipitation amount for Annual and Belg (February–May) season, is between − 19.9 to − 7.0% and − 33.0 to − 4.7%. For the Kiremt (June–September) and Bega (October to January) seasons, the range of change is − 25.0 to 4.7% and − 32.6 to 26.0%, respectively. The average rainfall amount over three seasons and annually in the 2050s (2041–2070) will likely change by − 20.0, − 11.6, − 7.0, and − 12.8% respectively. Climate model simulations such as (MPI-ESM-LR, EC-Earth, and HadGEM2-ES) show mixed monthly rainfall variation signals between the baseline period 1971–2000 and the future period (2041–2070), as shown in Fig. 5.

The RCP4.5 scenario exhibits mixed signals in terms of monthly precipitation change. The range of projected precipitation changes for EC-Earth, MPI-ESM-LR,

and HadGEM2-ES for all months is between − 48 to 50%, − 81 to − 4%, and − 57 to 16%, respectively, and average precipitation will likely change by − 27, 9 and − 20% for all climate models, as shown in Fig. 6. The climate model simulations exhibit a mixed monthly precipitation change signal between the reference period (1971–2000) and the future period (2041–2070). For each of the months, simulations from two models show increased precipitation amount while the remaining one shows decreased precipitation.

As indicated by Fig. 7, except for EC-Earth, all the models predicted that, under the RCP4.5 scenario, the average annual rainfall for the 2050s (2041–2070) would drop from 17.42% to 7.34% (Fig. 4.5). HaDGEM2-ES predicted the biggest decrease in yearly rainfall, whereas CM5A-MR anticipated the smallest increase.
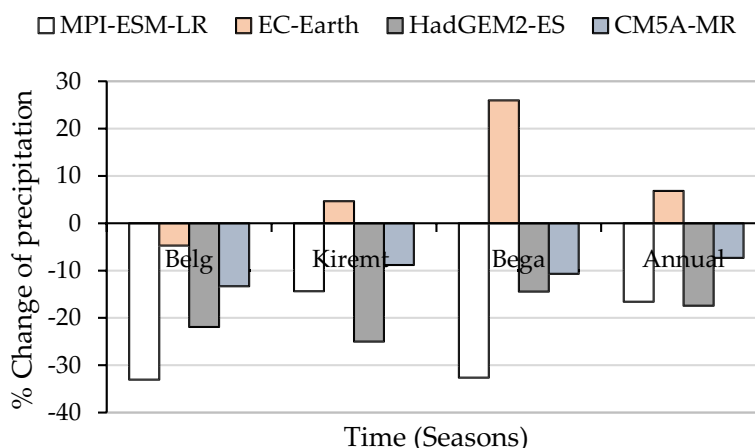

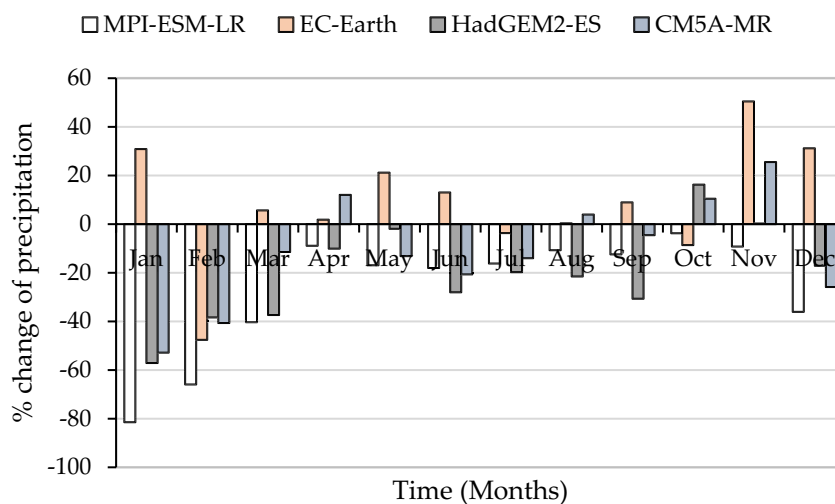**Fig. 5** Seasonal rainfall changes in the Baro basin from 2041 to 2070

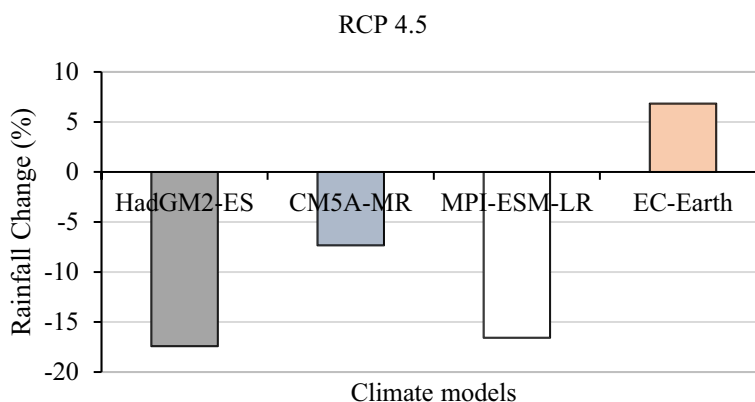**Fig. 6** Changes in monthly rainfall in the Baro basin from 2041 to 2070

RCP 4.5

Fig. 7 Annual rainfall change over the period (2041–2070)

In comparison to the baseline period, the mean temperature annual maximum over the Baro basin has increased from − 2.1 to 2.5 ^{0}C for the MPI-ESM-LR, − 1.8 to 2.1 ^{0}C for the EC-Earth, and − 14.7 to − 9.3 ^{0}C for HadGEM2-ES under the RCP4.5 intermediate emission scenario. Under the RCP 4.5 scenario, the annual average temperature minimum will rise from 0.64 ^{0}C to 3 ^{0}C for all climate models in the period 2041 to 2070, compared to the baseline period. In comparison to the baseline period, the monthly average Baro basin potential evapotranspiration will likely increase from 2 to 17% for all models under RCP4.5 scenarios Fig. 8. The overall results of the magnitude of projected change in temperature show a large difference in Kiremt (June–September) than Bega (October to January), and Belg (February–May). The findings that were obtained provide additional insight into future water balance and assistance in water resource planning and management (Adeyeri et al. 2022; Getahun et al. 2020; Feyissa et al. 2018).

As indicated by Fig. 9, for all models under the RCP4.5 scenario, the annual average Potential Evapotranspiration (PET) in the 2050s (2041–2070) is probably going to grow. The HadGM2-ES model projected the smallest increment of 3.59% among all climate models, while the CM5A-MR model showed the most increment of 19.92%.

Annual and seasonal flow effects

The expected shifts in streamflow over the medium period (2041–2070) are shown in Fig. 10. The EC-Earth climate model water flow of Baro will most likely increase in entire months under RCP4.5. These increases are mostly between − 2 and 46%. The MPI-ESM-LR and HadGEM2-ES basins will see a decline in streamflow in all months. The range for MPI and HadGEM2 is from − 41 to − 1% and − 38 to 15% for all months, except for HadGEM2 May, November, and December, and the MPI-ESM-LR, EC-Earth, and HadGEM2-ES average streamflow will likely change by − 20, 13 and − 15% for all climate models, respectively. The streamflow of the Baro
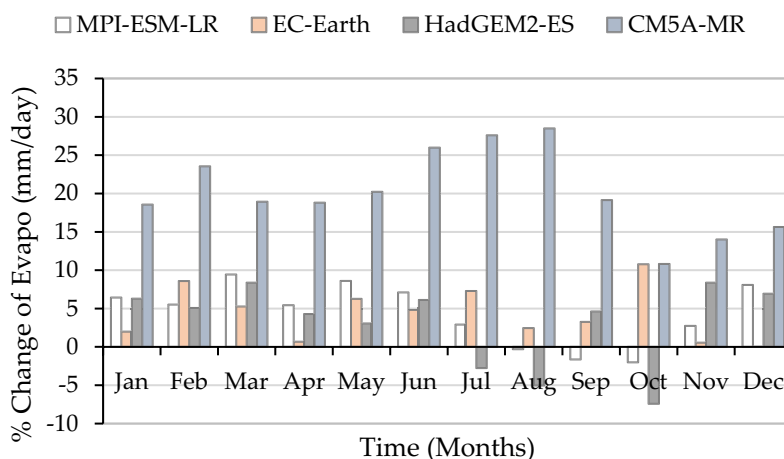

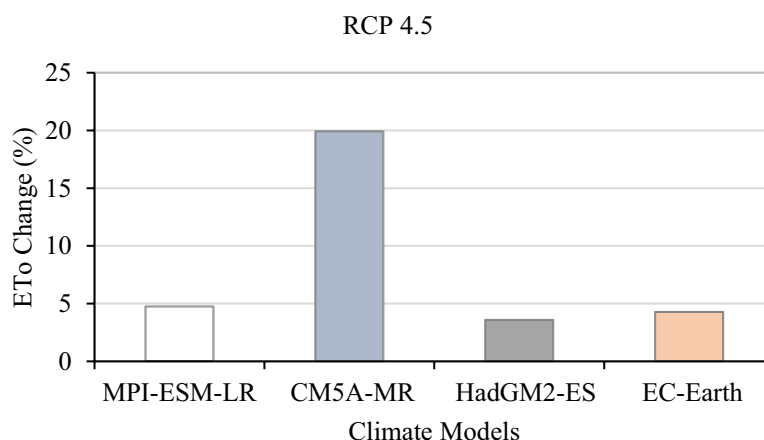**Fig. 8** Monthly evapotranspiration changes in the Baro basin from 2041 to 2070

RCP 4.5

Fig. 9 Annual average evapotranspiration changes over the period (2041–2070)
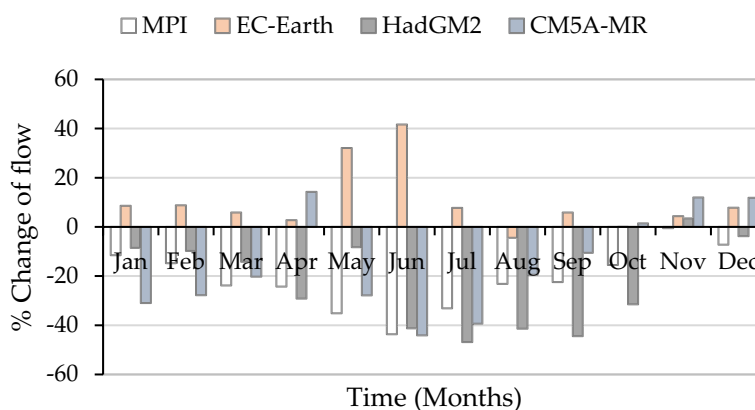

Fig. 10 Stream flow variation in the Baro basin from 2041 to 2070

basin will probably decrease under RCP4.5, except for November and December. All models project this, except for EC-Earth; there will be the greatest reduction in streamflow in June and July. November's flow will probably increase, but the models' predictions for December's flow are inconclusive.

For three seasons, using RCP4.5 climate scenarios, the streamflow of the Baro basin will likely increase for EC-Earth and decrease for the MPI-ESM-LR and HadGEM2-ES. For streamflow direction, RCP4.5 climate scenarios predict mixed results. Generally, this study emphasizes the significance of using climate models multiple to recognize the various projected variations in water resource availability in the basin.

The stream flow of the Baro basin is expected to decline in seasonal and annual periods, as indicated by Fig. 11, which presents the results based on all models except EC-Earth. During the rainy season (Kiremt), a maximum stream-flow drop of up to 28.36% was predicted (CM5A-MR). It is predicted that during the 2050s, the annual rainfall will decrease by up to 35.2%. Aside from

the Belg season, when MPI-ESM-LR showed the greatest decrease, CM5A-MR regularly generated the largest magnitude of streamflow change. The annual decrease in streamflow is in line with the annual rise in evapotranspiration and decrease in precipitation. As a result, it was discovered that fluctuations in temperature and precipitation might affect the streamflow.

The direction of streamflow changes found by previous studies is less inconsistent in our study under the RCP4.5 scenario than for the UBN under the SRES scenario (Abdo et al. 2009; Abdo 2009; Dile et al. 2013).

Climate change's impact on extreme flows
The most important factors influencing extreme annual flows and total flow volume are rainfall and temperature. In water resource systems, extreme streamflow (low, medium, and high) flow is critical. Because of this, three climate models for RCP 4.5 scenarios were used to examine climate change's impact on extreme flows. All trends in the Baro River sub-basin are positive, with significant increases in extreme flow. Under RCP 4.5, the change
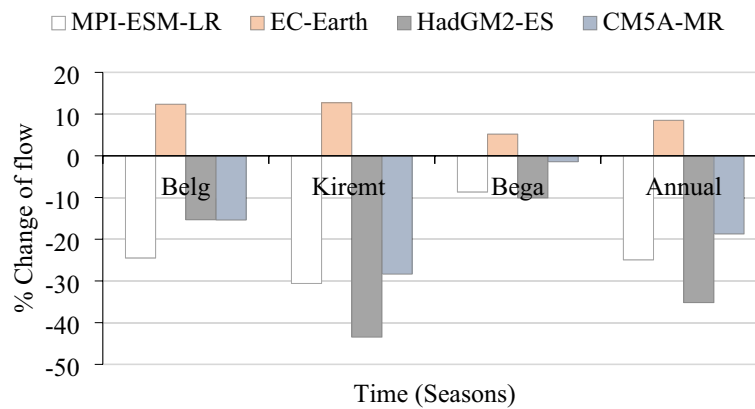
Fig. 11 Change in seasonal and annual stream flow over the period (2041–2070)

directions for the climate model in high flow (Q10) variability will likely increase from 12 to 28%, while the change directions for the climate model in medium flow (Q50) variability will likely increase from 7 to 20%. Also, under RCP 4.5, the climate model's change directions will likely increase from 7 to 20% in low flow (Q90) variability. Figure 12 shows visual representations of Climate Change's Impact on Extreme Flows.

Conclusion

According to this study, climate change has a significant impact on hydrological responses in the Baro River basin. Four GCM-RCM data outputs, all produced as part of the CORDEX-Africa project, were used as input to a hydrological simulation model to investigate the impact of climate change on hydrological responses in the Baro River basin. Before assessing the future climate change impact, the ability of the RCMs-GCMs

ensemble to simulate historical climate and discharge was evaluated. The baseline scenario spans the years 1971–2000, while the medium future spans the years 1941–2070.

The calibrated parameters of the HBV-96 model software rainfall-runoff model were used in this study to simulate the Baro River basin stream flow. The model reproduced the observed streamflow satisfactorily with an NSE and RVE value. The model performance can be considered satisfactory in terms of capturing the volume and pattern of the observed hydrograph. The HBV-96 model software and climate data such as HadGEM2-ES, MPI-ESM-LR, CM5A-MR, and EC-Earth climate models were used to simulate historical and future streamflow. The results of four GCM-RCM sets of data, along with RCP 4.5 scenario references, were entered into a hydrological simulation model to examine the impact of climate change on hydrological responses in the Baro basin.
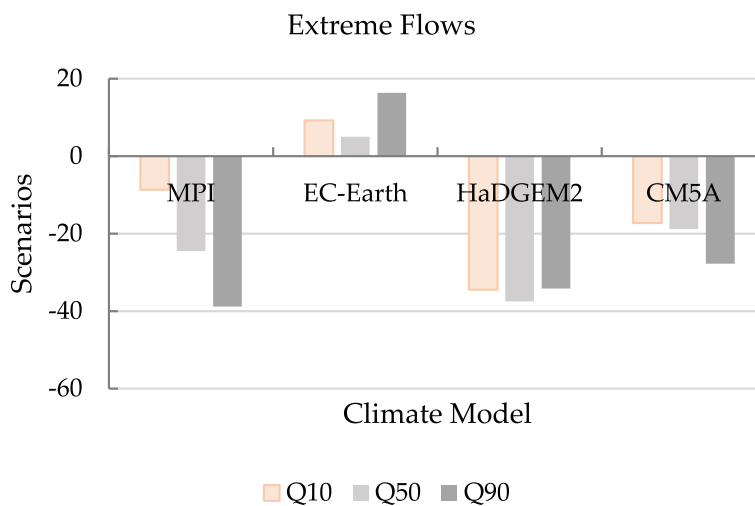

Fig. 12 Climate Change's Impact on Extreme Flows

The direction of streamflow changes found by previous studies is less inconsistent in our study under the RCP4.5 scenario than for the UBN under the SRES scenario (Driessen et al. 2010; Driessen et al. 2010). The differences in terms of inconsistency in direction of change relate to the different model inputs and parameterizations by the RCP and SRES scenarios. The magnitude of the flow reduction reported here is considerably larger when compared to the findings of (Driessen et al. 2010), who reported that the flow of the UBN will decline on average by 15% under the SRES scenario. Our result is also somewhat contradictory to the findings of (Driessen et al. 2010) who reported future increases in streamflow in the basin under the RCP2.6 and 8.5 scenarios. Differences in findings between this study and the above-mentioned two studies can be explained by many factors, including the use of different scenarios, models, observed data, analysis techniques and scale of analysis.

Before assessing the future climate change impact, the ability of the RCMs-GCMs group to simulate historical climate and discharge was estimated. Therefore, future year's streamflow in the Baro basin was forecasted using the calibrated parameter. Except for the CM5A-MR model, the monthly rainfall arrangement from dynamically downscaled climate data fits the observed precipitation for all chosen climate models for the Belg (February to May) and Dry times of year. Nevertheless, the models were unfit to represent the observed rainfall value, which is varied. The results show that according to all climate models, the simulated rainfall over the Baro River basin varies significantly from the observed precipitation.

EC-Earth climate model, annual precipitation in the Baro River basin will likely decrease, this means that climate models are converging on the direction of projected precipitation change. For all climate models, the temperature maximum and average potential evapotranspiration will likely increase between (2041 and 2070). Since the findings of two of four models agree on the direction of change, potential evapotranspiration is expected to rise in most months in the future. As a result, it was revealed that stream flow is sensitive to deviations in temperature and rainfall. For November and December, RCP4.5 is predicted to reduce streamflow in the Baro River basin.

In general, medium-term outcomes show that the size of rainfall annually is expected to change under a 2 °C global warming threshold. Rainfall during the small rainy period of Belg (February–May) is predicted to decline in the future. We concluded that the medium-term, annual potential evapotranspiration is predicted to rise during both arid and rainy months. Because of the expected variations in precipitation under RCP4.5 streamflow is reduced. Generally, this work emphasizes the significance of climate models multiple to know the variety of estimated variations in hydrological responses in the catchment. Overall, this study demonstrates the importance of employing multiple climate models to comprehend the range of projected changes in water resource availability in a basin.

Based on this study, we recommended that multiple models be evaluated in the highest climate variation impact analysis studies to investigate a wide range of climate change scenarios that could result from different hydrological impacts. Further investigation should incorporate modified Global Circulation Model outcomes and emission scenarios. As a result, other researchers will be able to conduct additional studies on the impact of changing climates in the Baro River basin.

The Eco hydrological evaluation approach is suitable for presenting the impact of climate variation on watershed hydrology; however, because the perception is an innovative idea for the country, it is intended for additional investigation. More research ought to be carried out through numerous Global Circulation Models to guarantee the expansion of water sources and agricultural productivity in poor countries such as Ethiopia, which includes the effect of changing climates on land use and land cover change, as well as sediment inflow to reservoirs.

Author contributions
Tolossa Negassa Ebissa, conceptualized the study, conducted data analyses, and wrote the manuscript; Shimelash Molla Kassaye and Demelash Ademe Malede, framed the design and participated in review, editing, and supervision; Conceptualized the study, participated in review and editing, and formatted the analyses; and S.M.K. Provided software. All authors have read and agreed to the published version of the manuscript.

Data availability
All data models and codes generated or used during the paper can be found in the submitted article. No datasets were generated or analysed during the current study.

Declarations

Institutional review board statement
Not applicable.

Informed consent
Not applicable.

Competing interests
The authors declare no competing interests.

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