

Evaluating watershed hydrological responses to climate changes at Hangar Watershed, Ethiopia

Abdata Wakjira Galata, Kiyya Tesfa Tullu and Abebe Chala Guder

ABSTRACT

The aim of this study is to model the responses of Hangar Watershed hydrology to future climate changes under two representative concentration pathway (RCP) scenarios. Future changes in precipitation and temperature were produced using the output of dynamically downscaled data of a regional climate model (RCM) 0.44° resolution under RCP 4.5 and 8.5 scenarios for 2025–2055 and 2056–2086. The future projection of the RCM model of precipitation and temperatures showed an increasing trend relative to the base period (1987–2017). At 2025–2055 average annual precipitation increments of +15.7 and +19.8% were expected for RCP 4.5 and RCP 8.5, respectively. For 2056–2086 of RCP 4.5 and 8.5, a similar trend was also shown as average annual precipitation may increase by +20.1 and +23.4%, respectively. The changes of climate parameters were used as input into the SWAT hydrological model to simulate the future runoff at Hangar Watershed. The increment in precipitation projection resulted in a positive magnitude impact on average runoff flow. The average annual change in runoff at 2025–2055 of both RCP 4.5 and 8.5 may increase by +24.5 and +23.6%, respectively. In 2056–2086, a change in average annual runoff of +73.2 and +73.2% for RCP 4.5 and 8.5 may be expected, respectively.

Key words | climate change projection, CORDEX data, hydrological process, precipitation, temperature

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HIGHLIGHTS

- Climate change scenarios were reviewed and bias correction was carried out for simulated Regional Climate Model data.
- Future precipitation and temperature were projected.
- Impact of future climate changes on runoff was evaluated.

INTRODUCTION

The issues related to climate change are of prime concern for every nation around the globe in general and Africa in particular as its implications are posing negative impacts on society. The positive and negative impacts of global climate change on both the natural and social environment

are confirmed by the Intergovernmental Panel on Climate Change (IPCC) and altered stream flow in rivers (Whitehead *et al.* 2015; Vaighan *et al.* 2019). Different studies revealed that Africa, home to a wide variety of climate zones (Thomas & Nigam 2018), is highly vulnerable to climate change (Serdeczny *et al.* 2017; Abera *et al.* 2018). Water resources of Ethiopia, like many other countries of the world, are highly sensitive to climate change and variability (Dile *et al.* 2013; Chaemiso *et al.* 2016).

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There are two major reasons for global climate change: the Earth's magnetic field changes and greenhouse gases in the lower levels of Earth's atmosphere (Mikhaylov *et al.* 2020). According to Hussain *et al.* (2018), the primary cause of global climate change is greenhouse gases (GHGs), such as CO₂, CH₄, and N₂O emissions, that result in warming of the atmosphere. Increased anthropogenic activities in industries and population expansion towards forested areas has resulted in an increase of GHGs concentration in the Earth's atmosphere which has resulted in rising global surface temperature, sea level rises, arctic and land ice decrease and erratic precipitation (Abraham *et al.* 2018), conversion of natural landscapes for human use and different land management practices have transformed large portions of the Earth's land surfaces which influences the processes of infiltration, ground water recharge (Vaighan *et al.* 2019), and evapotranspiration, which in turn influences local climate. Olivier *et al.* (2019) reported that fossil CO₂ emissions are the largest source of global GHG emissions, with a share of about 72%, followed by CH₄ (19%), N₂O (6%) and fluorinated gases, so called F-gases (3%). The foremost sources of rise in the GHG emissions are human activities through fossil fuel combustion, industrial production processes, agriculture and forestry, human society, and vehicle usage (Hussain *et al.* 2018). Global climate change caused by increasing concentrations of GHGs is likely to cause intensification of the global hydrologic cycle (Abeysingha *et al.* 2020). Any changes to the land and how it is used can effect exchanges of water, energy, and GHGs between the land and the atmosphere (IPCC 2019).

The other factor that affects climate is land use and land cover change (LULCC). According to Brovkin *et al.* (2013), LULCC affects climate in two different pathways. First, through biogeophysical pathways which affect climate through alteration of the physical characteristics of the land surface such as albedo, soil moisture, and roughness; second, through biogeochemical pathways which consider alterations of the atmospheric concentrations of greenhouse gases in response to changes land-atmosphere fluxes of these trace gases. Changes in land conditions, either from land-use or climate change, affect global and regional climate. At the regional scale, changing land conditions can reduce or accentuate warming and affect the intensity, frequency and

duration of extreme events. The magnitude and direction of these changes vary with location and season (IPCC 2019).

Climate change can be a significant driver of desertification and land degradation and can affect food production, thereby influencing food security (Mbow *et al.* 2017) and it has a direct impact on the hydrological cycle which in turn starts a chain reaction impacting agriculture, energy and ecology, to name a few (Mehan *et al.* 2016). Climate change will exacerbate the impending water resources management challenge in some regions by reducing total physical water availability and altering the river flow regime (Ferguson *et al.* 2018). Evaluating the hydrological response to an increased climate change is critical for the proper management of water resources within agricultural systems. Consequently, such impacts of climate change have been widely studied, mainly using water balance models coupled with climate models (Musau *et al.* 2015). Given the vital role of water resources in socio-economic development, the potential hydrological impacts of climate change pose a significant challenge for water resource planning and management (Musau *et al.* 2015).

Climate models facilitate the understanding of how a warming climate may affect the distribution of freshwater globally. Global climate models (GCMs) can give insight into the possible future climate of an area based on emission scenarios known as representative concentration pathways (RCPs). GCMs are based on mathematical representations of the physical laws governing the Earth's climate (Hidalgo & Alfaro 2015). However, GCMs cannot accurately reproduce certain features of regional and global climate due to their coarse spatial resolution (Hidalgo & Alfaro 2015; Shiru *et al.* 2020). Therefore, the downscaling technique, which involves the transfer of large-scale changes in atmospheric variables called predictors which are simulated reliably from GCMs to local weather series, have been popularly used in their applications. The downscaling technique is broadly divided into statistical and dynamical methods. The dynamical downscaling method (DDM), which was used in this study, involves the use of limited area models (LAMs) or regional climate models (RCMs) in the production of outputs of higher resolutions, by using large-scale and lateral boundary conditions from GCMs.

Hydrological models are mainly used for predicting system behavior and understanding various hydrological

processes (Devia et al. 2015). SWAT is one of the most widely used models for simulating basin hydrology and assessing the effect of land use and climate change at basin scale (Abeyasingha et al. 2020). The model has been used by several researchers to investigate the climate change impacts on hydrology and water resources availability in different parts of the world using GCM projected climate change scenarios (Ouyang et al. 2015; Abera et al. 2018; Abeyasingha et al. 2020) For example, Ouyang et al. (2015) assessed the impacts of climate change on streamflow for the Huangnizhuang catchment (HNZ) in China using six GCMs from Coupled Model Intercomparison Project Phase 5 (CMIP5) under three RCPs, namely RCP2.6, RCP4.5 and RCP8.5, and a SWAT model to simulate the hydrological processes. The results indicated that the SWAT model performed well in the study area. Further, Bhatta et al. (2019) assessed the climate change impact on the hydrology of the complex Himalayan River Basin, based on an ensemble of CMIP5

and four RCMs under RCP4.5 and RCP8.5 scenarios using a SWAT model to simulate the future stream flows of the basin.

The objective of this study was to evaluate hydrological responses to climate changes of Hangar Watershed using a Soil and Water Assessment Tool (SWAT) and Coordinated Regional climate Downscaling Experiment over the African domain (CORDEX-Africa) Regional Climate Model (RCM) under RCP climate scenarios RCP4.5 and RCP8.5.

MATERIALS AND METHODS

Study area description

The study area is located at the upper reaches of the Didessa River basin (Figure 1). The river is fed by tributaries flowing from the north-western slopes of Jardaga Jarte district. It

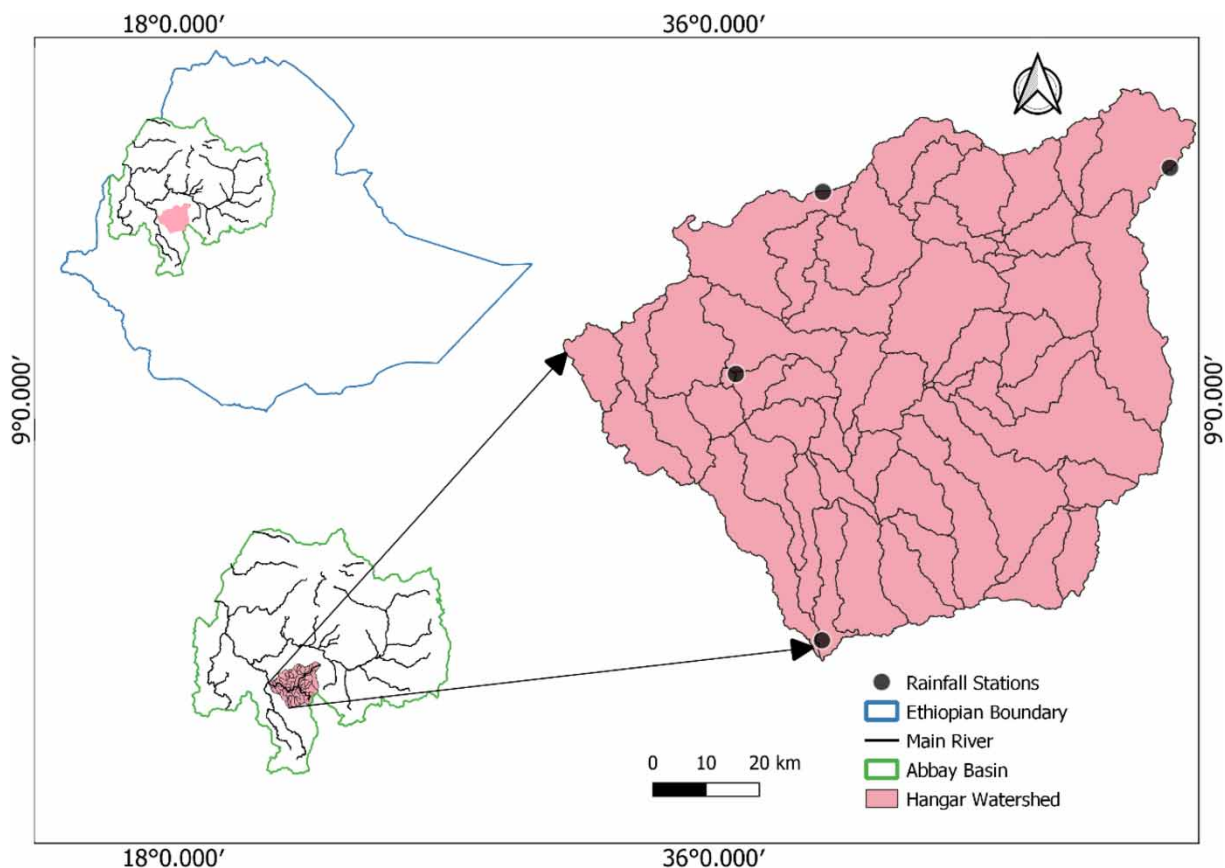


Figure 1 | Map of the study area.

drains to the southwest into the Blue Nile River. The catchment area for this study is about 7,674 km², located between longitudes 36°31'41" and 37°06'50"E, and latitudes 9°41'58" and 9°59'56"N. The area has high topographic relief characterized by steeply sloping uplands and elevation ranging from 844 to 3,207 m a.s.l. Most of the study area is covered with intrusive Precambrian rocks, mainly granite with coarse-grained texture and massive in nature, which is overlaid by thick black to brownish cotton soil. As per the data collected from the National Metrological Service Agency (NMSA), the study area receives heavy rainfall from June to September and experiences a limited amount of rainfall for the remaining seven months. Hangar Watershed experienced the average maximum temperature experienced in the months of February, March, and April whereas the average minimum temperature occurred in the months of September, October and November.

SWAT model

The Soil and Water Assessment Tool (SWAT) is a physically-based semi-distributed model that operates on a continuous time scale and was developed to assist water resource managers in assessing the impact of management on water supplies and nonpoint source pollution in watersheds and large river basins (Arnold et al. 1998). The model is process based, computationally efficient, and is capable of simulating over long time periods (Arnold et al. 2012). It is the best among the different hydrological models due to its capability for application to large-scale watersheds (>100 km²), interface with a Geographic Information System (GIS), continuous-time simulations performance, and generation of the maximum number of sub-basins and ability to characterize the watershed in enough spatial detail (Desta & Lemma 2017). The SWAT model was developed with the ability to simulate surface runoff, percolation, lateral and underground flow, evapotranspiration, snow and drainage network flow, climatic aspects, plant growth, nutrients and pesticides in agricultural practices, and water quality aspects (de Oliveira Serrão et al. 2020). This model is coupled with Arc SWAT in an ArcGIS Geographical Information System interface to process the datasets and construct the required input for the initial modeling setup. Major model

components include DEM, weather, hydrology, soil and properties and land management (Neitsch et al. 2011). In SWAT, a watershed is divided into multiple sub watersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, topographical, and soil characteristics (Arnold et al. 2012). Hydrological components are then calculated in the HRUs based on the water balance equation. Watershed simulation processes using SWAT are split into land-based phase and routing phase (channel-based phase). The land-based phase controls the loadings like runoff, sediment, nutrient and pesticides while the channel-based phase routes runoff, sediment, nutrient and pesticides throughout the stream network (Taylor et al. 2016). The hydrological components in the model are based on the water balance equation (Neitsch et al. 2011) given in Equation (1) below. Water balance is the driving force behind all the processes in SWAT because it impacts plant growth and the movement of sediments, nutrients, pesticides, and pathogens (Arnold et al. 2012):

$$SW_t = SW_0 + \sum_{i=1}^t (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \quad (1)$$

where SW_t is the final soil water content in mm H₂O, SW_0 is the initial soil water content on day i in mm H₂O, t is the time in days, R_{day} is the amount of precipitation on day i in mm H₂O, Q_{surf} is the amount of surface runoff on day i in mm H₂O, E_a is the amount of evapotranspiration on day i in mm H₂O, W_{seep} is the amount of water entering the vadose zone from soil profile on day i in mm H₂O, Q_{gw} is the amount of return flow on the day i in mm.

SWAT input data used

The SWAT model requires spatial and temporal data. Spatial data include a digital elevation model (DEM), land-use/land cover and soil data. The temporary data include hydrological data (stream flow and sediment yield) and climatic data (precipitation, temperature, solar radiation, relative humidity, and wind speed) (Welde & Gebremariam 2017). The details of the data needed to simulate the runoff in the study basin and their sources are presented in Table 1.

Table 1 | Data type used in the study

Input data	Format	Data details	Data source
DEM	Raster	12.5 m	https://www.asf.alaska.edu/sar-data/palsar/
Land use/Cover	Raster	30 m	MoWIEE
Soil	Shape file		MoWIEE
Weather Data	Text file	Data from station	NMSAE
Hydrological Data	Text file	Data from station	MoWIEE
CORDEX Data	NETCDF	50 km	https://climate4impact.eu/impactportal/data/esgsearch.jsp

MoWIE, Ministry of Water, Irrigation and Electricity of Ethiopia; NMSAE, National Meteorological Service Agency of Ethiopia.

DEM, land use/land cover and soil data

A digital elevation model (DEM) was used for the delineation and topographic characterization of the watershed. It was also used to determine the hydrological parameters of the watershed such as slope, flow accumulation, direction and stream network. These data were used as the input to the SWAT hydrological model to define the hydrological responses units. Of the total area under study, the agricultural land is the most dominant land use (68.0%), followed by range land (24.6%). Physical and chemical properties of the soil texture, water content, hydraulic conductivity, bulk density, organic carbon content, depth of horizon, and percentage of sand, silt, and clay for each soil horizon are required in the SWAT model (Desta & Lemma 2017). There are eight soil types in the study watershed: haplic alisols (38.14%), eutric leptosols (2.37%), haplic nitisols (3.6%), eutric vertisols (0.1%), dystric leptosols (12.94%), haplic acrisols (26.84%), rhodic nitisols (16.0%) and haplic arenosols (0.01%). About 66.67% of the study area is predominantly with a slope range of greater than 30%, while 22.22% of the area under study has a slope range of 8–30%.

Observed meteorological and stream flow data

The SWAT model needs full daily weather data to analyze and generate the results. The missed daily rainfall data was filled by multiple linear regression while the missed maximum and minimum daily temperature data was filled by average multiple imputation methods of the Xlstat2018 program. During data recording, inconsistency of climatic data could occur because of changes in conditions,

instrumentation, gauge location and observation practices. Before using any weather data, it is necessary to analyze and check whether it is consistent or not. For this particular study, the consistency of recorded data for four stations was checked by double mass curve and there was no need for corrections because they correlated. The three stations (Alibo, Hangar Gute, and Gelila) contain only precipitation and temperature (minimum and maximum) data. However, Nekemte station contains all climatic data such as precipitation, temperature (minimum and maximum), sunshine, relative humidity, and wind speed. Therefore, sunshine, relative humidity, and wind speed data generated for Alibo, Hangar Gute and Gelila stations were generated from Nekemte station. The parameters required for weather generator were calculated using software programs PCP STAT.exe and dew02.exe (Tibebe et al. 2017). Using daily precipitation, the program PCP STAT.exe calculated the statistical parameters of daily precipitation data, whereas the program dew02.exe calculated the average daily dewpoint temperature per month using daily air temperature and humidity data. The calculated parameters for weather generator were adjusted and added into the SWAT weather database table. Stream flow data is required for calibration and validation of the SWAT model.

Climate scenario data

A climate scenario is a representation of future climate conditions (temperature, precipitation and other climatological phenomena). Regional climate models (RCMs) provide a new opportunity for climate change effects analysis since they have a higher spatial resolution and more reliable

results on a regional scale compared to general circulation models (GCMs) (Turco *et al.* 2017). CORDEX-Africa, initiated by the World Climate Research Program (WCRP), provides an opportunity for the generation of high-resolution regional climate projections over Africa that is used to assess future impacts of climate change at regional and local scales. In this research, climate change scenarios data from the newly available CMIP5 (Kim *et al.* 2014) RCM ensemble output of CORDEX-Africa for African domain projections under RCPs 4.5 and 8.5 were used as input to the hydrological model. The Coupled Model Intercomparison Project phase 5 (CMIP5) models include parameterization of physical processes, new physical processes representation and high model resolution (Abeyasingha *et al.* 2020). CORDEX-Africa climate projections use RCPs 4.5 and 8.5 climate scenarios and RCPs represent pathways of radiative forcing, not linked with exclusive socio-economic assumption in contrary to the Special Report on Emission Scenarios (SRES) (Abera *et al.* 2018). RCPs are new climate scenarios based on emissions pathways and greenhouse gas concentrations (Vaighan *et al.* 2019). RCP scenarios have a better resolution that helps in performing regional and local comparative studies compared to previous climate scenarios, and RCP scenarios also represent an attractive potential approach for further research and assessment, including emissions mitigation and impact analysis (Van Vuuren *et al.* 2011). RCP 4.5 mid-range and RCP 8.5 high-level climate scenarios with assumed stabilization of radiative forcing to 4.5 and 8.5 W/m² by 2,100 respectively (Riahi *et al.* 2011) were expected to capture a reasonable range in climatic and hydrological projections. RCP 4.5 is a mid-range scenario that stabilizes radiative forcing at 4.5 W/m² (approximately 650 ppm CO₂-equivalent) in the year 2100 without exceeding this value (Riahi *et al.* 2011; Van Vuuren *et al.* 2011), whereas RCP 8.5 is upper bound of all RCP scenarios that stabilizes radiative forcing at 8.5 W/m² (greater than 1,370 ppm CO₂-equivalent) in the year 2100 (Riahi *et al.* 2011). Therefore, in this study, the results of CORDEX-Africa ensemble RCM simulations for the historical and future climate projections under RCP 4.5 mid-range and RCP 8.5 high-level climate scenarios with a spatial resolution of 50 km (0.44°) were used and four grid points were considered for this study area. The RCM used in this study was RCA4.

The future scenario period (2025–2086) and historical/baseline scenario period (1987–2017) were considered to evaluate patterns of change in the climate data. The RCM climate data outputs in CORDEX-Africa under emission scenarios RCP 4.5 and 8.5 were bias corrected for application in the SWAT hydrological model for climate change impact studies in the Hanger Watershed. Bias correction was considered for precipitation, as well as minimum and maximum temperatures. Other weather variables, including solar radiation, relative humidity and wind speed, in the baseline period were considered in the future scenarios without making any change as the changes in these variables may not have a significant impact in modelling the climate change scenarios on local hydrology (Gadissa *et al.* 2018).

Bias correction

Bias correction is a statistical method that is used to correct the climate model's outputs deviation from observed data. This approach is commonly used to adjust simulated climate data at an appropriate spatial and temporal scale to use in hydrological modeling. Numerous studies have shown that RCM outputs improve the representation of climate change information at the mesoscale by providing spatially and physically coherent outputs with observations (Chen *et al.* 2013). However, the original RCM outputs still contain considerable bias, which is inherited from the forcing of GCMs or is produced by systematic model error (Herrera *et al.* 2010). Furthermore, such biases may be amplified when climate change effects are included, such as in hydrological effect studies (Chen *et al.* 2013). Therefore, bias correction of RCM data is the prerequisite step to the data being used in any climate change effects analysis. Many bias correction methods, ranging from simple scaling techniques to the rather more sophisticated distribution mapping techniques, have been developed to correct biased RCM outputs (Teutschbein & Seibert 2012). The scaling approach mainly includes linear or nonlinear approaches that adjust the climatic factors based on the differences between observed and RCM means in a linear or nonlinear formula, such as the linear scaling method (LS) (Crochemore *et al.* 2016) and the power transpiration method (PT) (Lenderink *et al.* 2007). For this study the

linear scaling method served as a basis for the precipitation and temperature corrections before using CORDEX-RCM outputs for a climate impact study, because the linear scaling method is the simplest bias correction method. The multiplicative correction approach was applied to precipitation. In this case, the ratio of the mean monthly observed precipitation and that of the model is used to scale model data at each time step (Equation (2)). Temperature was corrected by the additive correction approach under linear scaling. The mean monthly difference of the model and observed data was calculated and added to the model data at each time step (Equation (3)). Hence, the projected values of climate variables after bias correction were used in the Soil and Water Assessment Tool (SWAT) hydrological model to estimate the runoff in the basin. The linear scaling approach can be defined as:

$$P_{cor} = P_{unc} * \frac{\bar{P}_{obs}}{\bar{P}_{rcm}} \quad (2)$$

$$T_{cor} = T_{unc} + (\bar{T}_{obs} - \bar{T}_{rcm}) \quad (3)$$

where P_{cor} is corrected precipitation, P_{unc} is uncorrected precipitation, \bar{P}_{obs} and \bar{P}_{rcm} are the mean value of observed and simulated precipitation, respectively, and $T_{corrected\ temperature}$, T_{unc} is uncorrected temperature, \bar{T}_{obs} and \bar{T}_{rcm} are the mean values of observed and simulated temperature, respectively (Gadissa et al. 2018).

SWAT model set-up

The SWAT model was designed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying conditions over long periods of time (Arnold et al. 2012). It used spatial data such as land use, soil, and slope to create different hydrologic response units (HRUs) analysis systems. In order to delineate the sub-basins networks, a critical threshold value is required to define the minimum drainage area required to form the origin of a stream. As Vilaysane et al. (2015) indicated, the smaller the threshold area, the more detailed the drainage networks and the number of sub-basins and HRUs. The multiple scenarios that account for 15% land use, 15% soil and 15% slope threshold combination give a better estimation of runoff (Gashaw et al. 2018). Taking the objective of the study into consideration and paying attention to characteristics of

HRUs as the key factors affecting the runoff, a land use, soil and slope class threshold of 10, 15, and 15% were used, respectively. Hence, the Hangar River basin results in 196 HRUs in the whole basin. Categorizing sub-basins into HRUs increases accuracy and provides a much better physical description (Nobert & Jeremiah 2012). Spatial scale data such as land use/land cover, soil and slope were defined and analyzed in HRU analysis. The prepared soil layers, classified LULC and slope layers and delineated watershed by Arc SWAT were overlapped 100%. The input to the model is finalized and the output is generated and read after running the model in the SWAT simulation.

Parameter sensitivity analysis

Sensitivity analysis is the process of determining the rate of change in model output with respect to changes in model inputs (parameters) (Moriassi et al. 2007). It is a necessary process to identify key parameters and parameter precision required for calibration and validation of the SWAT model. For this study, to identify the most important SWAT parameters, at the beginning 18 flow parameters were selected from SWAT-CUP (Absolute_SWAT_Value.txt). In the SWAT-CUP, sensitivity analysis of parameters can be performed in two ways: Global sensitivity analysis which allows changing each parameter at a time and one-at-a-time sensitivity analysis which performs one parameter at a time only (Arnold et al. 2012). For this purpose, global sensitivity analysis was employed in SWAT-CUP 2012. The measure and significance of sensitivity were provided by indices such as t -stat and p -value, respectively (Abbaspour 2012; Chaibou Begou et al. 2016) where a higher t -test in absolute values measures high sensitivity and zero p -value represents more significance.

Uncertainty analysis

As Yang et al. (2008) suggested, uncertainties in distributed models may arise from model input uncertainty, conceptual model (structural uncertainty), parameter uncertainty and response uncertainty. To obtain a good result and support decisions about alternative management strategies in the areas of land use and land cover change, climate change, water allocation, and pollution control, it is important that

the model passes through a careful calibration and uncertainty analysis. For this study uncertainty analysis was carried out through an SUFI-2 algorithm which performed parameter uncertainty and accounted for all uncertainty.

Model calibration and validation

Calibration is the tuning or adjustment of model parameters and their values, within the recommended ranges, to optimize the model output so that it matches with the measured set of data (Vilaysane et al. 2015). These parameters could be adjusted manually or new parameters of past iteration would be copied from New_pars.txt to par_inf.txt for the continued iteration until the model output best matches with the observed data. This involves comparing the model results, generated with the use of historic meteorological data, to recorded stream flows. This study used the Sequential Uncertainty Fitting-2 (SUFI-2) algorithm in SWAT-CUP 2012 for calibrating model outputs using gauged stream flow. The validation is the process of determining the degree to which a model or simulation is an accurate representation of the observed set of data from the perspective of the intended uses of the model (Abraham et al. 2007). It is a comparison of the model outputs with an independent dataset without further adjustment of the values of the parameters (Abraham et al. 2007). The process continued until the simulation of validation period of the stream flows confirmed that the model performs satisfactorily. Therefore, in this study, calibration and validation were carried out using 25 years (1987–2011) of daily-observed flow data. The data was divided into model warm-up (1987–1989), calibration (1990–2002) and validation (2003–2011) periods. For a better parameterization of the SWAT model and to reduce the model output uncertainty (Gashaw et al. 2018), a longer calibration period was used.

Standard regression statistics like coefficient of determination (R^2) and Nash–Sutcliffe efficiency (NSE) determine

the strength of the linear relationship between simulated and measured data (Moriassi et al. 2007). R^2 ranges from zero to one, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable (Santhi et al. 2001; Van Liew et al. 2007). NSE ranges between $-\infty$ and one, with $NSE = 1$ being the optimal value. Values between zero and one are generally viewed as acceptable levels of performance, whereas values less than zero indicates that the mean observed value is a better predictor than the simulated value, which shows unacceptable performance (Moriassi et al. 2007). Percent bias (PBIAS) measures the average tendency of the simulated data to be larger or smaller than their observed counterparts in which the optimal value of PBIAS is 0.0, with low-magnitude values indicating accurate model simulation (Gupta et al. 1999). The SWAT model evaluation guideline based on performance rating is given in Table 2. Hence, for this study, the performance of the SWAT model was checked using values of coefficients of determination (R^2), Nash–Sutcliffe efficiency (NSE) and percent bias (PBIAS) based on their performance rating (Table 2). These statistics were calculated using Equations (4)–(6):

$$R^2 = \frac{\sum_{i=1}^n [(Q_{mi} - \bar{Q}_m)(Q_{si} - \bar{Q}_s)]^2}{\sqrt{\sum_{i=1}^n (Q_{mi} - \bar{Q}_m)^2 \sum_{i=1}^n (Q_{si} - \bar{Q}_s)^2}}; 0 \leq R^2 \leq 1 \quad (4)$$

$$NSE = 1 - \frac{\sum_{i=1}^n [(Q_{mi} - \bar{Q}_{si})]^2}{\sum_{i=1}^n [(Q_{mi} - \bar{Q}_m)]^2}; -\infty \leq NSE \leq 1 \quad (5)$$

$$PBIAS = 100 \left(\frac{\sum_{i=1}^n Q_{mi} - \sum_{i=1}^n Q_{si}}{\sum_{i=1}^n Q_{mi}} \right) \quad (6)$$

Table 2 | Reported performance ratings for R^2 , NSE and PBIAS for SWAT model

Modeling phase	R^2	NSE	PBIAS	Performance rating
Calibration and validation	$0.75 < R^2 \leq 1.00$	$0.75 < NSE \leq 1.00$	$PBIAS \leq \pm 10$	Very good
Calibration and validation	$0.65 < R^2 \leq 0.75$	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS \leq \pm 15$	Good
Calibration and validation	$0.50 < R^2 \leq 0.65$	$0.50 < NSE \leq 0.65$	$\pm 15 \leq PBIAS \leq \pm 25$	Satisfactory

Source: Van Liew & Garbrecht (2003).

In the above equations, Q_m is the measured discharge, Q_s is the simulated discharge, \bar{Q}_m is the average measured discharge, and \bar{Q}_s is the average simulated discharge (Dibaba et al. 2020).

FINDINGS AND DISCUSSION

Sensitivity analysis

The SWAT model generated an output which was processed using land use land cover, soil, slope and metrological data as an input. The model output needs analysis under the changed parameter, after which hydrological responses to climate change could be discussed. The sensitivity of output of the SWAT model to changes in the parameters was studied under sensitivity analysis. Parameter sensitivity analysis helps focus the calibration and uncertainty analysis and is used to provide statistics for goodness-of-fit (Arnold et al. 2012).

Because of the involvement of a wide range of data and parameters in the simulation process, calibration of outputs of large hydrological models like SWAT was quite a bulky task (Shimelash et al. 2018). Hence, sensitivity analysis minimizes the number of parameters to be used in the calibration and/or validation iteration and shortens the time required for it by identifying the most sensitive parameters largely controlling the behavior of the simulated process (Zeray et al. 2006). Sensitive parameters are selected randomly at the beginning of calibration and modified looking at their degree of sensitivity in SWAT-CUP SUFI2 from global sensitivity at the end of each iteration. The success of the calibration is due to the physical factors of the model input data (soil types, climate, and land use) and the dependence on the sensitivity analysis and calibration of the model (de Oliveira Serrão et al. 2020). Galata et al. (2020) pointed out that due to deforestation and grazing, types of soils in these basins facilitate the water processes of surface runoff. With regard to metrology, more specifically the availability of water is due to precipitation, favoring the water processes mentioned. Regarding land use, most of the watershed is occupied by agricultural processes and the more homogeneous, the better for

modeling (Arnold et al. 2012). For the case of sensitivity analysis and calibration of the model, the relevant parameters in the sub-basins are parameterized based on the available data, literature and modeler's experience. According to Abbaspour et al. (2015, 2018), the sensitivity analysis was carried out using 18 SWAT parameters and goodness-of-fit was reached with the 13 most sensitive parameters controlling the output variable. Based on Desta & Lemma (2017), the 13 most sensitive parameters are ranked based on the t -stat and p -value in the study area (Table 3).

SWAT model calibration and validation

The model generated output using model input parameters which remained within a realistic uncertainty range (Arnold et al. 2012). Therefore, to obtain the physical knowledge of the watershed, calibration was carried out using SWAT-CUP (SWAT-Calibration and Uncertainty Programs) through Sequential Uncertainty Fitting-2 (SUFI-2). The SWAT model output was calibrated using 13 years of measured streamflow data (1990–2002). The obtained R^2 , NSE and PBIAS value during calibration were 0.87, 0.82 and +1.4 respectively. For the catchment with a long time series a split sample test is involved (Shimelash et al. 2018) for which one part is used to calibrate the model, and the

Table 3 | Sensitivity rank of hydrological parameters

No	Parameter name	t-stat	p-value	Rank of sensitivity
1	r_CANMX.hru	1.63	0.13	3
2	r_REVAPMN.gw	0.58	0.57	10
3	r_SOL_ALB.sol	0.01	0.99	13
4	r_CN2.mgt	-4.53	0	1
5	v_ALPHA_BF.gw	0.94	0.37	7
6	v_GW_DELAY.gw	1.31	0.22	4
7	v_GWQMN.gw	-0.82	0.43	8
8	v_GWQMN.gw	-0.97	0.35	6
9	v_GWQMN.gw	-0.2	0.85	12
10	r_ALPHA_BNK.rte	0.7	0.5	9
11	r_SOL_AWC.sol	0.46	0.65	11
12	r_SURLAG.bsn	-2.02	0.07	2
13	r_EPCO.hru	1.23	0.24	5

second part is used for testing (validating) if calibrated parameters produced simulations which satisfy goodness-of-fit tests. Therefore, since it has 31 years of data, the split sample test was applied in this watershed for which measured streamflow data of 22 years was scaled 60% (1990–2002) for calibration to 40% (2003–2011) for validation. The values of R^2 , NSE and PBIAS obtained during validation were 0.89, 0.88 and +1.2. R^2 is used to evaluate the accuracy of the simulated value when compared with the observed values, whereas the goodness-of-fit is measured with NSE (Shimelash *et al.* 2018). In general, the performance indices gained during the calibration and validation periods indicated an acceptable performance rate of the model in simulating the hydrological impacts of climate change at Hangar Watershed (Figure 2).

Base period climate projection

In addition to the observed metrological data, the down-scaled RCM climate data was used to evaluate the hydrological responses to climate change. The comparison of average monthly projected minimum and maximum temperature and precipitation data with respect to observed data showed uniformity pattern. For the minimum and maximum temperature the coefficient of determination R^2 is 0.89 and 0.92 respectively, whereas it is 0.99 for precipitation (Figure 3).

Except for differences in the approaches and model used, the study carried out by Teye *et al.* (2011) indicated

that the average climate projection output resembled the observed climate variables for the base period over the Nile River basin. This similarity indicated that the output of RCM simulated the reality of the observed temperature and precipitation in a good manner with a small amount of over estimation and under estimation.

Future climate change projection

Precipitation

The results of analysis showed an increasing average monthly precipitation for both RCP 4.5 and 8.5 scenarios except during the months of January, March and September as compared to the base line period. The decrease in average monthly precipitation in January and March showed that they are categorized under the months of the dry season and short rainy season respectively in Ethiopia. For 2025–2055, average projected seasonal precipitation change varied from +9.8 to +25.8% and +12.1 to +27.3% for RCPs 4.5 and 8.5 respectively. The maximum expected precipitation change was projected to be higher in dry seasons (October–February) and in short rainy seasons (March–May) than in wet seasons (June–September). During dry and short rainy seasons different parts of the country gain rainfall varying in volume that made changes greater. In contrast, the months from June to September are known as the rainy season in Ethiopia when the study area received an almost uniform amount of precipitation that

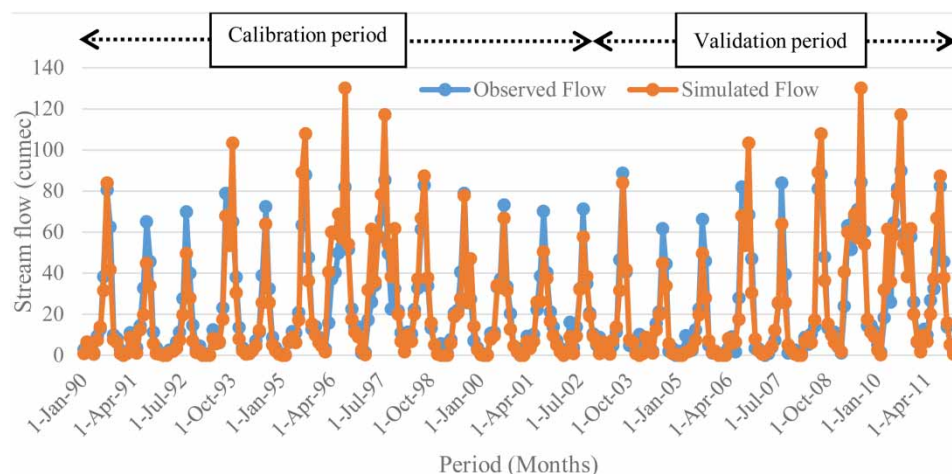


Figure 2 | Graph of calibration and validation results of observed flow versus simulated flow.

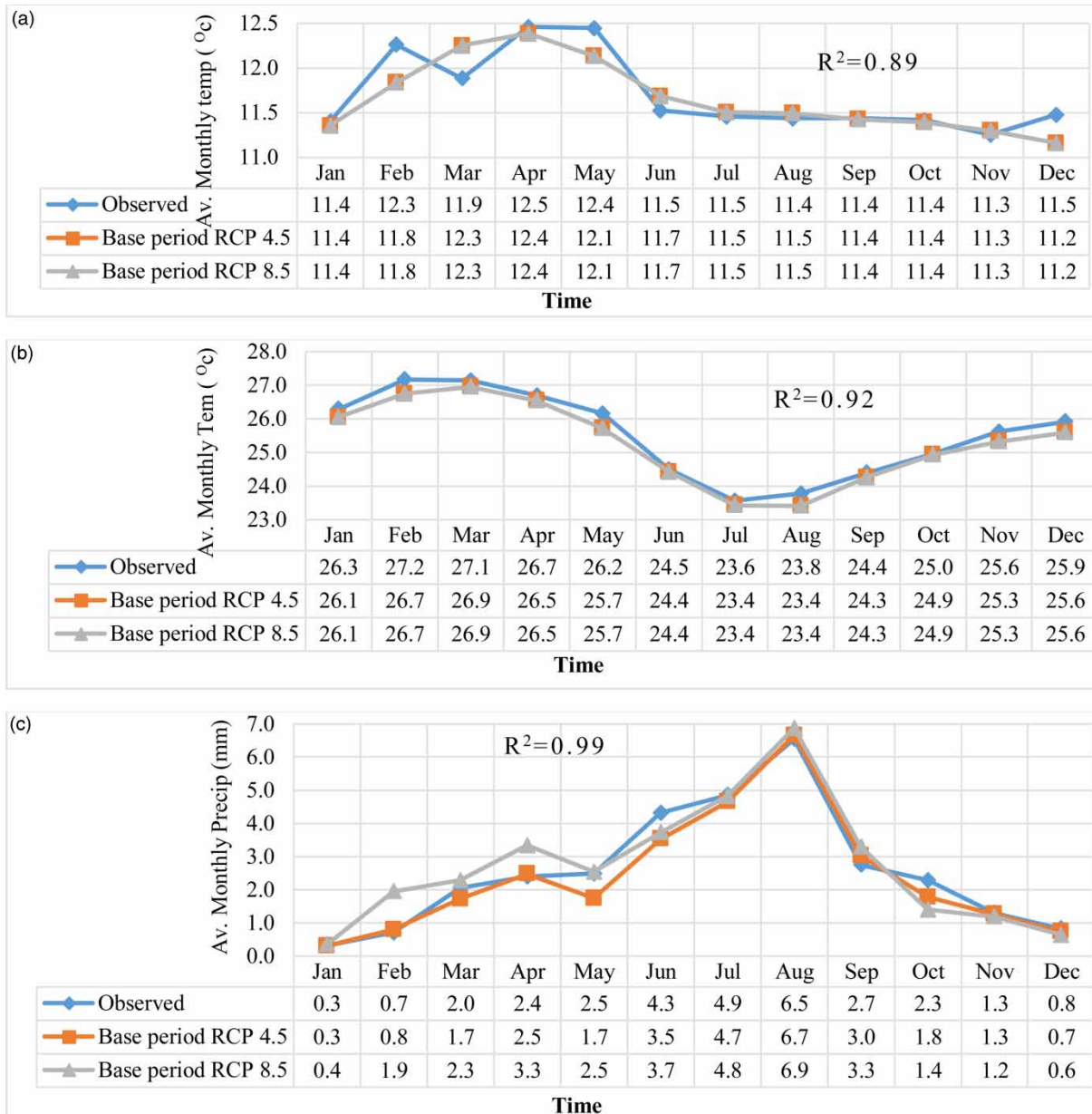


Figure 3 | Comparison of average monthly observed and projected minimum (a), maximum temperature (b) and precipitation (c) during base period (1987–2017) at Hangar Watershed.

resulted in the small precipitation difference. In 2056–2086 the average seasonal precipitation change of +15.7 to +30.3% and +15.5 to 38.9% is expected for RCPs 4.5 and 8.5, respectively (Figure 4). The results discussed in this study are within the range of other studies which projected and presented over the Didessa catchment, the difference is the methodology and model they used (Gebre et al. 2015).

Temperature

Minimum temperature

The trend of minimum temperature showed an increase in both scenario projections where the maximum percentage change is expected in the months of February and December. Relatively, the minimum percentage change of

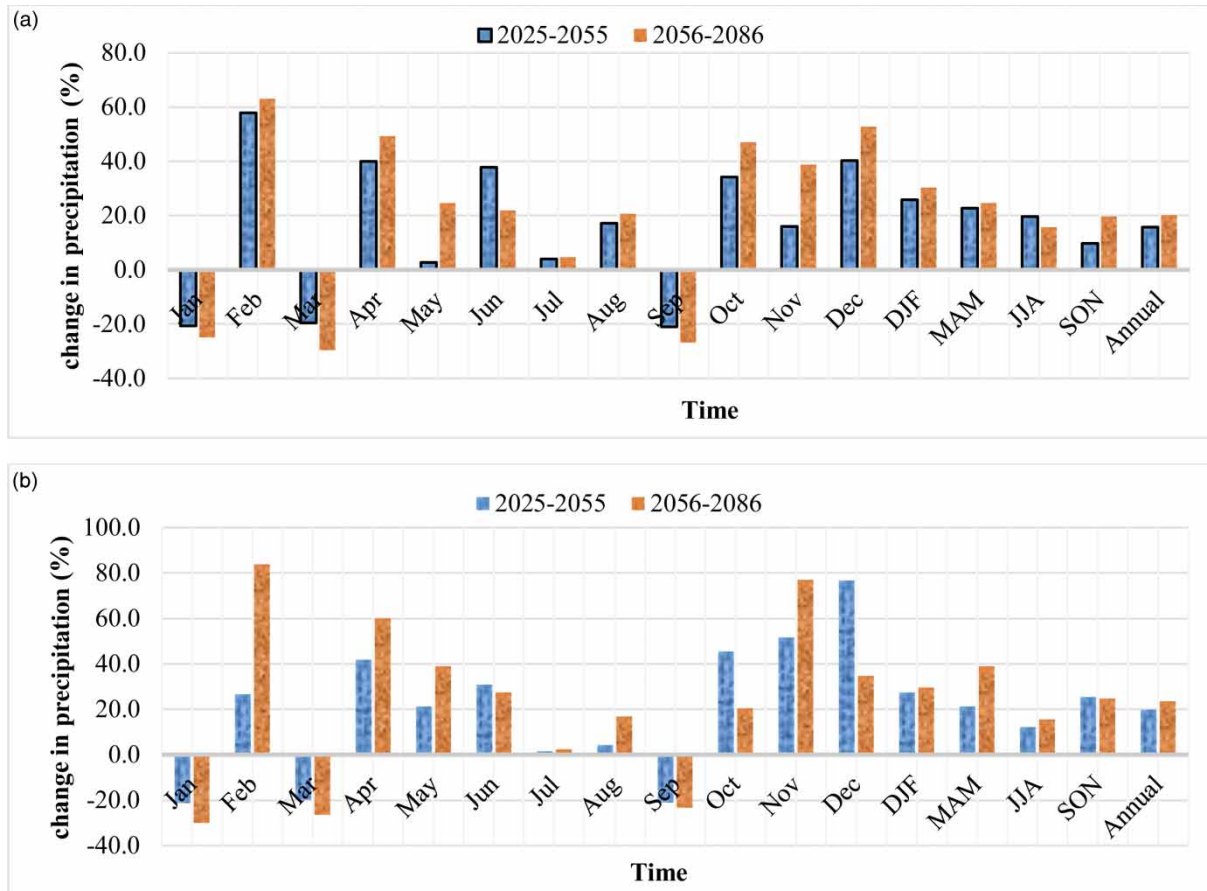


Figure 4 | Change of projected average precipitation for 2025–2055 and 2056–2086 with respect to the base period (1987–2017) at Hangar watershed under RCP 4.5 (a) and RCP 8.5 (b) scenarios.

temperature is expected in November for both climate periods of RCPs. During November, the average monthly minimum temperature change expectation varied from +5.2 to +5.8% and +6.1 to +6.9% at both climate projection horizons for RCPs 4.5 and 8.5, respectively. For RCP 4.5 in 2056–2086, the maximum percentage change is +9.9 and +9.2% in February and December, respectively. The maximum percentage change projected in February and December are +9.6 and +9.5% respectively for 2056–2086 for RCP 8.5 (Figure 5).

Maximum temperature

The projected percentage change of average monthly maximum temperature also showed an increasing trend. In 2025–2055 and 2056–2086 for RCP 4.5, the average monthly

change in maximum temperature varied from +2.1 to +7.4% and +2.7 to 9.7%, respectively. For RCP 8.5 the change in average monthly maximum temperature ranges from +2.6 to +8.6% and from +3.2 to +9.8% in 2025–2055 and 2056–2086, respectively. The projected minimum and maximum temperature in both future time horizons of RCPs for the watershed is consistent with the projection presented by other researchers over the Blue Nile River basin (Setegn et al. 2011) (Figure 6).

Future impacts of climate change on runoff

A change in climate parameters, especially temperature and precipitation, have had significant impacts on the amount of runoff. Figure 7 shows the projected average monthly runoff increases varying from +2.3 to +75.6%, and from -0.4 to

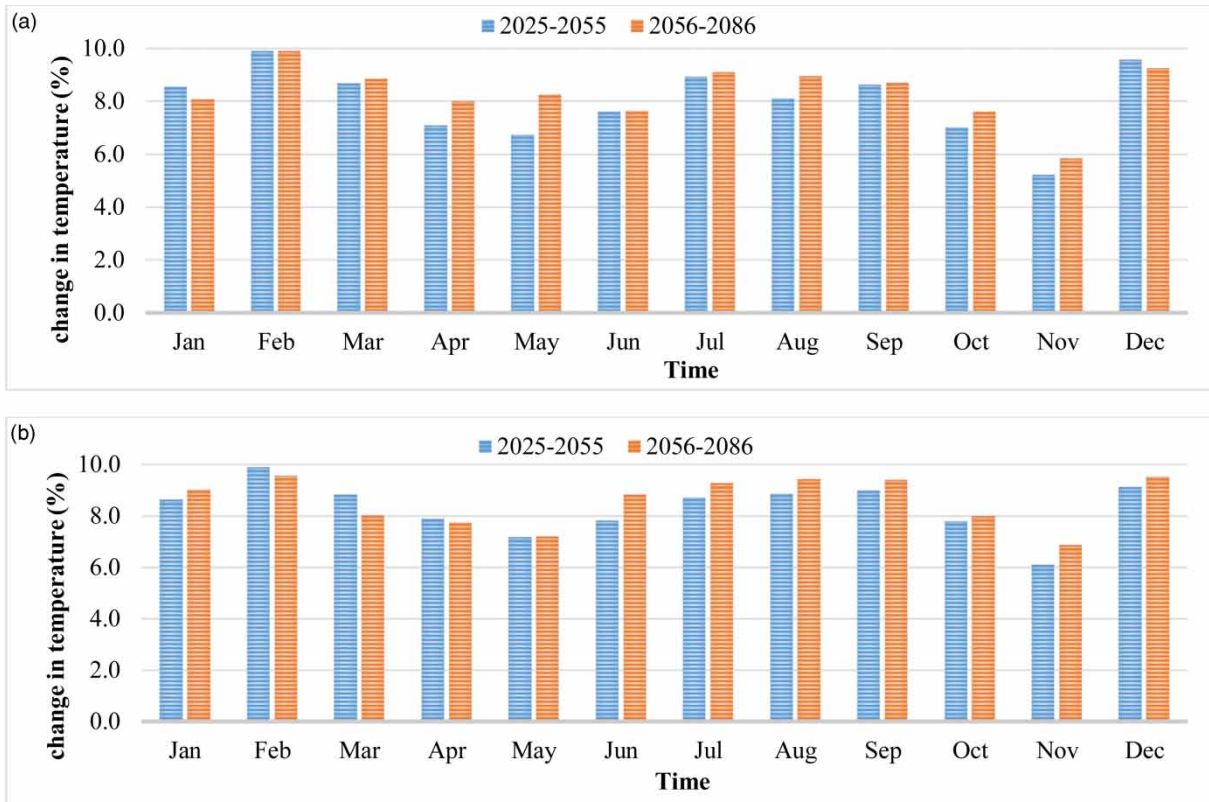


Figure 5 | Change of projected mean minimum temperature for 2025–2055 and 2056–2086 with respect to the base period (1987–2017) at Hangar Watershed under RCP 4.5 (a) and RCP 8.5 (b) scenarios.

+90.5% at 2025–2055 and 2056–2086 for RCP 4.5 respectively as compared to the base line period (1987–2017). In 2025–2055 and 2056–2086 for RCP 8.5, the average monthly runoff also showed an increase ranging from +0.4 to +87.9% and –22.1 to +75.6%, respectively. Generally, average seasonal runoff projection showed that runoff increases in most of the months, especially during wet seasons (June–July–August). The increase in projected runoff is expected due to increases in precipitation. Average annual runoff may be expected to increase by +24.5 and +73.2% in 2025–2055 and 2056–2086 of RCP 4.5 respectively compared to the base line period (1987–2017). Similarly, in 2025–2055 and 2056–2086 for RCP 8.5, the runoff increments of +23.6 and +73.2% respectively are expected compared to the base line period (Figure 8). Relatively, for both RCP scenarios for 2056–2086 the percentage change of runoff increased. The increment will be expected due to expansion of urbanization that can result in impervious land. Surface runoff increases more in impervious/paved

land than in unpaved land. The average seasonal and annual increment of runoff due to climate change at Hangar Watershed is in line with other researcher projected presentations over Didessa catchment (Gebre et al. 2015).

CONCLUSIONS

This study assessed the effects of climate change on the hydrology of Hangar Watershed for 2025–2055 and 2056–2086 under (RCM) RCPs 4.5 and 8.5 climate scenarios using a SWAT hydrological model to simulate runoff. Future projections of temperature and precipitation produced an increasing trend in both future periods of RCPs as compared to the base period. A change in climate variables (temperature and precipitation) has significant impacts on the magnitude of runoff. Generally, average seasonal and annual runoff projection showed an increase. Average annual runoff may increase by +24.5 and +23.6%



Figure 6 | Change of projected mean maximum temperature for 2025–2055 and 2056–2086 with respect to the base period (1987–2017) at Hangar Watershed under RCP 4.5 (a) and RCP 8.5 (b) scenarios.

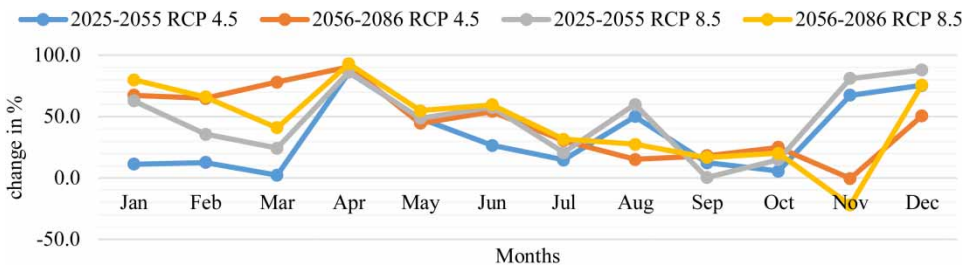


Figure 7 | Change in projected mean monthly runoff for both 2025–2055 and 2056–2086 for RCPs 4.5 and 8.5.

in 2025–2055 for RCPs 4.5 and 8.5 and by +23.6 and +73.2% in 2056–2086 for RCPs 4.5 and 8.5 respectively compared to the base line period (1987–2017). These results indicated that the changes in temperature and precipitation due to climate change may result in increasing runoff of Hangar Watershed. However, there are many sources of uncertainty during downscaling of climate and the

simulation of hydrological models. Hence, the findings of this study should be accepted with care and be considered as an indicator of the future expectation rather than accurate predictions. The calibrated model and results provide information support to lay the basis for further assessment of the impact of climate change on water availability and quality of the Hangar Watershed. This study may be useful for

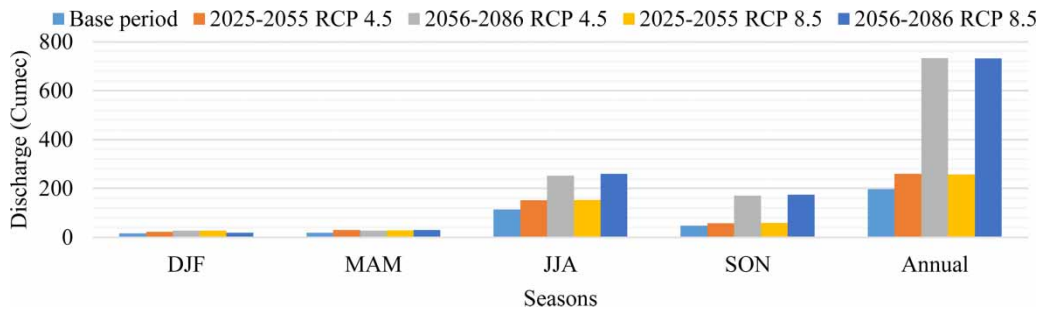


Figure 8 | Comparison of mean seasonal and annual runoff for both 2025–2055 and 2056–2086 for RCPs 4.5 and 8.5 as compared to the base period (1987–2017).

planning sustainable management and decision-making to assist future public policies in designing and implementing different water resources schemes. For this study, only two climate scenarios of RCM were used and the hydrological model did not consider land use land cover changes for different periods during the simulations. However, it is expected that changes in land use and land cover may interact with climate leading to different projections of future hydrological conditions. Therefore, future research needs to be conducted on related topics and should include land use and land cover changes explicitly.

DATA AVAILABILITY STATEMENT

All relevant CORDEX data are available from an online repository or repositories (<https://climate4impact.eu/impactportal/data/esgfsearch.jsp>).

REFERENCES

- Abbaspour, K. C. 2012 *SWAT-CUP-2012: SWAT Calibration and Uncertainty program—A User Manual*. Swiss Federal Institute of Aquatic Science and Technology, Dübendorf.
- Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H. & Klove, B. 2015 A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology* **524**, 733–752.
- Abbaspour, K. C., Vaghefi, S. A. & Srinivasan, R. 2018 A guideline for successful calibration and uncertainty analysis for soil and water assessment: a review of papers from the 2016 International SWAT Conference. *Water* **10** (1), 1–18.
- Abera, F. F., Asfaw, D. H., Engida, A. N. & Melesse, A. M. 2018 Optimal operation of hydropower reservoirs under climate change: the case of Tekeze reservoir, Eastern Nile. *Water* **10** (3), 1–18.
- Abeysingha, N. S., Islam, A. & Singh, M. 2020 Assessment of climate change impact on flow regimes over the Gomti River basin under IPCC AR5 climate change scenarios. *Journal of Water and Climate Change* **11** (1), 303–326.
- Abraham, L. Z., Roehrig, J. & Chekol, D. A. 2007 Calibration and validation of SWAT hydrologic model for Meki watershed, Ethiopia. In: *Conference on international agricultural research for development*, University of Kassel-Witzenhausen and University of Göttingen, 9–11 October 2007.
- Abraham, T., Woldemicheala, A., Muluneha, A. & Abateb, B. 2018 Hydrological responses of climate change on Lake Ziway catchment, Central Rift Valley of Ethiopia. *Journal of Earth Science and Climatic Change* **9** (474), 1–16.
- Arnold, J. G., Srinivasan, R., Muttiah, R. S. & Williams, J. R. 1998 Large area hydrologic modeling and assessment part I: model development 1. *JAWRA Journal of the American Water Resources Association* **34** (1), 73–89.
- Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Van Griensven, A., Van Liew, M. W. & Kannan, N. 2012 *SWAT: Model use, calibration, and validation*. *Transactions of the ASABE* **55** (4), 1491–1508.
- Bhatta, B., Shrestha, S., Shrestha, P. K. & Talchabhadel, R. 2019 Evaluation and application of a SWAT model to assess the climate change impact on the hydrology of the Himalayan River Basin. *Catena* **181**, 104082.
- Brovkin, V., Boysen, L., Arora, V. K., Boisier, J. P., Cadule, P., Chini, L., Claussen, M., Friedlingstein, P., Gayler, V., Van Den Hurk, B. J. J. M. & Hurtt, G. C. 2013 Effect of anthropogenic land-use and land-cover changes on climate and land carbon storage in CMIP5 projections for the twenty-first century. *Journal of Climate* **26** (18), 6859–6881.
- Chaemiso, S. E., Abebe, A. & Pingale, S. M. 2016 Assessment of the impact of climate change on surface hydrological processes using SWAT: a case study of Omo-Gibe river basin, Ethiopia. *Modeling Earth Systems and Environment* **2** (4), 1–15.
- Chaibou Begou, J., Jomaa, S., Benabdallah, S., Bazie, P., Afouda, A. & Rode, M. 2016 Multi-site validation of the SWAT model

- on the bani catchment: model performance and predictive uncertainty. *Water* **8** (5), 178.
- Chen, J., Brissette, F. P., Chaumont, D. & Braun, M. 2013 Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins. *Journal of Hydrology* **479**, 200–214.
- Crochemore, L., Ramos, M.-H. & Pappenberger, F. 2016 Bias correcting precipitation forecasts to improve the skill of seasonal streamflow forecasts. *Hydrology and Earth System Sciences* **20**, 3601–3618.
- de Oliveira Serrão, E. A., Silva, M. T., Ferreira, T. R., da Silva, V. D. P. R., de Sousa, F. D. S., de Lima, A. M. M., de Ataides, L. C. P. & Wanzeler, R. T. S. 2020 Land use change scenarios and their effects on hydropower energy in the amazon. *Science of the Total Environment* **744**, 140981.
- Desta, H. & Lemma, B. 2017 SWAT based hydrological assessment and characterization of Lake Ziway sub-watersheds, Ethiopia. *Journal of Hydrology: Regional Studies* **13**, 122–137.
- Devia, G. K., Ganasri, B. P. & Dwarakish, G. S. 2015 A review on hydrological models. *Aquatic Procedia* **4**, 1001–1007.
- Dibaba, W. T., Demissie, T. A. & Miegel, K. 2020 Watershed hydrological response to combined land use/land cover and climate change in highland Ethiopia: finchaa catchment. *Water* **12** (6), 1–25.
- Dile, Y. T., Berndtsson, R. & Setegn, S. G. 2013 Hydrological response to climate change for Gilgelabay River, in the Lake Tana basin-upper Blue Nile Basin of Ethiopia. *PLoS One* **8** (10), 1–13.
- Ferguson, C. R., Pan, M. & Oki, T. 2018 The effect of global warming on future water availability: CMIP5 synthesis. *Water Resources Research* **54** (10), 7791–7819.
- Gadissa, T., Nyadawa, M., Behulu, F. & Mutua, B. 2018 The effect of climate change on loss of lake volume: case of sedimentation in central rift valley basin, Ethiopia. *Hydrology* **5** (4), 1–18.
- Galata, A. W., Demissei, T. & Leta, M. K. 2020 Watershed hydrological responses to changes in land use and land cover at Hangar Watershed, Ethiopia. *Iranian (Iranica) Journal of Energy & Environment* **11** (1), 79–85.
- Gashaw, T., Tulu, T., Argaw, M. & Worqlul, A. W. 2018 Modeling the hydrological impacts of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia. *The science of the Total Environment* **619**, 1394–1408.
- Gebre, S. L., Tadele, K. & Mariam, B. G. 2015 Potential impacts of climate change on the hydrology and water resources availability of Didessa Catchment, Blue Nile River Basin, Ethiopia. *Journal of Geology and Geosciences* **4**, 1–7.
- Gupta, H. V., Sorooshian, S. & Yapo, P. O. 1999 Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering* **4** (2), 135–143.
- Herrera, S., Fita, L., Fernández, J. & Gutiérrez, J. 2010 Evaluation of the mean and extreme precipitation regimes from the ensembles regional climate multimodel simulations over Spain. *Journal of Geophysical Research: Atmospheres* **115**, D21117.
- Hidalgo, H. G. & Alfaro, E. J. 2015 Skill of CMIP5 climate models in reproducing 20th century basic climate features in Central America. *International Journal of Climatology* **35** (12), 3397–3421.
- Hussain, M., Liu, G., Yousaf, B., Ahmed, R., Uzma, F., Ali, M. U., Ullah, H. & Butt, A. R. 2018 Regional and sectoral assessment on climate-change in Pakistan: social norms and indigenous perceptions on climate-change adaptation and mitigation in relation to global context. *Journal of Cleaner Production* **200**, 791–808.
- IPCC 2019 *Climate Change and Land 2019: Special Report on Climate Change, Desertification, Land, Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems*. Cambridge University Press, Cambridge, UK. <https://ipcc.ch/report/srccl>
- Kim, J., Waliser, D. E., Mattmann, C. A., Goodale, C. E., Hart, A. F., Zimdars, P. A., Crichton, D. J., Jones, C., Nikulin, G., Hewitson, B. & Jack, C. 2014 Evaluation of the CORDEX-Africa multi-RCM hindcast: systematic model errors. *Climate Dynamics* **42** (5), 1189–1202.
- Lenderink, G., Buishand, A. & Deursen, W. V. 2007 Estimates of future discharges of the river rhine using two scenario methodologies: direct versus delta approach. *Hydrology and Earth System Sciences* **11**, 1145–1159.
- Mbow, H. O. P., Reisinger, A., Canadell, J. & O'Brien, P. 2017 *Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems (SR2)*. IPCC, Geneva.
- Mehan, S., Kannan, N., Neupane, R. P., McDaniel, R. & Kumar, S. 2016 Climate change impacts on the hydrological processes of a small agricultural watershed. *Climate* **4** (4), 1–22.
- Mikhaylov, A., Moiseev, N., Aleshin, K. & Burkhardt, T. 2020 *Global climate change and greenhouse effect*. *Entrepreneurship and Sustainability Issues* **7** (4), 2897–2913.
- Moriassi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D. & Veith, T. L. 2007 Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50** (3), 885–900.
- Musau, J., Sang, J., Gathenya, J. & Luedeling, E. 2015 Hydrological responses to climate change in Mt. Elgon watersheds. *Journal of Hydrology: Regional Studies* **3**, 233–246.
- Neitsch, S. L., Arnold, J. G., Kiniry, J. R. & Williams, J. R. 2011 *Soil and Water Assessment Tool Theoretical Documentation Version 2009*. Texas Water Resources Institute, Texas.
- Nobert, J. & Jeremiah, J. 2012 Hydrological response of watershed systems to land use/cover change. a case of Wami River Basin. *The Open Hydrology Journal* **6** (1), 78–87.
- Olivier, J. G., Schure, K. M. & Peters, J. A. H. W. 2019 Trends in global CO₂ and total greenhouse gas emissions. *PBL Netherlands Environmental Assessment Agency*. 2019 Report **5**, 1–85.

- Ouyang, F., Zhu, Y., Fu, G., Lü, H., Zhang, A., Yu, Z. & Chen, X. 2015 Impacts of climate change under CMIP5 RCP scenarios on streamflow in the Huangnizhuang catchment. *Stochastic Environmental Research and Risk Assessment* **29** (7), 1781–1795.
- Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N. & Rafaj, P. 2011 RCP 8.5 A scenario of comparatively high greenhouse gas emissions. *Climatic Change* **109** (1–2), 33–57.
- Santhi, C., Arnold, J. G., Williams, J. R., Dugas, W. A., Srinivasan, R. & Hauck, L. M. 2001 Validation of the swat model on a large RWER basin with point and nonpoint sources 1. *JAWRA Journal of the American Water Resources Association* **37** (5), 1169–1188.
- Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M. & Reinhardt, J. 2017 Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. *Regional Environmental Change* **17** (6), 1585–1600.
- Setegn, S. G., Rayner, D., Melesse, A. M., Dargahi, B., Srinivasan, R. & Wörman, A. 2011 Climate change impact on agricultural water resources variability in the Northern Highlands of Ethiopia. In: *Nile River Basin* (A. M. Melesse, ed.). Springer, Dordrecht, pp. 241–265.
- Shimelash, M., Tolera, A. & Tamene, A. 2018 Investigating climate change impact on stream flow of Baro-Akobo River Basin. *Case study of Baro Catchment. Global Scientific Journals* **6**, 180–216.
- Shiru, M. S., Chung, E. S., Shahid, S. & Alias, N. 2020 GCM selection and temperature projection of Nigeria under different RCPs of the CMIP5 GCMS. *Theoretical and Applied Climatology* **141** (3), 1611–1627.
- Taye, M. T., Ntegeka, V., Ogiramo, N. P. & Willems, P. 2011 Assessment of climate change impact on hydrological extremes in two source regions of the Nile River Basin. *Hydrology and Earth System Sciences* **15** (1), 209–222.
- Taylor, S. D., He, Y. & Hiscock, K. M. 2016 Modelling the impacts of agricultural management practices on river water quality in Eastern England. *Journal of Environmental Management* **180**, 147–163.
- Teutschbein, C. & Seibert, J. 2012 Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. *Journal of Hydrology* **456**, 12–29.
- Thomas, N. & Nigam, S. 2018 Twentieth-century climate change over Africa: seasonal hydroclimate trends and Sahara desert expansion. *Journal of Climate* **31** (9), 3349–3370.
- Tibebe, M., Melesse, A. M. & Hailu, D. 2017 Rainfall-runoff relation and runoff estimation for Holetta River, Awash subbasin, Ethiopia using SWAT model. *International Journal of Water Resources and Environmental Engineering* **9** (5), 102–112.
- Turco, M., Llasat, M. C., Herrera, S. & Gutiérrez, J. M. 2017 Bias correction and downscaling of future RCM precipitation projections using a MOS-Analog technique. *Journal of Geophysical Research: Atmospheres* **122** (5), 2631–2648.
- Vaighan, A. A., Talebbydokhti, N., Bavani, A. M. & Whitehead, P. 2019 Modeling impacts of climate and land use change on streamflow, nitrate, and ammonium in the Kor River, southwest of Iran. *Journal of Water and Climate Change* **10** (4), 818–834.
- Van Liew, M. W. & Garbrecht, J. 2003 Hydrologic simulation of the little Washita river experimental watershed using SWAT 1. *JAWRA Journal of the American Water Resources Association* **39** (2), 413–426.
- Van Liew, M. W., Veith, T. L., Bosch, D. D. & Arnold, J. G. 2007 Suitability of SWAT for the conservation effects assessment project: Comparison on USDA agricultural research service watersheds. *Journal of Hydrologic Engineering* **12** (2), 173–189.
- Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J. F. & Masui, T. 2011 The representative concentration pathways: an overview. *Climatic Change* **109** (1–2), 5–31.
- Vilaysane, B., Takara, K., Luo, P., Akkharath, I. & Duan, W. 2015 Hydrological stream flow modeling for calibration and uncertainty analysis using the SWAT model in the Xedone river basin, Lao PDR. *Procedia Environmental Sciences* **28**, 380–390.
- Welde, K. & Gebremariam, B. 2017 Effect of land use land cover dynamics on hydrological response of watershed: case study of Tekeze Dam watershed, northern Ethiopia. *International Soil and Water Conservation Research* **5** (1), 1–16.
- Whitehead, P. G., Sarkar, S., Jin, L., Futter, M. N., Caesar, J., Barbour, E., Butterfield, D., Sinha, R., Nicholls, R., Hutton, C. & Leckie, H. D. 2015 Dynamic modeling of the Ganga river system: impacts of future climate and socio-economic change on flows and nitrogen fluxes in India and Bangladesh. *Environmental Science: Processes & Impacts* **17** (6), 1082–1097.
- Yang, J., Reichert, P., Abbaspour, K. C., Xia, J. & Yang, H. 2008 Comparing uncertainty analysis techniques for a SWAT application to the Chaohe Basin in China. *Journal of Hydrology* **358** (1–2), 1–23.
- Zeray, L., Roehrig, J. & Alamirew, D. 2006 Climate change impact on Lake Ziway watershed water availability, Ethiopia. Conference on International Agricultural Research for Development, Tropentag, 11–13 October 2006.

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