Future climate change and impacts on water resources in the Upper Blue Nile basin

Gebiyaw Sitotaw Takele a,*, Geremew Sahilu Gebrie b, Azage Gebreyohannes Gebremariama a and Agizew Nigussie Engidab b

a Ethiopian Institute of Water Resources, Addis Ababa University, P.O. BOX. 150461, Addis Ababa, Ethiopia
b Addis Ababa Institute of Technology, Addis Ababa University, P.O. BOX. 150461, Addis Ababa, Ethiopia
*Corresponding author. E-mail: gebiyaw@gmail.com

ABSTRACT

This study aims to assess the impact of climate change on the water resources of the Upper Blue Nile basin using an integrated climate and hydrological model. The impact of climate change on water resources is being assessed using the regional climate model (RCM) under the representative concentration pathway (RCP4.5 and RCP8.5) scenarios and the Soil and Water Assessment Tool (SWAT) hydrological model. Future climate scenarios have been developed for the 2030s (2021–2040) and the 2050s (2041–2060). The study found that the projected rainfall shows a decreasing trend and is not statistically significant, while the temperature shows an increasing trend and is statistically significant. Due to the sharp rise in temperature, the annual evapotranspiration increased by about 10.4%. This and the declining trend of rainfall will reduce streamflow up to 54%, surface runoff up to 31%, and water yield up to 31%. Climate change causes seasonal and annual fluctuations in the water balance components. However, the projected seasonal changes are much greater than the annual changes. Therefore, the results of this study will be useful to basin planners, policymakers, and water resources managers in developing adaptation strategies to offset the adverse effects of climate change in the Upper Blue Nile basin.

Key words: bias correction, climate change, regional climate model, SWAT, Upper Blue Nile basin, water resources

HIGHLIGHTS

- The baseline rainfall trend is increasing but insignificant, whereas the ensembled regional climate model (RCM)-simulated rainfall trend is decreasing.
- Despite some RCMs having a seasonal shift in rainfall, there is no discernible seasonal movement in surface runoff and water production.
- Ensembled rainfall, streamflow, surface runoff, and water output reveal a decrease in the 2030s and 2050s climate conditions.
1. INTRODUCTION

Climate change has a significant impact on water resources, as it changes the components of the climate (Versini et al. 2016; Aduah et al. 2017). These changes are expected to have a significant impact on water resources, the water available in the region, and the temporal and spatial patterns of their distribution (UNESCO, UN-Water 2020). In addition, climate change can affect various characteristics of water resources, such as water quality and quantity to meet basic human needs, extreme hydrological events, event timing, and water temperature (Kim et al. 2008; Nan et al. 2011; Versini et al. 2016; Biao 2017). In addition, climate change not only leads to higher average temperatures, but also changes in annual and seasonal precipitation that affect the water cycle (Mohammed et al. 2016).

One of the rivers most affected by climate change is the Upper Blue Nile basin (Abdo et al. 2009; Taye et al. 2011). The basin covers 10% of the Nile basin and produces about 60% of the water that reaches Egypt and Sudan (Roth et al. 2018). Hundreds of millions of Ethiopians and those living downstream of the river depend on the availability of water in the Upper Blue Nile basin, which is strongly influenced by the sensitivity and variability of climatic conditions (Gelete et al. 2019; Mengistu et al. 2021). The basin is expected to experience year-to-year temperature and rainfall fluctuations in the future, which may change the patterns and trends of hydrology and water resources in the basin (Cherie 2013). It is very
important to understand the possible effects of climate change on hydrological components to understand such changes in water resources (Singh & Saravanan 2020; Fatehifar et al. 2021).

Several studies, including studies by Taye et al. (2011), Dile et al. (2013), Gebre (2015), Fentaw (2018), Worqlul et al. (2018), and Boru et al. (2019), studied the effects of climate change on the water resources of the Upper Blue Nile sub-basin. Some studies such as Koch & Cherie (2013), Mellander et al. (2013), Haile et al. (2017), Roth et al. (2018), Mengistu et al. (2021), and Tariku et al. (2021) also studied the potential impact of climate change on the water resources of the entire basin. These studies generally investigated climate change and its consequent hydrological features. Some studies have used one or more emission scenarios, different downscaling methods (i.e., statistical or dynamical), and bias-corrected or raw data without bias correction. These methodological differences can really determine the outcome of an impact study. For example, some studies have simulated a decrease in runoff (Koch & Cherie 2013; Haile et al. 2017) and water availability (Koch & Cherie 2013; Mengistu et al. 2021) as a result of reduced water supply. Other studies (Roth et al. 2018) have simulated increases in discharge and water availability due to increased rainfall and water production.

This indicates that there is no general agreement on the impacts of climate change on water resources in the Upper Blue Nile basin. It challenges policymakers, water resource managers, and the entire community. So, continuous efforts are required to understand the hydrological processes and develop efficient water management strategies under changing environmental conditions (Zhang et al. 2018). To assess the impact of climate change on water resources, different emission scenarios and preferred bias correction techniques should be used. Hence, further research is needed to understand the impact of climate change on water resources and to expand knowledge of effective adaptation measures and other water-related development plans in the Upper Blue Nile basin.

The main objective of this study was to assess the impact of climate change on the water resources of the Upper Blue Nile basin. This study creates climate change scenarios for the 2030s (2021–2040) and 2050s (2041–2060), examines climate change trends, especially rainfall and temperature changes, and evaluates how changes in rainfall and temperature affect changes in streamflow and hydrological components using Soil and Water Assessment Tool (SWAT) model products. Since the livelihoods of the majority of the population in the Upper Blue Nile basin are based on rain-fed agriculture, there is an urgent need for detailed information on climate change and variability.

To this end, the bias-corrected regional climate models (RCMs) have been integrated into the SWAT model in various climatic scenarios. Therefore, the results of the study are important for the development of robust hydrological scenarios for water resource management, water security planning, and the design of optimal climate change strategies for the proposed water developments in the Upper Nile Blue basin. In addition, the methodology presented in this document may be a useful approach for studying the impact of climate change on the water resources of other river basins. The contents of the rest of this paper are as follows: Section 2 highlights the study area, data sets, and methods, while Section 3 presents the results and corresponding discussions. Finally, conclusions and recommendations are presented in Section 4.

2. METHODS AND MATERIALS

2.1. Description of the study area

The study was conducted in the Upper Blue Nile basin, the primary subbasin of the Nile River basin located in the highland region of Ethiopia. The absolute location of the basin covers a 7°44′32″–12°45′19″N latitude in the south-north direction and a 34°29′20″–39°48′17″E longitude in the west-east direction (Figure 1). The drainage area of the basin at the border station is about 174,166 km² (Takele et al. 2021). The basin covers 10% of the Nile basin and produces approximately 60% of the water that reaches Egypt and Sudan (Roth et al. 2018). Approximately 55.94% of the Upper Blue Nile basin is covered by agricultural land, 18.04% by closed forest, 14.5% by mixed forest, 6.12% by shrubs, and the remaining 5.4% by other land-use classes (Takele et al. 2021). Soil types in the basin include eutric nitosols (30%), eutric cambisols (24%), humic cambisols (16%), cambic arenosols (14%), dystric cambisols (5%), eutric regosols (3%), water bodies (2), eutric fluvisols (2), chromic vertisols (2%), pellic vertisols (1%), and orthic acrisols (1%).

The basin experiences a monomodal rainfall pattern from June to September and receives about 74% of the annual rainfall during the rainy season. The average annual rainfall in the basin ranges from 770 mm at the eastern end of the basin to 2,117 mm at the southern end. The seasons in this area are named concerning rainfall: from September to November is Tsedey (in Amharic) which means the post rainy of Autumn; October to February is Bega which means the dry winter
season; from March to May is Belg which means the small rains of spring; June to September is Kiremt that means the wet summer season (Mellander et al. 2013).

2.2. Input data

SWAT hydrological simulations at the watershed or catchment level require spatial and temporal data. Temporal data, such as climatic and hydrological data, are used to build the model and hydrological processes, as well as spatial data such as the digital elevation model (DEM), the land-use map, and the soil map. The Alaska Satellite Facility (ASF) provided the DEM with a 12.5-m resolution, and the DEM was used to extract the drainage pattern of the catchment area of the basin. In addition, the DEM was used to derive the subarea parameters required for the SWAT model, such as the steepness of the slope, the length of the slope of the terrain, and the properties of the stream network.

The Copernicus Global Land Service (CGLS) provided a land-use map of the study basin with a resolution of 100 m. The extracted land-use map contains 10 land-use classes, which are agricultural land, bare land, closed forest, grassland, mixed forest, open forest, shrub, urban, water, and wetland (Takele et al. 2021). The physical and chemical properties of the soil map of the study basin were taken from the database of the World Food and Agriculture Organization of the United Nations (FAO).

The National Meteorological Services Agency (NMSA) of Ethiopia provided daily weather data for 32 stations from 1987 to 2016. A double mass curve procedure was used to verify the consistency of the data. Handling of missing data should be prioritized in data preparation procedures, especially in an event where all available resources, including partial information, must be used (Hamzah et al. 2021). The missing data were filled and homogeneity analysis was performed in R with the CLIMATOL v3.3 package (Takele et al. 2021). These data were used for bias correction for the RCM simulation, the impact assessment, and the SWAT model simulation. The Ministry of Water, Irrigation and Energy of Ethiopia provided daily streamflow data for the Kessie and Border stations from 2001 to 2014. These data were used to calibrate and validate the SWAT model and generate a water balance component for the reference period.

In this study, simulated rainfall and temperature data from the Coordinated Regional Climate Downscaling Experiment (CORDEX) Africa project were used. The latest RCM of the Rossby Centre regional atmospheric model (RCA) was used.
Table 1 | Description of the selected RCMs

| Institute                                                                 | GCM name                          | Abbreviated name |
|---------------------------------------------------------------------------|-----------------------------------|-----------------|
| Centre National de Recherches Météorologiques (France)                    | CNRM-CRAFACS-CNRM-CM5             | CNRM-CM5        |
| Consortium of European Research Institution and Researchers               | ICHEC-EC-EARTH                    | EC-EARTH        |
| National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (MIROC), Japan | MIROC-MIROC5                      | MIROC5          |
| Max Planck Institute for Meteorology (Germany)                            | MPI-M-MPI-ESM-LR                  | MPI-ESM-LR      |

to generate these climate data sets, which were forced by four global climate models (GCMs): CNRMC-M5, EC-EARTH, MPI-ESM-LR, and MIROC5. Table 1 contains a description of the selected RCM. Two emission scenarios (RCP4.5 and RCP8.5) of the representative concentration pathway (RCP) were taken into account: RCP4.5 is a medium stabilization scenario with a carbon dioxide equivalent concentration range of 580–720 ppm in 2100, while RCP8.5 is a very high emission scenario with a carbon dioxide equivalent concentration of 1,000 ppm at 2100 (IPCC 2014).

2.3. Bias correction of the RCM simulation

GCMs are the most important source of information for the development of climate scenarios and form the basis for assessing the effects of climate change at all levels, from local to global. Although regional-scale climate models represent important mesoscale meteorological and climate characteristics much better than global models, the simulations are still subject to biases. RCM relies on higher-level GCM, so it inherits some, if not all, of the bias. Some may argue that the RCM is better suited for regional impact studies. However, because RCM is controlled by GCM as a boundary condition, it is affected by the robustness and accuracy of GCM for the particular area under investigation (Taye et al. 2018). And they are sensitive to the boundary conditions where the RCM is embedded (Tapiador et al. 2020).

A common drawback of dynamic RCM data is the overestimation of days with very low rainfall (Teutschbein & Seibert 2012). This issue is related to the size of the RCM grid cells combined with the convection of moist air. Humid air is completely saturated at certain altitudes as the temperature drops, resulting in massive precipitation within the RCM (Willkofer et al. 2018). In addition, RCM requires high computational work, and their effectiveness depends primarily on the input observation data (Willkofer et al. 2018).

Several statistical methods have been developed to correct these biases, including transformation algorithms that are statistically consistent with the observations (Willkofer et al. 2018). The bias correction methods, which require the correction algorithm and its parameterization for current weather conditions, also apply to future stationary weather conditions (Teutschbein & Seibert 2012). The purpose of using bias correction methods is to bring the climate model simulations closer to the actual observations during a specific reference period (Chen et al. 2020). Furthermore, a bias correction is ultimately performed to provide realistic climate change scenarios to assess the effects of climate change. To obtain acceptable hydrological simulations, these distortions must be eliminated.

In this study, the bias correction of the RCM simulations was carried out using the climate model for the hydrological modeling tool (CMhyd) at the station level. This tool provides simulated climate data representing meteorological gauges used in setting up a watershed model (Rathjens et al. 2016). The CMhyd is ideal for preparing simulated climate variables for SWAT model climate change impact studies (Zhang et al. 2018). The tool suggested several methods of bias correction, including linear scaling, nonlinear scaling, and distribution mapping. In this study, RCM-simulated rainfall and temperatures were extracted and corrected using the linear scaling method. It works with monthly corrections based on the difference between the observed data and the raw data (in this case the raw data simulated by RCM). Rainfall is usually corrected monthly by a multiplier, and temperature is corrected by an additive term (Fang et al. 2015). We chose this method based on simplicity, accuracy, parameter considerations, and reliability results from observational data (Tukimat 2018). In addition, the linear scaling method is suitable for water resources research in the context of climate change. Therefore, a simple method of bias correction is accessible to more users in the water resources research community (Shrestha et al. 2017).
2.4. Hydrological modeling

SWAT is a semi-distributed, physical based, continuous-time hydrological model (Arnold et al. 2012), and it was designed to study the impact of land management on water, sediment, and pesticide yields in ungauged catchments (Gassman et al. 2007; Devia et al. 2015). Physiological data used in the model include elevation, land and soil data, climate inputs such as daily rainfall, maximum, and minimum temperatures, humidity, solar radiation, and wind speed.

The model divides the study area into several subbasins, and the subbasins can be further divided into a series of hydrological response units useful for more detailed hydrological studies (Yu et al. 2018). The hydrological simulation of the SWAT model can be performed in two stages: the first controls the amount of water, sediments, and nutrients that flow from each subbasin into the main channel of the basin, and the second describes the movement of water, sediments, and nutrients through the canal from the watershed areas, which is determined by the surface topography (Neitsch et al. 2011; Arnold et al. 2012).

The hydrological effects of climate change in the Upper Blue Nile basin were evaluated using the SWAT model previously calibrated by Takele et al. (2021). The model ran from 1987 to 2016. The model was successfully calibrated and validated using the observed flow from 2001 to 2009 and 2010 to 2014 at the Kessie and Border stations. The SUFI2 optimization algorithm from SWAT CUP ver2012 was used to identify the sensitive parameters of the model and calibrate it. During the validation period, the performance of the model is evaluated using the most used statistical evaluation indices such as the Nash–Sutcliffe efficiency (NSE) (Nash & Sutcliffe 1970), the coefficient of determination ($R^2$) (Krause et al. 2005), and the percent of bias (PBIAS) (Gupta et al. 1999). Further details on model parameterization and performance are available in Takele et al. (2021).

2.5. Estimating climate change impact on hydrology

The prediction of changes in climate variables was required to assess the impact of climate change on the hydrology of the study area. Therefore, this study used the bias-corrected RCM output (rainfall and temperature) under the RCP4.5 and RCP8.5 emission scenarios as inputs to the hydrological model. The major hydrological components such as surface runoff (SURQ), potential evapotranspiration (PET), water yield (WYLD), groundwater flow, and lateral flow were estimated. However, the first three key parameters were evaluated in detail using a SWAT model calibrated under baseline climate (1987–2016) and future climate scenarios (the 2030s (2021–2040) and the 2050s (2041–2060)). Furthermore, for streamflow, change detection is done annually, and for hydrological components, it is done monthly.

2.6. Trend analysis of climate variables

Trend analysis is considered one of the most critical topics in global climate studies (Yacoub & Tayfur 2018). Various statistical techniques have been used in studies to identify trends and other changes in climate and hydrological variables. These techniques are classified as parametric and non-parametric. Parametric methods assume a normal distribution of variables, non-parametric methods do not. Therefore, in this study, the non-parametric Mann–Kendall test was used to identify monotonic trends and statistical distributions of climatic variables (rainfall and temperature). The Mann–Kendall test was used for this study because it makes no assumptions about the distribution of the data, is resistant to outliers, and does not require the removal of outliers prior to trend detection.

The Mann–Kendall test is calculated as follows:

\[ Z_s = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \text{sgn}(x_j - x_i) \]  

where \( x_j \) and \( x_i \) are the time-series data, the annual values in year \( j \) and \( i \) correspondingly, sgn is the signum function that takes on the values 1, 0, or \(-1\). A positive (negative) value of \( Z_s \) signifies an increasing (decreasing) trend in the time-series data.
In this study, the Theil–Sen slope estimator was used to compute the linear rate of change, or the magnitude of change in the variable at any given time, each year. As a result, the Theil–Sen test computes the median of the slopes ($\beta$) as follows:

$$\beta = \text{median} \left( \frac{x_j - x_i}{j - i} \right)$$  \hspace{1cm} (3)

where $i=1$ to $n-1$, $j=2$ to $n$, and $x_j$ and $x_i$ are the data values at time $j$ and $i$ (j>i), respectively.

3. RESULTS AND DISCUSSION

3.1. SWAT model calibration and validation

The SUFI-2 algorithm was used to perform the sensitivity analysis for the entire catchment area. Twenty-six hydrological parameters were tested, of which 13 were found to be the most sensitive. SCS runoff curve number, deep aquifer percolation fraction, threshold depth of water in the shallow aquifer for ’revap’ to occur, groundwater delay, soil evaporation compensation factor, effective hydraulic conductivity in main channel alluvium, baseflow $\alpha$-factor, groundwater ’revap’ coefficient, available water capacity of the soil layer, saturated hydraulic conductivity, threshold depth of water in the shallow aquifer required for return flow to occur, maximum canopy storage, and manning’s $n$ value for the main channel were the most hydrologically sensitive parameters. Takele et al. (2021) document the details of the sensitive flow parameters and their fitted values.

The selected parameters were calibrated and validated at the Kessie and Border gauging stations. There was a good agreement between the observed and simulated discharges, as indicated by the high values of the $R^2$ and NSE, and low PBIAS. Takele et al. (2021) summarized the performance of the model at the Kessie and Border stations during the calibration and validation periods. Takele et al. (2021) identified the components of the water balance of the basin. The results showed that evapotranspiration lost 50.17% of precipitation during the calibration period and 48.58% during the validation period. During the calibration and validation periods, SURQ contributes 44.95 and 45.26%, respectively, to the watershed’s WYLD, while groundwater contributes 40.15 and 40.28%, respectively, to the WYLD.

3.2. Bias correction of the RCMs

In order to increase the predictability of climate models, it is often necessary to correct the deficiencies of the current GCM/RCM, which is useful as an input to assess the impacts of climate change. Figures 2 and 3 show the performance of the bias correction for the 30-year series of climatic averages for rainfall and temperature of the uncorrected (raw) values of the selected models and the bias-corrected values. The linear scaling method was used to adjust the discrepancy between the RCM-simulated temperature and rainfall data with the measured data.

The method has adjusted the extreme values of rainfall and has also adjusted the distribution of monthly rainfall, in particular the maximum values of rainfall. As a result, once the bias is corrected, the climate model simulations are closer to the values observed during a given reference period (1987–2016). In this case, the bias correction adjusts the RCMs simulation and the predictability of the average monthly rainfall (Figure 2). Other studies have examined how bias correction methods can be used to improve climate model simulations (Luo et al. 2018; Chen et al. 2020; Mendez et al. 2020). Similarly, the underestimation and overestimation of the RCM simulations for TMAX and the overestimation of TMIN were adjusted using the linear scaling bias correction method with the observed average monthly TMAX and TMIN (Figure 3).

![Figure 2](http://iwaponline.com/jwcc/article-pdf/13/2/908/1014074/jwc0130908.pdf) Bias correction performance in adjusting the average monthly rainfall of the RCMs in the Upper Blue Nile basin.
3.3. Future climate projection

Future climate change scenarios have been developed for the Upper Blue Nile basin, taking into account various RCM and emission scenarios. The average annual rainfall in RCMs shows a visible change of −13 to +6% in all scenarios and scenario periods (Table 2). The rainfall change signals show significant differences between the RCMs for the 2030s and 2050s under different emission scenarios. In the RCP8.5 emission scenario, changes range from −10 to +2% in the 2030s and from −13 to +6% in the 2050s. In this emission scenario, rainfall is expected to decline further in the 2050s (Table 2). In the RCP4.5 emission scenario, rainfall is expected to decline sharply (i.e., −8%) under the climatic conditions of the 2050s.

During the scenario periods, significant seasonal fluctuations in rainfall are observed. Table 3 shows the mean seasonal rainfall and the corresponding percentage changes predicted by all climate models in the 2030s and 2050s in both RCP emission scenarios, along with the reference period. In projection periods, rainfall is expected to decrease more in autumn (September–November), following spring (March–May). Rainfall forecasts for the main rainy season of the basin.
June–August) show no significant changes. In the RCP8.5 emission scenario, winter precipitation is expected to increase by up to 17% in the 2030s, up to 21% in the 2050s, and 3% in the RCP4.5 emission scenario of the 2030s.

Individually, in the RCP8.5 emission scenario, almost all RCMs, with the exception of MIROC5 in the 2050s, show a decrease in average monthly rainfall in the 2030s and 2050s. In the RCP4.5 emission scenario, all RCMs show a decrease in average monthly rainfall over the scenario periods. Other studies have reported on the unpredictability of future rainfall in the basin. Elshamy et al. (2009), for example, reported expected changes in the basin’s total annual rainfall ranging from 15 to 14% using 17 GCMs, but more models report reductions (10) than increase (7) by the end of the 21st century. According to Kim & Kaluarachchi (2009), the average annual rainfall over the basin will vary from 11 to 44% in the mid-century for the A2 emission scenarios. Tariku et al. (2021) estimate that the basin’s precipitation will vary from 10.3 to 19.4% under the RCP4.5 and RCP8.5 emission scenarios in the 2050s and 2080s.

In future climate scenarios, each climate model predicts an increase in the average annual maximum and minimum temperatures in both emission scenarios (Table 4). The average annual maximum temperature of the basin rises from 0.96 to 2.04 °C, and the average annual minimum temperature rises from 0.95 to 2.1 °C. There are some differences in emission scenarios, and TMAX and TMIN are expected to constantly increase at RCP8.5 instead of RCP4.5. However, the rate of increase in TMAX and TMIN between RCMs is consistent across emission scenarios. TMAX and TMIN are expected to increase significantly in the climate of the 2050s compared to the climate of the 2030s. In both emission scenarios, all individual RCMs show an increase in TMAX and TMIN over the 2030s and 2050s. Previous research in the Upper Blue Nile basin shows an increasing trend in the average annual temperatures (maximum and minimum) (e.g., Kim et al. 2008; Beyene et al. 2009; Elshamy et al. 2009; Cherie 2013; Haile et al. 2017; Liersch et al. 2018; Roth et al. 2018; Mengistu et al. 2021; Tariku et al. 2021).

### 3.4. Trend of rainfall and temperature under baseline and future scenarios

Table 5 shows baseline and future rainfall, TMAX, and TMIN annual trend statistics (Mann–Kendall test and Sen’s slope estimator) for various climate scenarios in the study area. Based on the Z-test and Sen’s slope values, baseline rainfall (1987–2016) shows an increasing trend, but it is not statistically significant. Nevertheless, rainfall in the 2030s and 2050s is declining and not statistically significant (Figure 4). The rate of decrease in rainfall during the 2050s forecast period is 0.26 mm/year in the RCP4.5 emission scenario and 4 mm/year in the 2050s in the RCP8.5 emission scenario (Table 5).

### Table 3 | Seasonal variation in projected rainfall under the RCP4.5 and RCP8.5 emission scenarios in the Upper Blue Nile basin for the baseline period

| Season               | Baseline (1987–2016) | 2030s (2021–2040) | 2050s (2041–2060) |
|----------------------|----------------------|------------------|------------------|
| Summer (June–August) | 749                  | 756 (1%)         | 754 (1%)         |
| Autumn (September–November) | 264              | 222 (−16%)       | 199 (−25%)       |
| Winter (December–February) | 32               | 33 (3%)          | 32 (0%)          |
| Spring (March–May)    | 202                  | 187 (−7%)        | 192 (−5%)        |

### Table 4 | Average annual maximum and minimum temperatures in the RCMs of the Upper Blue Nile basin under the RCP4.5 and RCP8.5 emission scenarios for the scenario period (2030s and 2050s)

| RCM Runs | Change in maximum temperature (°C) | Change in minimum temperature (°C) |
|----------|------------------------------------|------------------------------------|
|          | 2021–2040                          | 2041–2060                          |
|          | RCP4.5 RCP8.5                       | RCP4.5 RCP8.5                       |
| CNRM-CM5 | 0.8 0.9                             | 1.5 1.8                            |
| EC-EARTH | 0.9 1.0                             | 1.5 2.0                            |
| MPI-ESM-LR | 1.04 1.30                       | 1.66 2.27                          |
| MIROC5   | 1.1 1.2                             | 1.7 2.1                            |
| Average  | 0.96 1.10                           | 1.59 2.04                          |
3.5. Impact of climate change on streamflow

Table 6 summarizes the SWAT model’s estimate of the impact of climate change on streamflow in the Upper Blue Nile basin. In the event of future climate change, annual streamflow may be reduced compared to the reference period. In the RCP4.5 emission scenario, the change in average annual streamflow ranges from −48 to −10% in the 2030s and from −35 to −7% in the 2050s, whereas in the RCP8.5 emission scenario, the change in average annual streamflow ranges from −49 to −4% in the 2030s and from −54 to +15% in the 2050s.

In different scenarios, there are significant differences in streamflow changes between RCMs in the 2030s and 2050s. Under the RCP8.5 emission scenario, a significant reduction in streamflow is simulated in the 2050s climate condition. High-streamflow reduction is projected in the 2030s climate condition under the RCP4.5 emission scenario. Individually, almost all RCMs except MIROC5 showed a decrease in annual streamflow in the 2030s and 2050s in the RCP8.5 emission scenario. In general, the direction of streamflow changes in response to changes in rainfall (Table 2). According to Elshamy et al. (2009), there is some evidence of the impact of reduced rainfall on reduced runoff and average annual streamflow. For example, in Tables 6 and 7, a 14.2% decrease in average annual rainfall by EC-EARTH leads to a 30.8% decrease in average annual runoff and a 54% decrease in mean annual streamflow. On the other hand, a 7.2% increase in average annual rainfall by MIROC5 leads to a 33.8% increase in average annual runoff and a 15% increase in annual streamflow.

3.6. Climate change impact on water balance components

This section describes the main components of the water cycle: SURQ, PET, and WYLD. It has been observed that future climate change in rainfall and temperature will cause a change in the components of the water balance in the Upper Blue Nile basin. Annual SURQ decreased in some climate scenarios and increased in others. The total annual average SURQ simulated by SWAT across the entire basin in the 2030s and 2050s is shown in Table 7. As can be seen from the table, changes in SURQ range from −18.7% (2030s) to +33.8% (2050s) in the RCP4.5 emission scenario and from −26.9% (2030s) to +18.3% (2030s) in the RCP8.5 emission scenario.

Independently, CNRM-CM5 and EC-EARTH RCM show a decrease in SURQ, while MPI-ESM-LR and MIROC5 RCM show an increase over the projection periods in both emission scenarios. This variation may be due to changes in rainfall in future climatic conditions. Figure 5 shows the monthly mean distribution of SURQ and rainfall in various emission scenarios.
scenarios, along with the reference period. As can be seen from the figure, in future climate scenarios, SURQ will decrease during the dry season (October–May) and increase during the rainy season (June–September). However, the MIROC5 run in the rainy season showed some changes in monthly SURQ. These results are consistent with other studies in the Upper Blue Nile basin, which predict an increase in SURQ during the rainy season (Mengistu et al. 2021). In general, the model result (Table 7) indicated an 8% change in rainfall, resulting in a 16% change in SURQ for the CNRM-CM5 and EC-EARTH RCMs, and a 3% increase in rainfall, resulting in a 22% increase in SURQ for the MPI-ESM-LR and MIROC5 RCMs.

Previous studies have linked changes in SURQ to changes in rainfall, temperature, and evapotranspiration (Kim et al. 2008; Elshamy et al. 2009; Mengistu & Sorteberg 2012; Cherie 2013). Mengistu & Sorteberg (2012) found that a 10% change in

Figure 4 | Average annual precipitation trends in the base and future scenario periods under emission scenarios. a) Baseline period (1987-2016), (b) RCP4.5 (2030s), (c) RCP4.5 (2050s), (d) RCP8.5 (2030s), and (e) RCP8.5 (2050s).
Table 6 | Percentage change in the average annual streamflow of RCMs in the Upper Blue Nile basin under the RCP4.5 and RCP8.5 emission scenarios for the scenario periods (2030s and 2050s)

| Change in Streamflow (%) | 2030s (2021–2040) | 2050s (2041–2060) |
|--------------------------|------------------|------------------|
| RCM Runs                 | RCP4.5           | RCP8.5           |
| CNRM-CM5                 | –14              | –16              |
| EC-EARTH                 | –48              | –49              |
| MPI-ESM-LR               | –10              | –8               |
| MIROC5                   | –11              | –4               |
| Average                  | –21              | –19              |

Table 7 | Projected and percentage change in the water balance components of RCMs in the Upper Blue Nile basin under the RCP4.5 and RCP8.5 emission scenarios for the scenario periods (2030s and 2050s)

| RCMs | RCPs | Time | Baseline | Rainfall  | Surf_Q | PET  | Gw_Q | Lat_Q | WYLD |
|------|------|------|----------|-----------|--------|------|------|-------|------|
|      |      |      |          | mm 1,313 | Δ% 265 | Δ% 1,594 | Δ% 245 | Δ% 82 | Δ% 606 |
| CNRM-CM5 | RCP4.5 | 2030s | 1,233 | –6.1 | 229 | –13.4 | 1,611 | 1.1 | 193 | –21 | 71 | –12.5 | 506 | –16.5 |
|        | RCP8.5 | 2030s | 1,281 | –2.4 | 253 | –4.5 | 1,595 | 0 | 202 | –17.5 | 74 | –9.3 | 539 | –11.1 |
|        | RCP4.5 | 2050s | 1,225 | –6.7 | 236 | –10.8 | 1,651 | 3.5 | 190 | –22.3 | 72 | –12.2 | 510 | –15.9 |
|        | RCP8.5 | 2050s | 1,227 | –6.5 | 241 | –9.1 | 1,667 | 4.6 | 183 | –25.5 | 70 | –13.8 | 509 | –16 |
| EC-EARTH | RCP4.5 | 2030s | 1,239 | –5.6 | 227 | –14.2 | 1,608 | 0.9 | 200 | –18.2 | 74 | –9.4 | 513 | –15.3 |
|        | RCP8.5 | 2030s | 1,151 | –12.3 | 193 | –26.9 | 1,557 | –2.4 | 178 | –27.2 | 68 | –16.9 | 450 | –25.7 |
|        | RCP4.5 | 2050s | 1,198 | –8.7 | 215 | –18.7 | 1,643 | 3 | 186 | –24.1 | 71 | –13.4 | 483 | –20.3 |
|        | RCP8.5 | 2050s | 1,127 | –14.2 | 183 | –30.8 | 1,664 | 4.4 | 158 | –35.6 | 65 | –20.1 | 416 | –31.4 |
| MPI-ESM-LR | RCP4.5 | 2030s | 1,111 | –15 | 283 | 6.9 | 1,687 | 5.8 | 190 | –22.3 | 69 | –15.0 | 554 | –8.6 |
|        | RCP8.5 | 2030s | 1,131 | –14 | 306 | 15.4 | 1,698 | 6.5 | 204 | –16.8 | 71 | –13.4 | 592 | –2.2 |
|        | RCP4.5 | 2050s | 1,063 | –19 | 280 | 5.7 | 1,728 | 8.4 | 190 | –22.3 | 66 | –24.1 | 527 | –13.0 |
|        | RCP8.5 | 2050s | 1,064 | –19 | 289 | 9.0 | 1,760 | 10.4 | 167 | –31.9 | 66 | –19.6 | 531 | –12.3 |
| MIROC5 | RCP4.5 | 2030s | 1,323 | 0.7 | 313 | 18.3 | 1,604 | 0.6 | 265 | 8.3 | 86 | 5 | 679 | 12.1 |
|        | RCP8.5 | 2030s | 1,356 | 3.3 | 320 | 20.9 | 1,605 | 0.7 | 269 | 9.8 | 87 | 6.1 | 691 | 14.1 |
|        | RCP4.5 | 2050s | 1,314 | 0.1 | 310 | 17.1 | 1,632 | 2.3 | 263 | 7.4 | 86 | 4.8 | 674 | 11.2 |
|        | RCP8.5 | 2050s | 1,407 | 7.2 | 354 | 33.8 | 1,638 | 2.7 | 276 | 12.8 | 90 | 10.1 | 737 | 21.6 |

rainfall resulted in a 19% change in SURQ in the Upper Blue Nile basin. Elshamy et al. (2009) found that a 10% change in PET resulted in a 14% change in SURQ. In addition, Elshamy et al. (2009) and Mengistu & Sorteberg (2012) assumed that a 1 °C increase in temperature would increase PET by 4% which leads to a decrease in SURQ. In addition, Krisnayanti et al. (2021) correlate changes in runoff depth with rainfall.

In addition to SURQ, other important factors in the water balance, such as PET and WYLD, are considered to investigate the effects of climate change in the Upper Blue Nile basin. PET increases in all climate scenarios due to rising temperature. Figure 6 shows the monthly mean distribution of PET and rainfall in various emission scenarios, along with the reference period. As a result of the driest and warmest conditions in the basin during the dry season (February–May), higher PET is estimated. In contrast, lower PET is estimated during the rainy season (June–September) in the basin as a result of increased cloud coverage and humidity associated with the rainy condition. According to Elshamy et al. (2009), there are signs that a significant decrease in rainfall may be associated with a significant increase in PET, probably as a result of a decrease in cloud cover. In Table 7, for example, a 14.2% decrease in mean annual rainfall by EC-EARTH results in a 4.4% increase in mean annual PET, while a 19% decrease in mean annual rainfall by MPI-ESM-LR results in a 10.4% increase in mean annual PET. A 7.2% increase in average annual rainfall with MIROC5 leads to a 2.7% increase in average annual PET.
WYLD was also taken into account in this study, as it can represent the availability of water resources in the basin. Due to climate change, the projected WYLD of the Upper Blue Nile basin may change in the 2030s and 2050s. With the exception of MIROC5 RCM, the decline in WYLDs under climatic conditions in the 2030s and 2050s was estimated under the RCP emission scenarios (Table 7). Predicted WYLDs in the 2030s are low in the RCP8.5 emission scenario and high in the RCP4.5 emission scenario. The decrease in WYLD is mainly due to the expected decrease in rainfall and the consequent SURQ.

Previous studies have linked a decrease in water from the basin to a decrease in rainfall, an increase in evaporation, and an increase in temperature. Mengistu et al. (2021) combine a decrease in WYLD and rainfall, an increase in evapotranspiration loss due to rising temperatures, followed by a decrease in groundwater recharge due to a decrease in lateral and

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**Figure 5** | Monthly distribution and changes in rainfall and surface runoff (Surf_Q) for (a) CNRM-CM5 under RCP4.5, (b) CNRM-CM5 under RCP8.5, (c) EC-EARTH under RCP4.5, (d) EC-EARTH under RCP8.5, (e) MPI-ESM-LR under RCP4.5, (f) MPI-ESM-LR under RCP8.5, (g) MIROC5 under RCP 4.5, and (h) MIROC5 under RCP 8.5.
MIROC5 is expected to have a higher WYLD under the RCP4.5 and RCP8.5 emission scenarios, owing to the higher projected rainfall and SURQ. According to RCM runs, the estimated monthly WYLDs in the basin are not constant throughout the year. Figure 7 shows the monthly mean distribution of WYLD and rainfall in various emission scenarios, along with the reference period. The result shows higher estimated WYLDs during the rainy season (June–September) due to lower PET, higher rainfall, and higher SURQ. Compared to the rainy season, the dry season (October–May) is projected to have less WYLD due to higher evapotranspiration, lower rainfall, and lower SURQ. Further according to Pulighe et al. (2021), a decrease in WYLD is associated with an increase in temperature and the consequent decrease in humidity.

Figure 6 | Monthly distribution and changes in rainfall and potential evapotranspiration (PET) for (a) CNRM-CM5 under RCP4.5, (b) CNRM-CM5 under RCP8.5, (c) EC-EARTH under RCP4.5, (d) EC-EARTH under RCP8.5, (e) MPI-ESM-LR under RCP4.5, (f) MPI-ESM-LR RCP8.5, (g) MIROC5 under RCP 4.5, and (h) MIROC5 under RCP 8.5.
4. CONCLUSION

During the rainy season, about 80% of the Nile water comes from the Upper Blue Nile basin. The water resources of the basin are used for irrigation, hydropower, and domestic purposes. Climate change can affect the water resources of the basin, as rainfall is the main source. The bias-corrected RCMs have been integrated into a semi-distributed SWAT hydrological model to assess the future climate and water resources of the Upper Blue Nile basin for the years 2021–2040 (2030s) and 2041–2060 (2050s).

During the scenario periods, the projected average climate shows a decrease in rainfall and an increase in temperature. The rainfall change signals show differences between the selected climate scenarios. Seasonally, predicted rainfall provides various signals of future climatic conditions. In all climate conditions, especially under the RCP8.5 scenario, the projected

Figure 7 | Monthly distribution and changes in rainfall and water yield (WYLD) for (a) CNRM-CM5 under RCP4.5, (b) CNRM-CM5 under RCP8.5, (c) EC-EARTH under RCP4.5, (d) EC-EARTH under RCP8.5, (e) MPI-ESM-LR under RCP4.5, (f) MPI-ESM-LR under RCP8.5, (g) MIROC5 under RCP4.5, and (h) MIROC5 under RCP 8.5.
rainfall increases during the winter season. However, the projected rainfall does not change significantly during the rainy season (June–August). This results in a seasonal shift in rainfall in some RCM runs and emission scenarios.

Decreasing rainfall and rising temperatures can have a devastating impact on community life, as approximately 85% of the population of the basin depends on rain-fed agriculture. Decreasing rainfall and rising temperature change runoff regimes and thus change water availability. Hence, a strong correlation is found between rainfall, SURQ, and total WYLD. SURQ decreases sharply in the dry season and increases during the rainy season. This suggests that SURQs are particularly sensitive to changes in rainfall. Similarly, due to the dryness of the basin, high PET is expected in the dry season, and low PET is expected in the rainy season due to humid and rainy conditions.

In the rainy season, PET is low, rainfall is high, and SURQ is high, so the total amount of water is expected to increase. On the other hand, in the dry season, the possibility of evaporation in the basin is high, the amount of rainfall is small, and the SURQ is small, so the total amount of water is small. Overall, the declining trend of water resources in the study area suggests that water resources are inadequate to support the water development in the Upper Blue Nile basin. Therefore, strategies for managing the water resources of the basin are needed to prevent future impacts of climate change on water availability. In order to develop water resource management strategies, predicted climate change scenarios and simulated impacts of climate change need to be incorporated into basin adaptation decision analysis. Such strategies can provide optimal benefits in terms of maintaining the availability of water resources, mitigating and adapting to adverse climatic conditions, and thus maintaining or ensuring the development of water resources.

The limitation of this study is that it does not take into account future land-use/land-cover changes and the impact of socioeconomic conditions on water resources in river basins. Therefore, future studies need to consider the combined effects of climate change, land-use/land-cover, and the socioeconomic conditions of the Upper Blue Nile basin.

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AUTHORS’ CONTRIBUTIONS

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by G.S.T., G.S.G., A.G.G., and A.N.E. The first draft of the manuscript was written by G.S.T., and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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CONFLICT OF INTEREST

There is no conflict of interest

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

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