Modeling the impact of climate change on streamflow responses in the Kessem watershed, Middle Awash sub-basin, Ethiopia

Mamush Tekle Assfaw*, Bogale Gebremariam Neka and Elias Gebeyehu Ayele
Hydraulic and Water Resource Engineering, Arba Minch Water Technology Institute, Arba Minch University, Arba Minch, Ethiopia
*Corresponding author. E-mail: dewaytekle@gmail.com

ABSTRACT

In this study, we examined how future climate change will affect streamflow responses in the Kessem watershed. Climate variables from SSP2-4.5 and SSP5-8.5 emission scenarios were extracted from GCMs for the 2040s (2031–2060) and 2070s (2061–2090). The bias-corrected precipitation and temperature were converted into streamflow using a calibrated SWAT model. The simulated output of the future streamflow for the periods 2040s and 2070s was compared with the base period (1992–2020) and presented as percentage changes. During calibration and validation, the SWAT model showed Nash–Sutcliffe efficiency (NSE) values of 0.79 and 0.77, as well as coefficient of determination ($R^2$) values of 0.8 and 0.79, demonstrating its capability of simulating streamflow. The annual mean maximum and minimum temperatures are predicted to increase, with a pronounced increase in the minimum temperature for the mid-term and long-term futures under both emission scenarios. As we approach the end of the century, we see an increase in annual mean rainfall and streamflow under the SSP5-8.5 emission scenario. The increment in annual mean rainfall (streamflow) is expected to be 3% (12.5%) and 23% (48.8%) for the 2040s and 2070s, respectively, under the SSP5-8.5 emission scenario.

Key words: climate change, GCMs, Kessem watershed, SSPs, SWAT model, streamflow

HIGHLIGHTS

• The output of five Global Climate Models (GCMs) was used to extract climate variables for SSP2-4.5 and SSP5-8.5 emission scenarios.
• Temperature and precipitation systematic errors were corrected using the distribution mapping bias correction approach.
• We integrated the bias-corrected climate variables with a calibrated SWAT model to evaluate streamflow response due to the impact of climate change.
INTRODUCTION
Climate change affects temperature trends and precipitation patterns, which can affect hydrological processes such as heavy precipitation, rising evaporation, and variations in river discharge (Maurya et al. 2023). The burning of fossil fuels, which research suggests is the main driver, and human pressures are thought to be contributing to an increase in the concentration of greenhouse gases (GHGs) in the atmosphere (Bekele et al. 2019). Climate change affects community service components such as water resources, ecology, and agriculture intensely (Pirnia et al. 2019). Extreme hydrological events like floods and
droughts are the main causes of natural catastrophes in various parts of the world (Bekele et al. 2019). Climate change has a significant impact on several factors, including the hydrological cycle, biodiversity, territorial ecology, water resources, environment, agriculture and food security, and human health (Gupta 2015). The amount of rainfall is one of the main climatic factors, and it has an impact on the temporal and spatial patterns of water availability for agriculture, energy balance, hydropower, industry, and food security (Ayehu et al. 2018).

Scientific evidence now indicates that the average temperature of the Earth’s atmosphere will continue to rise as the Earth’s surface GHG concentration rises. While temperature is predicted to climb consistently, precipitation exhibits variable results depending on various climate models and emission scenarios (IPCC 2014; Tessema et al. 2021). The mid-latitudes and subtropical dry regions are expected to experience a drop in precipitation under the RCP8.5 scenario, while precipitation is expected to increase in the high latitudes, the equatorial Pacific, and the mid-latitudes of the wet region (Sesana et al. 2019). In East Africa, rainfall projections from various GCM scenarios have revealed uncertain magnitudes and trends (Getahun et al. 2020). For instance, the IPCC (2021) stated that unless significant reductions in CO₂ and other GHG emissions take place, warming of 1.5 and 2 °C will be exceeded over the 21st century. The expected temperature for Africa in the 21st century is higher than the average global temperature (IPCC 2013).

The world is not equally affected by climate change (Thornton et al. 2008; Kotir 2011). Africa is the continent most at risk from climate change (Collier et al. 2008); in particular, Sub-Saharan Africa is the most vulnerable region because 96% of all crops are grown there using rain-fed agriculture, which could exacerbate the problem (Serdeckzny et al. 2017). Physical and economic water scarcity has a compounding impact in the Greater Horn of Africa (GHA), frequently leading to severe water and food shortages (Nicholson 2014; Awange et al. 2016). Future water scarcity problems in the area could be exacerbated by the region’s rapid population expansion and highly unpredictable climate (Hirpa et al. 2019). In East Africa, rainfall projections from various GCM scenarios have revealed uncertain magnitudes and trends (Getahun et al. 2020). For instance, in the upcoming years, streamflow in the Nile Basin is expected to decrease (Haile et al. 2017), yet other research findings (Worqlul et al. 2018) indicate that streamflow in the Nile Basin is estimated to increase for the coming decades. As reported by Haile et al. (2017) strong evidence indicates that climate change in Ethiopia has changed during the past 50 years. The former Ethiopian National Meteorological Agency (NMA) under the 2007 Climate Change National Adaptation Program of Action (NAPA), it was determined that the national mean annual temperature rose by 1.3 °C between 1960 and 2006. This figure suggests an increase of 0.28 °C each decade during the previous 46 years. According to this study’s findings, the increment most noticeable in the major wet season is when increases are most noticeable.

The inability of coarse global climate model (GCM) resolutions to capture small-scale rainfall patterns, the high degree of uncertainty in both GCM and RCM rainfall projections, and the lack of model validation using measured streamflow in East Africa have all impeded hydrological impact studies (Otieno & Anyah 2013; Shiferaw et al. 2018; Endris et al. 2019). General Climate Models (GCMs) have been utilized extensively since the introduction of Coupled Model Intercomparison Projects (CMIP; Chen et al. 2022). Extensive application of downscaled GCMs gained popularity as a result of their precise and trustworthy projection of potential future climatic scenarios (Bhatta et al. 2019; Bermúdez et al. 2020; Touseef et al. 2020; Ji et al. 2021). The biases and internal variability of different climate models may create entirely different projections of future climate. As a result, to better characterize structural uncertainty and improve climate predictions, ensembles of climate models are preferred instead of a single model (Gaur et al. 2021).

Among the 12 river basins of Ethiopia, the Awash River Basin (ARB) is the most environmentally vulnerable and extensively exploited (Tadesse et al. 2019). Increased population, settlement, intensified farming practices, highland erosion, and pollutants have all contributed to the decline of freshwater availability in the ARB (Bekele et al. 2019). The Kessem watershed was selected to study the impact of climate change on streamflow for a number of reasons. First, the Kessem River is a significant tributary of the Awash River providing greater flows to water users downstream. Second, in the downstream area of the Kessem watershed, there is a 25,000-hectare government-owned irrigation project planned to yield 500,000 tons of sugar annually (Hailu 2020). Third, the watershed is home to a large number of people whose livelihoods are being negatively affected by the decline of potential rainy seasons and climate change (CSA 2011). Climate change has been studied in different subbasins of the ARB using Representative Concentration Pathways (RCPs) (e.g. Bekele et al. 2019; Daba & You 2020; Getahun et al. 2020). Projections from these studies showed that climate change has great implications for streamflow changes in the ARB. However, climate change scenarios are changing with time. Currently, the Shared Socio-Economic Pathway (SSP) scenarios were developed based on global developments leading to different challenges for mitigation and adaptation to climate change (O’Neill et al. 2017).
According to Riahi et al. (2017), the SSP scenarios include SSP1 ‘green roads’ (low challenges for mitigation and adaptation), SSP2 ‘middle of the road’ (medium challenges for mitigation and adaptation), SSP3 ‘regional rivalry’ (a rocky road) (high challenges for mitigation and adaptation), SSP4 ‘inequality’ (a road divided) (low challenges for mitigation, high challenges for adaptation), and SSP5 ‘fossil-fueled development taking the highway’ (high challenges to mitigation, low challenges to adaptation). A more likely scenario, known as SSP2-4.5, predicts that modest mitigation efforts will limit global warming to 2.5 °C over pre-industrial levels by the end of the 21st century. On the other hand, SSP5-8.5 is also known as ‘business as usual,’ suggesting a nightmarish future that is heavily reliant on fossil fuels, lacks strict climate mitigation, and causes nearly 5 °C of warming by the end of the century (O’Neill et al. 2017).

Despite the fact that the Kessem watershed offers many benefits to the government and nearby people, the impact of climate change on streamflow using SSP2-4.5 and SSP5-8.5 emission scenarios has not yet been researched for the watershed. In order to evaluate how future climate change will impact streamflow, this study integrated the SSP2-4.5 and SSP5-8.5 emission scenarios with the SWAT model. This study is primarily intended to investigate how streamflow responds to changes in temperature and precipitation, and the occurrences of extreme flow events in the study area.

MATERIALS AND METHODS
Description of the study area
The Kessem watershed is situated in eastern Ethiopia’s Middle Awash River Basin (MARB), with latitudes ranging from 8° 50’ to 90° 30’ N and longitudes between 39° and 40° E (Figure 1). The Kessem River is the major water source for the ARB, the most-used among the 12 basins of Ethiopia (Tedla & Cho 2021). The watershed has a total area of 2,908.4 km² with an elevation range of 767–3,540 m. The lower portion of the watershed has a depressed environment, and the upper boundary has taller mountains. The northern half of the watershed is flanked by plateaus and mountains (Tessema et al. 2020). The

Figure 1 | Location map of the study area.
The majority of the Kessem Subbasin is located on the Great East African Rift Valley, which extends from Ethiopia’s northeastern corner to its southwesterly corner. Large topographic diversity is a factor in the great variety of climate systems seen in the Kessem subbasin. The Kessem watershed encompasses the watersheds of the Amhara region of the North shoa woredas (Minjar Shenkora, Hageremariam, and Bereht) and Oromia region woredas (Berehinia, Aleltu, and Kinbibit) (Abebe & Tolessa 2020).

Two major hydrologic soil groups (group C and group D) have been distinguished depending on the global hydrological soil group (HYSOGs250m) for curve number-based runoff modeling. The hydrologic soil group (HSG) D is the most abundant and has the highest runoff potential and very low infiltration rates when thoroughly saturated. The HSG-D mainly consists of soils with a permanent high-water table, shallow soils over nearly impervious material, clay soil with a high swelling potential, and soils with a clay layer or claypan at or near the surface (Tedla & Cho 2021).

The annual north-south movement of the Inter-Tropical Convergence Zone (ITCZ) controls the temporal and spatial distribution of climatological rainfall over the complex topography of Ethiopia. Due to terrain, Ethiopia’s spring rains (March–May) are only experienced in the south, specifically in the southeast and east. Orographic rain is common between March and May over south-central, east-central, and southwestern Ethiopia as a result of the ITCZ’s northward shift. The ITCZ’s passage over the Ethiopian region results in a bi-modal rainfall pattern in southern and southeastern Ethiopia, with rainfall seasons from March through May (ITCZ migrating north) and from September through November (ITCZ migrating south), and a mono-modal pattern in northern and western Ethiopia, with rainfall seasons from June through September (Gizaw et al. 2017). Kessem Subbasin, located in the east-central region of Ethiopia, experiences orographic rainfall at a lower level, with higher amounts occurring in the region’s northwestern portions from March to May (locally called belg) and higher amounts of rainfall occurring in June-September (locally called kiremt rainfall). The main portion of the watershed is located in the sub-humid and humid climate zones. The southeast of the watershed falls in the arid zones and receives a low mean annual rainfall of 159 mm, while the northwest and northern parts of the watershed receive a mean annual precipitation of 807–1,030 mm. The highest and lowest mean monthly temperatures are 28 and 12 °C, respectively (Abebe & Tolessa 2020).

Input data
Spatial and temporal data are required to simulate hydrological processes with the SWAT model. The spatial data includes the Digital Elevation Model, soil data and land use land cover (LULC) data. The soil and LULC maps are presented in Figure 2.

DEM data
The DEM data with a 12.5-m resolution were freely acquired at https://search.asf.alaska.edu. The DEM was used to build the stream networks and border of the basin. The DEM was utilized to generate the slope and to overlay the land use, land cover, and soil data that were needed to define the hydrologic response unit (HRU).

Soil data
Table 1 presents soil data as area and percentages for each class used for input to the SWAT model. To determine the hydrological characteristics of each soil type within each sub-watershed and HRU, the SWAT model requires soil data. The soil data with 1-km resolution was obtained from the Ministry of Water and Energy (MoWE) of Ethiopia. The necessary soil properties were obtained from the Harmonized World Soil Database (FAO downloaded from http://www.fao.org/data/en/). In the analysis, the main soil physio-chemical properties were taken into account, including soil depth, soil hydrological group, bulk density, available water capacity, saturated hydraulic conductivity, organic carbon content, soil albedo, rock fragments, and soil erodibility parameters.

LULC data
The LULC classes used in this study are represented in Table 2. The LANDSAT imagery data were downloaded from US Geological Survey https://earthexplorer.usgs.gov/. ERDAS Imagine 2014 was used to prepare the LULC map obtained from Landsat imagery. During the land use image classification procedure, the maximum likelihood algorithm was used for supervised image classification. For further hydrological simulation, the entire spatial datasets were resampled to the 12.5 m resolution and projected to WGS 1984 UTM Zone 37 using ArcGIS.
Hydro-meteorological data

The daily streamflow data from 1990 to 2008 were obtained from the Ethiopian MoWE. These hydrologic and climatic data were used to create the hydrological and climate balance components as well as to calibrate and test the hydrological model. Baseline climate data (1990–2020) in and close to the Kessem watershed were collected from the Ethiopian Meteorology Institute (EMI). The maximum temperature (\(T_{\text{max}}\)) and minimum temperature (\(T_{\text{min}}\)), as well as the daily precipitation data, were gathered from six stations. Table 3 presents the standard deviation (STDVE) and coefficient of variation (CV) for rainfall in the study area. Over the Kessem watershed, meteorological stations are sparsely spaced out, as is common in other parts of the country. Sholagebeya is the only first-class station in the Kessem watershed that has long-term and

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**Table 1** | Soil type and slope of the watershed used for the SWAT model inputs

<table>
<thead>
<tr>
<th>SWAT soil codes</th>
<th>Description of soil codes</th>
<th>Area (km(^2))</th>
<th>Area coverage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cmv</td>
<td>Vertic cambisols</td>
<td>637.9</td>
<td>21.93</td>
</tr>
<tr>
<td>Cme</td>
<td>Eutric cambisols</td>
<td>1,491.0</td>
<td>51.26</td>
</tr>
<tr>
<td>Vre</td>
<td>Eutric vertisols</td>
<td>297.1</td>
<td>10.21</td>
</tr>
<tr>
<td>Lpe</td>
<td>Eutric leptosols</td>
<td>423.8</td>
<td>14.57</td>
</tr>
<tr>
<td>Lvx</td>
<td>Chromic luvisols</td>
<td>58.6</td>
<td>2.01</td>
</tr>
<tr>
<td>Slope class</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0–3</td>
<td></td>
<td>140.0</td>
<td>4.8</td>
</tr>
<tr>
<td>3–8</td>
<td></td>
<td>647.2</td>
<td>22.3</td>
</tr>
<tr>
<td>8–15</td>
<td></td>
<td>474.5</td>
<td>16.3</td>
</tr>
<tr>
<td>15–30</td>
<td></td>
<td>684.9</td>
<td>23.6</td>
</tr>
<tr>
<td>&gt;30</td>
<td></td>
<td>961.2</td>
<td>33.1</td>
</tr>
</tbody>
</table>

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**Table 2** | Elevation, land use classes, and soil type of the Kessem watershed.

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**Figure 2** | Elevation, land use classes, and soil type of the Kessem watershed.
complete meteorological datasets for precipitation, maximum and minimum temperatures, wind speed, sunshine hours, and relative humidity.

For stations with no maximum and minimum temperature and precipitation data, the monthly observational precipitation and temperature reanalysis data were derived using the Climatic Research Unit (CRU TS 4.04) and the European Community Medium-range Weather Forecasts v5 (ECMWF-ERA5) (Hersbach et al. 2020).

Selection of the SSP scenarios

In this study, we have chosen two emission scenarios, SSP2-4.5 and SSP5-8.5. The SSP2-4.5 and SSP5-8.5 emission scenarios, and their counterparts RCP4.5 and RCP8.5 emission scenarios, are the most commonly used scenarios in climate change research in the study region. It is therefore easier to compare our results to those of other studies in this study area since there is available literature on their impacts. The SSP2-4.5 emission scenario combines the SSP2 and RCP4.5 emission scenarios. In essence, this combination represents a future with moderate societal fragility and moderate levels of force, as well as moderate GHG emissions. SSP5-8.5 combines SSP5 and RCP8.5 and SSP5 assumes the economy is expected to be heavily reliant on fossil fuels, while in SSP8.5 the use of fossil fuels is expected to grow rapidly and at a high rate, representing significant contributions to GHG emissions (Bai et al. 2023). Datasets for the medium (SSP2-4.5) and strong (SSP5-8.5) forcing scenarios were downloaded from the Earth System Grid Federation (ESGF) (Table 4). CMIP6 scenarios SSP2-4.5 and SSP5-8.5 are thoroughly discussed by O’Neill et al. (2017) and Gidden et al. (2019). The output of GCMs is stored as raster data that represents the value of the entire grid cell, which is made up of different rainfall stations. Consequently, the raster data from GCMs were interpolated to the associated rainfall stations using the spatial scale interpolation technique (Su et al. 2020).

Therefore, inverse distance weighting (IDW) interpolation is utilized in this investigation as Borges et al. (2016) confirmed that IDW has small errors, strong Nash–Sutcliffe efficiency (NSE), and regression coefficients.

Bias correction of GCM outputs

The statistical bias correction was performed using the Climate Model data for the Hydrologic modeling (CMhyd) tool. The CMhyd tool is developed to bias-correct climatic data obtained from RCMs and GCMs (Rathjens et al. 2016). Due to the

Table 2 | Land use land cover (LULC) of the Kessem watershed used for the SWAT model inputs

<table>
<thead>
<tr>
<th>SWAT LULC code</th>
<th>Description of LULC codes</th>
<th>Area (km²)</th>
<th>Area coverage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGRL</td>
<td>Agricultural land-generic</td>
<td>1972.4</td>
<td>67.7</td>
</tr>
<tr>
<td>URBAN</td>
<td>Built-up area</td>
<td>16.3</td>
<td>0.6</td>
</tr>
<tr>
<td>FRSE</td>
<td>Forest evergreen</td>
<td>56.0</td>
<td>1.9</td>
</tr>
<tr>
<td>SHRBD</td>
<td>Shrub land</td>
<td>519.3</td>
<td>17.8</td>
</tr>
<tr>
<td>GRAS</td>
<td>Grass land</td>
<td>237.1</td>
<td>8.1</td>
</tr>
<tr>
<td>BARR</td>
<td>Bare land</td>
<td>39.6</td>
<td>1.4</td>
</tr>
<tr>
<td>WATB</td>
<td>Water bodies</td>
<td>70.7</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Table 3 | Rainfall data of annual stations in and near Kessem watershed

<table>
<thead>
<tr>
<th>No</th>
<th>Station name</th>
<th>Lon</th>
<th>Lat</th>
<th>Elevation(m)</th>
<th>Year of record</th>
<th>Statistical properties</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Sholla Gebeya</td>
<td>39.6</td>
<td>9.22</td>
<td>2500</td>
<td>1990-2020</td>
<td>STDVE: 108.8 CV: 12.2</td>
</tr>
<tr>
<td>2</td>
<td>Debrebrhan</td>
<td>39.50</td>
<td>9.63</td>
<td>2750</td>
<td>1990-2020</td>
<td>STDVE: 102.7 CV: 10.9</td>
</tr>
<tr>
<td>4</td>
<td>Bologioorgis</td>
<td>39.35</td>
<td>8.81</td>
<td>1963</td>
<td>1990-2020</td>
<td>STDVE: 146.6 CV: 35.3</td>
</tr>
</tbody>
</table>
coarse nature of GCM and RCM data, bias correction is required (Siabi et al. 2023). CMhyd can be downloaded from https://swat.tamu.edu/software. As outlined by Siabi et al. (2023), CMhyd is compatible with CMIP6 data to simulate historical and future climates. The CMhyd tools provide eight types of algorithms for bias correction. The algorithms include variance scaling, power transformation of precipitation, delta change correction (additive and multiplicative), linear scaling (additive and multiplicative), precipitation local intensity scaling, and distribution mapping (DM). Post-processing of the Global Climate Model (GCM) is necessary to generate trustworthy estimates of local-scale climate. The intercomparison of various methods of bias correction highlights that all bias correction methods have comparable performance in average monthly and annual values. However, the frequency and intensity of extreme values are difficult to fix with the majority of bias correction techniques (Worku et al. 2021). In this study, the precipitation and temperature bias corrections were implemented using the DM bias correction method. When comparing the 90th percentile and wet day’s likelihood of RCM simulation with observed counterparts, the DM technique performed better (Worku et al. 2020). Works of literature verified that DM is a superior bias correction method over the others for adjusting temperature events and rainfall frequency (Fang et al. 2015; Azmat et al. 2018). Unlike other bias correction techniques, the DM method matches the distribution function (CDF) of simulated temperature and rainfall values to the matching CDF of observed values and it uses the scale parameter ($\beta$) and shape parameter ($\alpha$) to fit rainfall distributions (Worku et al. 2021).

$$f_g(x|\alpha, \beta) = x^{\alpha-1} \frac{1}{\beta^\alpha \Gamma(\alpha)} e^{-\frac{x}{\beta^\alpha}}; \ x \geq 0; \ \alpha, \beta > 0$$  \hspace{1cm} (1)

where $x$ is the random variable, $f_g$ is the cumulative distribution function (CDF) for gamma, $\Gamma$ is the function of gamma, and $\beta$ and $\alpha$ are the scale and form parameters, respectively.

Hydrological modeling

The study employed SWAT, an ArcGIS interface semi-distributed hydrological model. The SWAT model was chosen for this study because of its efficiency in simulating agricultural and forest land processes in comparison to urban regions, as well as the fact that it has earned international recognition as a reliable multi-purpose watershed scale-modeling tool. The SWAT model makes it easier to generate educated policy decisions and manage watersheds when numerous environmental processes are combined (Neitsch et al. 2011). The SWAT model is preferred for use in data-scarce locations due to its weather-generating capabilities that help users fill in the missing meteorological data during the simulation session. The SWAT weather-generating equipment will help us generate wind speed, solar energy, and relative humidity if we work with long-term minimum and maximum temperatures as well as a daily precipitation rate (Mengistu et al. 2019).

The final content of soil water can be calculated using Equation (2).

$$SW_t = SW_o + \sum_{t=1}^{t} [R_{day} - (Q_{surf} + E_a + W_{seep} + Q_{gw})]$$  \hspace{1cm} (2)

where $SW_t$ is final soil water content (mm), $SW_o$ is initial soil water content (mm), $R_{day}$ is the precipitation (mm), $Q_{surf}$ is the surface runoff (mm), $W_{seep}$ is the water entering vadose zone (mm), $E_a$ is the evapotranspiration (mm), $Q_{gw}$ is the return flow (mm) and $t$ is time (days).

### Table 4 | Description of global climate models (GCMs) used in this study

<table>
<thead>
<tr>
<th>No.</th>
<th>CMIP6 model name</th>
<th>Country</th>
<th>Horizontal resolution (lon.deg × lat.deg)</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>MIROC6</td>
<td>Japan</td>
<td>1.4° × 1.4°</td>
<td>Tatebe et al. (2019)</td>
</tr>
<tr>
<td>2</td>
<td>MRI-ESM2-0</td>
<td>Japan</td>
<td>1.1° × 1.1°</td>
<td>Kawai et al. (2019)</td>
</tr>
<tr>
<td>3</td>
<td>CNRM-CM6-1</td>
<td>France</td>
<td>1.4° × 1.4°</td>
<td>Voldoire et al. (2019)</td>
</tr>
<tr>
<td>4</td>
<td>IPSL-CM6A-LR</td>
<td>France</td>
<td>2.5° × 1.3°</td>
<td>Lurton et al. (2020)</td>
</tr>
<tr>
<td>5</td>
<td>BCC-CSM2-MR</td>
<td>China</td>
<td>1.1° × 1.1°</td>
<td>Wu et al. (2019)</td>
</tr>
</tbody>
</table>
Surface runoff was calculated using the soil conservation service curve number (SCS-CN) approach.

\[
Q_{\text{surf}} = \frac{(R_{\text{day}} - I_a)^2}{(P_{\text{day}} - I_a - S)}
\]  

where \(S\) is the retention parameter and \(I_a\) is the initial abstraction, which encompasses surface storage, interception, and infiltration prior to water runoff (mm).

The retention factor described by:

\[
S = 254 \left( \frac{100}{CN} - 1 \right)
\]

where \(CN\) is the curve number for the day, which ranges from 0 to 100 based on the permeability of the soil, the land use, and the proceeding soil water condition. Assuming that the starting value is about equal to 0.2\(S\), the equation becomes

\[
Q_{\text{surf}} = \frac{(P_{\text{day}} - 0.2S)^2}{P_{\text{day}} + 0.8S}
\]

Hydrological model setup

The model was set up and parametrized using the ArcSWAT 2012 interface. The SWAT model encompasses channel-routing, reservoir, and sub-basin components. The channel component routes pesticides, bacteria, degraded nutrients and sediments, and flows. The reservoir component detains pollutants, sediment, and water. Lastly, the sub-basin component is used to simulate carbon and soil nutrient cycle, crop growth and yield, evapotranspiration, soil water movement, runoff, and erosion (Douglas-Mankin et al. 2010). A threshold drainage area of 90 km\(^2\) was chosen to discretize the watershed into 21 sub-basins based on the DEM and stream network. The sub-basin was defined with various HRUs to allow for variation within the basin. The model was run in a monthly time step from 1992 to 2020 for a total simulation length of 29 years after the ready-made weather data were loaded before starting the program. The model was treated with a warm-up period from 1990 to 1991 to ease the initial condition and excluded from the analysis. For calibration and validation, the streamflow data from 1992 to 2008 at the Awara Melka gauge station, which is situated at the outlet of the Kessem watershed, were used.

Model calibration and validation

The SWAT model was calibrated and validated to characterize the hydrologic characteristics of the sub-basin before projecting the future impact of climate change. For ArcSWAT model uncertainty and auto-calibration study, the SWAT-CUP program was utilized. Many calibrations and uncertainty algorithms have been developed for the SWAT-CUP to facilitate the optimization process (Sao et al. 2020). In this work, the SWAT model was calibrated using the Sequential Uncertainty Fitting-2 (SUFI-2) algorithm. The model parameters sensitive to the SWAT model simulation outputs were identified using sensitivity analysis. During the calibration phase, the SWAT model parameters, which had greater t-statistic values and a smaller \(P\)-value, were chosen. By comparing predicted output with actual streamflow and testing using the numerical value of the verification criterion, the SWAT model’s performance was evaluated. Two statistical indicators are estimated by the SWAT-CUP to quantify the sources of all uncertainties (Mengistu et al. 2019). These statistical indices include the ‘R-factor’, which calculates the separation between the lower and upper 95PPU, and the ‘P-factor’, which shows the proportion of observed data that falls inside the 95% prediction uncertainty (95PPU) range (Abbaspour et al. 2004). Abbaspour (2022) proposed the ‘P-factor’ \(\geq 0.7\) and ‘R-factor’ \(\leq 1.5\) as a reference value for river discharge calibration. The 95PPU band’s average thickness \(P\) and R-factor are computed using Equations (6) and (7)

\[
P = \frac{1}{n} \sum_{i=1}^{n} (Q_U - Q_L)
\]

\[
R\text{-factor} = \frac{P}{\sigma_Q}
\]
where $Q_U$ and $Q_L$ are the corresponding 97.5th and 2.5th percentiles of the cumulative distribution for each simulated data point, and $n$ is the total number of observed data points. $\sigma_Q$ is the standard deviation of the measured variable $Q$.

Moriasi et al. (2007) suggested objective functions for measurable statistics of model performance assessment, including NSE, percent bias (PBIAS), root mean square error (RMSE), and coefficient of determination ($R^2$). The regression coefficient ($R^2$) defined as the squared value of the coefficient of correlation and equated as:

$$ R^2 = \frac{\sum (Q_{obs} - Q_{sim})^2}{\sum (Q_{obs} - \bar{Q}_{obs})^2 \times \sum (Q_{sim} - \bar{Q}_{sim})^2} \tag{8} $$

The $E_{NS}$ shows how well the plot of the simulated versus observed data fit at a 1:1 line (Tegegne et al. 2017). The value of NSE ranges from $-\infty$ to 1. The efficiency $E_{NS} = 0$ shows that the simulated values are as real as the mean observed data. The efficiency $E_{NS} < 0$ appears when the observed mean is a better predictor than the model prediction. The closer the efficiency of $E_{NS}$ to 1 the more trustworthy the model result is (Motovilov et al. 1999).

$$ E_{NS} = 1 - \frac{\sum (Q_{obs} - Q_{sim})^2}{\sum (Q_{obs} - \bar{Q}_{obs})^2} \tag{9} $$

The average tendency of the modeled data to be smaller or larger than their observed counterparts can be estimated by PBIAS. A positive PBIAS value shows the model is under-prediction of the measured values, whereas negative values indicate over-prediction of measured values. The optimum value of PBIAS is zero, with low-magnitude values representing realistic model prediction (Moriasi et al. 2007). The formula for PBIAS is given as follows:

$$ PBIAS = \frac{\sum_{i=1}^{n} (Q_{Oi} - Q_{o})}{\sum_{i=1}^{n} Q_{Oi}} \times 100 \tag{10} $$

RESULTS

Calibration and validation of the SWAT model

To calibrate the SWAT model, simulated streamflow values from 1992 to 2008 were compared with observations. Calibration of the SWAT model was conducted using the flow parameter values listed in Table 5. The 1990–1991 observed flow data were used for warm-up periods, and the relation between simulated and observed discharge for calibration (1992–2003) and validation (2004–2008) is shown in Figure 3. The simulated discharge sensitive to the model parameters was examined through the global sensitivity analysis using SUFI-2 of SWAT-CUP. Based on the results gained from the global sensitivity analysis, ten streamflow calibration parameters were found sensitive.

Amongst the sensitive parameters, soil evaporation compensation factor (ESCO.hru), initial soil conservation service (SCS) runoff curve number for moisture condition II (CN2.mgt), base-flow alpha factor ALPHA BF.gw), threshold depth of water in the shallow aquifer for ‘revap’ to occur (mm)(REVAPMN.gw), and depth from soil surface to bottom of layer (SOL_Z (...)sol) are the most sensitive parameters ($P < 0.05$). Figure 4 represents the parameters most sensitive to streamflow calibration with the lowest $P$-value on the left and a t-stat in absolute value on the right.

When modeling streamflow on a monthly basis, calibration results for the SWAT model are evaluated using model performance metrics like $R^2$, NSE, and percent bias. The comparison of model performance between simulated and observed monthly streamflow during the calibration and validation stages showed very good model performance. In Table 6, we summarize the values of the model performance indicators $R^2$, b$R^2$, RSR, and PBIAS obtained during the calibration and validation phase. In general, model calibration and validation results with a value of NSE of more than 0.50 are regarded as a satisfactory model performance indicator (Moriasi et al. 2007).
During validation at the Awra Melka gauge, the model also demonstrated satisfactory performance for $R^2$, $bR^2$, NSE, and RSR. The calibration performance of the goodness of fit after each calibration iteration is measured using the $P$-factor and $R$-factor before the model performance statistics are evaluated. The $P$-factor, which runs from 0 to 1, indicates the model’s accuracy. Thus, in this investigation, 79% of the calibrated data and 87% of the validated data fall within the 95PPU band. The $R$-factor, which measures model uncertainty, was obtained to be 1.41 during calibration and 1.49 during validation. The $P$-factor and $R$-factor analysis results in this study are within the bounds provided by Abbaspour (2022), where for river discharge calibration ‘$P$-factor’ $\geq 0.7$ and the ‘$R$-factor’ $\leq 1.5$.

### Table 5 | The final selected sensitive flow parameters and fitted values

<table>
<thead>
<tr>
<th>SN</th>
<th>Parameter name (r_ or v_)</th>
<th>Description of parameters</th>
<th>Lower</th>
<th>Upper</th>
<th>Fitted</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>V_ESCO.hru</td>
<td>Soil evaporation compensation factor</td>
<td>0</td>
<td>1</td>
<td>-0.072</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>r_CN2.mgt</td>
<td>Runoff curve number for moisture condition II</td>
<td>-0.2</td>
<td>0.2</td>
<td>-0.282</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>V_ALPHA_BF.gw</td>
<td>Base-flow alpha factor</td>
<td>0</td>
<td>1</td>
<td>-0.182</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>r_SOL_Z(...).sol</td>
<td>Depth from the soil surface to the bottom</td>
<td>0</td>
<td>1</td>
<td>-0.137</td>
<td>4</td>
</tr>
<tr>
<td>5</td>
<td>r_EPCO.hru</td>
<td>Plant uptake compensation factor</td>
<td>0</td>
<td>1</td>
<td>-0.137</td>
<td>5</td>
</tr>
<tr>
<td>6</td>
<td>V_GW_DELAY.gw</td>
<td>Groundwater delay (day)</td>
<td>30</td>
<td>340</td>
<td>161.88</td>
<td>6</td>
</tr>
<tr>
<td>7</td>
<td>r_REVAPMN.gw</td>
<td>Threshold depth of water in the shallow a unifer for re-evaporation to occur (mm)</td>
<td>0</td>
<td>8</td>
<td>67.99</td>
<td>7</td>
</tr>
<tr>
<td>8</td>
<td>r_RCHRG_DP.gw</td>
<td>Deep aquifer percolation fraction</td>
<td>0</td>
<td>1</td>
<td>0.602</td>
<td>8</td>
</tr>
<tr>
<td>9</td>
<td>V_GWQMN.gw</td>
<td>Threshold depth of water in the shallow aquifer required for return flow (mm)</td>
<td>0</td>
<td>500</td>
<td>601.99</td>
<td>9</td>
</tr>
<tr>
<td>10</td>
<td>r_SOL_AWC(...).sol</td>
<td>Available soil water capacity (mm)</td>
<td>0</td>
<td>1</td>
<td>0.554</td>
<td>10</td>
</tr>
</tbody>
</table>

The method (r_) refers to an existing parameter value multiplied by $(1 + a$ given value), whereas the method (v_) refers to replacing the default parameter with a value from the parameter range.

### Figure 3 | Observed and simulated hydrograph of the Kessem watershed: (a) calibration and (b) validation periods.
Bias correction
In this study, the bias correction was performed on a daily basis for both historical data (1990–2014) and future GCM data (2031–2060) and (2061–2090) with respect to the ground-observed data.

To evaluate the performance of the bias correction method, the rainfall and temperature bias-corrected data were compared with the observed data. The graphs in Figures 5 and 6 compare raw and bias-corrected precipitation, and maximum and minimum temperatures, respectively. DM bias correction is used to align historical simulation results from the CNRM-CM6-1, IPSL-CM6A-LR, MRI-ESM2-O, BCC-CSM2-MR, and MIROC6 models with recorded temperatures and precipitation patterns of the Kessem watershed.

Projections of GCMs climate variables under the SSP scenarios
The projections of the ensemble mean of the model output for the SSP2-4.5 and SSP5-8.5 scenarios for 2040 (2031–2060) and 2070 (2061–2090) were studied to assess how well GCMs predicted precipitation and temperature changes affect streamflow response at the study area. Five GCMs ensembles were compared to determine the percentage change in precipitation, and maximum and minimum temperature with respect to the control period. Utilizing ensembles of GCM model outputs allows for the reduction of the highest and lowest projections and minimization of uncertainties by working with GCM’s averages. The research area is characterized by three seasons: the wet season in summer (JJAS), the dry season in winter (ONDJ), and the spring season with the smallest amount of rainfall (FMAM).

Table 7 shows the relative change and annual ensemble mean of the maximum and minimum temperatures. As a result of ensemble means of the five GCM models, maximum temperature increases under the SSP2-4.5 scenario are expected to range from 0.84 to 1.34 °C for the mid-future and far-future. Under SSP5-8.5 scenarios, the increase in maximum temperature is more pronounced; it rises from 1.02 to 2.22 °C for the 2040 and 2070 periods.

Across both individual and ensemble means of the GCMs models, annual mean temperatures increased on average. Under the SSP2-4.5, the increase in minimum temperature ranges from 1.1 to 1.76 °C for the 2040s and 2070s. Likewise, the minimum temperature is expected to increase by 1.48 to 2.94 °C under the SSP5-8.5 scenarios for the 2040s and 2070s.
Figure 5 | Performance of the bias adjusting method in correcting monthly average precipitation.

Figure 6 | Performance of the bias correction in adjusting average monthly $T_{\text{max}}$ and $T_{\text{min}}$. 
respectively. Figure 7 shows the mean annual maximum and minimum temperatures for SSP2-4.5 and SSP5-8.5 emission scenarios using ensemble means GCM models.

### Changes in rainfall

The annual mean rainfall predicted by CNRM-CM6-1 for the periods 2031–2060 and 2061–2090 decreases under both SSP2-4.5 and SSP5-8.5. In both the SSP2-4.5 and SSP5-8.5 scenarios, the IPSL-CM6A-LR simulation shows a decrease in rainfall for the years 2031 through 2060, but an increase for the years 2061 through 2090 for both scenarios. All three models (MIROC6, BCC-CSM2-LR, and MRI-ESM2-O) simulate rising annual rainfall under both SSP2-4.5 and SSP5-8.5 scenarios for the periods 2031–2060 and 2061–2090, with the exception of CNRM-CM6-1 and IPSL-CM6A-LR. Figure 8 shows annual mean rainfall distributions from ensemble means of five GCMs for mid- and long-term futures under SSP2-4.5 and SSP5-8.5 emission scenarios.

The relative percentage changes of future rainfall with respect to the base period are presented in Table 8. As a result of the ensemble means of five GCMs, annual rainfall is predicted to decline by 2.78% by the 2040s and to increase by 1.9% by the

![Figure 7](http://iwaponline.com/jwcc/article-pdf/14/12/4837/1349640/jwc0144837.pdf)

**Figure 7** | Annual mean: (a) ensemble means of maximum temperature and (b) ensemble mean of minimum temperature.
2070s under the SSP2-4.5 scenario. Mean annual rainfall increases from 3 to 18.94% for the 2040s and 2070s, respectively, under the SSP5-8.5 emission scenario.

The percentage contribution of annual precipitation to seasonal precipitation increases for summer from 77.4 to 78.1 under SSP2-4.5 scenarios for the mid-future (2031–2060) and far-future (2061–2090), and under SSP5-8.5 scenarios, falling from 78.9 to 74.3. For the same period, the ratio of annual total rainfall to winter seasons will increase from 5.9 to 7.4% under the SSP2-4.5 scenario and 6.2 to 10% under the SSP5-8.5 scenario. For the spring season, the contribution decreases from 16.7 to 14.5% under the SSP2-4.5 and increases from 14.8 to 15.8% under the SSP5-8.5 scenarios for mid-future and far-future, respectively.

Analysis of streamflow under climate change

The bias-corrected climate variables were used as input to run the calibrated SWAT model for two time periods: 2040 (2031–2060) and 2070 (2061–2090). The comparison between the future SWAT simulated flow and the base period simulation (1992–2020) was done, and the results are presented as percentage changes. In the 2040s and 2070s, respectively, streamflow is predicted to increase from June to September and drop from February to March under the two scenarios SSP2-4.5 and SSP5-8.5. The flow for October-January decreases for the 2040s and 2070s, respectively, under the SSP2-4.5 and SSP5-8.5
scenarios, and increases for the 2070s under SSP5-8.5. Figure 9 presents the relative percentage changes in monthly and seasonal streamflow from ensemble means of five GCMs. The highest flow increase was detected for August and November of the 2070s under SSP5-8.5 scenarios.

In the mid- and long-term future, both SSP2-4.5 and SSP5-8.5 emission scenarios show a considerable increase in summer (JJAS) streamflow. Under SSP2-4.5 for the mid- and long-term futures, the increase in streamflow was predicted to be between 12 and 61% for the summer season. Streamflow in the wet season (JJAS) will increase from 56–88% under SSP5-8.5 for mid- and long-term futures, respectively. As shown in Table 9, the IPSL-CM6A-LR predicted a higher percentage change in annual average streamflow values under the SSP5-8.5 scenarios for long-term futures. Similar to the previous studies IPSL-CM6A-LR predicts higher rainfall and streamflow in annual and winter seasons under the SSP5-8.5 scenarios for our investigation and under RCP8.5 for the study findings by Getahun et al. (2020) at Melka Kuntre watershed of the ARB.

The increment in streamflow for the major rainy season obtained in this study was consistent with the findings of the study by Getahun et al. (2020)), which revealed an 11–32% increase in flow in the major rainy seasons (JJAS) in ARB.

Table 8 | Changes in seasonal rainfall from model ensemble means (%)

<table>
<thead>
<tr>
<th>Seasons</th>
<th>SSP2-4.5</th>
<th></th>
<th>SSP5-8.5</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2031–2060</td>
<td>2061–2090</td>
<td>2031–2060</td>
<td>2061–2090</td>
</tr>
<tr>
<td>Summer (JJAS)</td>
<td>–0.15</td>
<td>5.6</td>
<td>8</td>
<td>21.3</td>
</tr>
<tr>
<td>Winter (ONDJ)</td>
<td>–21.54</td>
<td>3</td>
<td>–12.3</td>
<td>69.23</td>
</tr>
<tr>
<td>Spring (FMAM)</td>
<td>–12.6</td>
<td>–20.5</td>
<td>–18</td>
<td>4.2</td>
</tr>
<tr>
<td>Annual</td>
<td>–2.8</td>
<td>1.9</td>
<td>3</td>
<td>23</td>
</tr>
</tbody>
</table>

Table 9 | Annual mean streamflow changes (%)

<table>
<thead>
<tr>
<th>GCM models</th>
<th>SSP2-4.5</th>
<th></th>
<th>SSP5-8.5</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2031–2060</td>
<td>2061–2090</td>
<td>2031–2060</td>
<td>2061–2090</td>
</tr>
<tr>
<td>CNRM-CM6-1</td>
<td>–47.8</td>
<td>–14.7</td>
<td>–1.9</td>
<td>18.8</td>
</tr>
<tr>
<td>IPSL-CM6A-LR</td>
<td>–34.4</td>
<td>30.3</td>
<td>4.7</td>
<td>146.9</td>
</tr>
<tr>
<td>MIROC6</td>
<td>0.94</td>
<td>8.75</td>
<td>3.1</td>
<td>29.4</td>
</tr>
<tr>
<td>MPI-ESM2-O</td>
<td>22.5</td>
<td>19.1</td>
<td>86.9</td>
<td>67.8</td>
</tr>
<tr>
<td>Ensemble</td>
<td>–16.8</td>
<td>4.3</td>
<td>12.5</td>
<td>48.8</td>
</tr>
</tbody>
</table>
Projected changes in streamflow events using flow duration curve

Flow regimes throughout various seasons of the year can be impacted by climate change. To implicate the changing tendency of flows in different seasons, the application of flow duration curve (FDC) analysis for a given percent of the time has paramount significance. With the help of an FDC, the signal of flows in response to climate change and the relative changes were analyzed for different flow ranges. For the 10, 50, and 90% (Q10, Q50, and Q90) probability of exceedance, the relative percentage change for three seasons has been investigated (Figure 10). For a 10% probability of exceedance, the maximum flow is reduced by 8.29% for the 2040s under the SSP2-4.5 scenarios and increases by 25.69% for the 2070s.

The streamflow projection under the SSP5-8.5 scenario increases from 28.45–53% for the 2040s and 2070s. Short rainfall season (FMAM) and the dry season (ONDJ) show a decrease under both scenarios except for the period 2061–2090 under the SSP5-8.5 scenarios for 10% exceedance maximum flows which increase by 8.54% and 52.38% respectively. Under both scenarios for the 2040s and 2070s, streamflow increases for the summer season by 5.5, 35.59, 39.4, and 68.64%, respectively, for a 50% (Q50) likelihood of exceedance. The streamflow is expected to decline in both seasons for the near- and long-term futures, except for a 28.49% increase in the dry season for the period 2061–2090. The spring season streamflow declines in the 2040s and 2070s under both scenarios, which implies a range of median flows. The decrement of flow in the spring season has a direct linkage to the decrement of rainfall for the 2040s and 2070s. For the 90% probability of exceedance, the occurrence of minimum flows is expected in the spring season across both emission scenarios for the 2040s and 2070s.

DISCUSSIONS

The future mean annual maximum and minimum temperature of the Kessem watershed are expected to increase for the 2040s and 2070s under both SSP2-4.5 and SSP5-8.5 emission scenarios. The changes in maximum and minimum temperatures are presented for individual and ensemble means of GCM models in Table 7. The increment in both minimum and maximum temperature obtained in this investigation is in line with the study results reported by Daba & You (2020), which found increases in maximum and minimum temperatures for RCP 4.5 and RCP 8.5 in the Upper Awash Basin (UPAB) of 0.5–0.9 °C and 0.6–1.2 °C, respectively. Similarly, the increasing trend in maximum and minimum temperature obtained in this study is in agreement with the study conducted by Yadeta et al. (2020) under RCP scenarios for two-time slices of 2030 and 2060 in the Kessem sub-basin. Additionally, the strong forcing scenarios under RCP8.5 for the previous study as well as SSP5-8.5 for our investigation show a pronounced increase in mean annual maximum and minimum temperatures. Furthermore, under high emission scenarios at the highland Ethiopian Fincha catchment, Dibaba et al. (2020) confirmed an increase in minimum and maximum temperatures, with the minimum temperature rising by 1.92 and 4.22 °C and the maximum temperature rising by 1.49 and 3.21 °C for the near future and mid-future, respectively. Similarly, a study conducted by Worku et al. (2021) indicates a higher increase in both maximum and minimum temperature under the RCP8.5 scenarios at Jemma Sub-Basin of the Upper Blue Nile Basin (UBNB). Temperature increases have been predicted in earlier studies on the UPAB by Tadese et al. (2020) using CMIP5 outputs for all scenarios and time periods.

The percentage changes in average seasonal rainfall for the Kessem watershed are shown in Table 8. The change in seasonal rainfall clearly shows that rainfall increases as time progresses to the end of the century. As we approach the 21st century,
RCP8.5/SSP5-8.5, the most aggressive scenarios, might become increasingly implausible despite significant mitigation efforts (Peters & Hausfather 2020). Nevertheless, these scenarios continue to assist policymakers in developing practical adaptation plans, particularly for the near term (Choi et al. 2023). Increasing rainfall is expected under both emission scenarios, with the exception of a 0.15% decrease in summer (JJAS) rainfall in the 2040s period under the SSP2-4.5 emission scenarios. As a result of both SSP2-4.5 and SSP5-8.5 emissions scenarios, spring rainfall is projected to decrease except during the 2070s period when aggressive emission scenarios (SSP5-8.5) predict an increase. These results are in line with the results reported by Tadesse et al. (2020) and Taye et al. (2018) indicating a decrease in the spring (MAM) rainfall and an increase in summer (JJAS) rainfall for both 2050s and 2070s under both the RCP4.5 and RCP8.5 scenarios in ARB. Moreover, enhanced wet season precipitation and pronounced warming summer was reported by Osima et al. (2018) and Nikulin et al. (2018) over East Africa. The results obtained do not imply a definite consensus regarding future rainfall changes. For instance, contrary to the above results Daba & You (2020) reported a decrease in both summer and spring rainfall for the same periods and scenarios. In support of this, Mengistu et al. (2021) reported that annual precipitation has decreased over the Ethiopian Highlands, although studies by Bichet et al. (2020) and Dosio et al. (2019) using CORDEX-Africa disagree with this drying condition.

As shown in Figure 9, the largest streamflow increase for the 2070s under the SSP5-8.5 scenario was found in August and October. The seasonal streamflow has varied increasing tendencies according to the emission scenarios utilized in this investigation. For instance, in SSP5-8.5 scenarios for long-term futures, larger increases in streamflow were observed. Under both scenarios for the near- and long-term futures, streamflow has shown a decrease during the short rainfall seasons (FMAM). Under the SSP2-4.5 scenario for the period 2031–2060 and the SSP5-8.5 scenario for the period 2061–2090, the spring flow is expected to decrease by 29–55% and 9–49%, respectively. For long-term futures, the SSP5-8.5 scenario exhibits more pronounced increases in streamflow. Under the SSP2-4.5 scenario, the annual average streamflow changes from the ensemble mean of the GCM climate model showed a decrease of 16.8% for the mid-futures and an increase of 4.34% for long-term futures. For the mid-and long-term futures, respectively, the mean annual streamflow is predicted to increase from 12.5 to 48.8% under SSP5-8.5 scenarios. This study shows an increase in mean annual streamflow consistent with the study reported by Eshete et al. (2022) for the Megech River of the Upper Blue Nile Basin which indicates an increase of 5.9–6.5% and 7.3–8.3%, respectively, under RCP4.5 and RCP8.5 for the 2050s and 2080s. Under the SSP5-8.5 emission scenarios for the winter (JJAS) season, a considerable increase of 88% in streamflow was seen for the 2070s. For the same period, a 61% increase in streamflow projection was detected under the SSP2-4.5 emission scenario. This increment in streamflow is in agreement with the studies reported by Amognehegn et al. (2023), which found a 38–57% increase in streamflow under SSP2-4.5 and SSP5-8.5 emission scenarios, respectively. The increment and decrement in streamflow suggest direct connections with the rise in temperature and rainfall. As shown in Figure 11, the slope of the trend line for mean annual streamflow indicates an increase. Under both emission scenarios, it is expected to increase on average for the mid- and long-term future. For the mean annual flow of the Kessem River, Tadesse et al. (2019) also reported an upward trend.

The classification of flow ranges is different by different scholars. For instance, Mohamoud (2008) classified flow ranges as low flows (Q70, Q80, Q90, Q95, Q99), median flows (Q20, Q30, Q40, Q50, Q60), and high flows (Q0.1, Q0.5, Q1, Q5, Q10), while Emiru et al. (2022) and Mulu et al. (2020) respectively classified low flows at 90% (95%), and high flows at 5%. In our study, FDC was constructed for Q10, Q50, and Q90 percentile flows to evaluate future seasonal streamflow events. The occurrence of high flows (10%), median flows (50%), and low flows (90%) were presented as percentage changes in Figure 12. The likelihood of receiving (192, 66, and 7 m³/s) streamflow for the summer, winter, and spring seasons, respectively, will be 10% under the SSP5-8.5 emission scenarios over the period 2061–2090. This means 3 times in a 30-year period. With the exception of winter flow, which indicates an increase under severe emission scenarios (SSP5-8.5) for the 2070s, both emission scenarios predict drier winter and spring streamflow for the 2040s and 2070s for Q90 percentile flows.

In summary, this study contributes important insights to the existing knowledge about climate change impacts on streamflow response in the Kessem Watershed. In the study, we used the most recent state-of-the-art SSP scenarios (SSP2-4.5 and SSP5-8.5), which are more representative of future climate conditions than older RCP scenarios used in previous studies. We recommend increasing measures to mitigate and adapt to climate change in light of the temperature increase over the Kessem watershed. The projected decline in spring rainfall will likely affect agricultural production as well as water resources, so we recommend residents build water harvesting structures and retain water during high-flow seasons. Storing water during high-flow summer season could help to compensate for water shortage and mitigate the effects of droughts, which are a major threat to food security in the region. The results of this study should be taken into account by watershed managers when they create watershed adaptation plans and make management decisions for their water resources. In spite of the
Figure 11 | Trend of mean annual streamflow for two future periods: (a) mid-term (2031–2060) ensemble mean of SSP2-4.5, (b) long-term (2061–2090) ensemble mean of SSP2-4.5, (c) mid-term (2031–2060) ensemble mean of SSP5-8.5, and (d) long-term (2061–2090) ensemble mean of SSP5-8.5.

Figure 12 | Flow duration curves for summer, winter, and spring seasons from ensemble of climate models.
aforementioned benefits, the study is subjected to the following limitations: The results of this study are not generalizable to other climate change scenarios since it only considers the SSP2-4.5 and SSP5-8.5 scenarios. Results of this study may not be generalizable to other hydrological models, because different hydrological models may produce different results.

CONCLUSIONS
This study examines streamflow response to climate change in the Kessem watershed using climate variables from two emission scenarios (SSP2-4.5 and SSP5-8.5). The DM method was used to bias-correct five GCMs’ output climate variables to eliminate systematic errors that could impair rainfall and streamflow simulations. Future climate variables were converted into projected streamflow using the calibrated SWAT model.

- In the mid- and long-term future, under both emission scenarios (SSP2-4.5 and SSP5-8.5), the increase in the magnitude of the annual mean minimum temperature will exceed the increase in the annual mean maximum temperature across the Kessem watershed.
- Under the high-level emission scenarios (SSP5-8.5), it is expected that rainfall will increase in the long-term futures for the summer, winter, and spring seasons over the Kessem watershed. On the other hand, the decrease in rainfall will be expected in the spring (Belg) season for the 2040s under SSP5-8.5 and for 2040s and 2070s under the SSP2-4.5 emission scenarios. The decrease in streamflow during the spring season is directly connected to the decrement in rainfall in the spring season.
- Streamflow response in the Kessem watershed is impacted by climate change. The models used in this study show that changes in streamflow occurred in parallel with changes in temperature and precipitation. Streamflow during the spring season is directly impacted by the reduction in rainfall throughout the spring season.
- The likelihood of receiving (192, 66, and 7 m³/s) streamflow for the summer, winter, and spring seasons, respectively, will be 10% under the SSP5-8.5 emission scenarios over the 2040s.
- The annual mean streamflow decreases under SSP2-4.5 emission scenarios for the mid-term; however, the flow increases with increasing time under both SSP2-4.5 and SSP5-8.5 emission scenarios by the end of the century.

Further studies should investigate the integrated impact of land use/land cover and climate change on the hydrology of the Kessem watershed to obtain more detailed information. It would be beneficial for future researchers to consider other SSP scenarios when studying the impact of climate change on hydrology since this study only used SSP2-4.5 and SSP5-8.5 emission scenarios.

AUTHOR CONTRIBUTIONS
M.T.A. conceived and designed the proposal, analyzed and interpreted the data; wrote the paper. B.G.N. and E.G.A. analyzed and interpreted the data. All authors contributed and agreed to the final manuscript.

DATA AVAILABILITY STATEMENT
All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST
The authors declare there is no conflict.

REFERENCES


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