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Response of Climate Change Impact on Streamflow in Sululta Catchment, Abay Basin, Ethiopia

Kiyya Tesfa Tullu[1]*

[1]*Hydraulic and Water Resources Engineering Department, Jimma Institute of Technology, Jimma University, Jimma 378, Ethiopia*

INFORMATION

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Contact
*Kiyya Tesfa Tullu
kiyyatesfa@gmail.com

ABSTRACT

Ethiopia is experiencing an increasing water security risk owing to a climate change, which caused frequent draught and flooding. The increase in temperature and precipitation variability has reduced streamflow amplifying water security problems. However, evaluation of how the long-term streamflow behaves under the future climate change in the catchment are limited. Thus, the purpose of this study was to investigate the impacts of climate change on streamflow of Sululta catchment using Soil and Water Assessment Tool (SWAT) model under the RCP4.5 and RCP8.5 climate scenarios. Precipitation and temperature outputs from Rossby Center Regional Atmospheric model (RCA4) regional climate model (RCM) was bias corrected against observed data using Power transformation and variance scaling, respectively. The SWAT model was calibrated and validated using observed stream flow. The performance of SWAT model in streamflow simulation showed a good agreement with R2 0.75 and 0.7 and NSE 0.71 and 0.7 during calibration and validation respectively. The projection of climate change shows precipitation decreases in dry season whereas temperature increases under both RCP4.5 and RCP8.5 scenarios. The simulation of streamflow shows that, mean annual stream flow will be increased by 11.91% in 2021s (2021-2050) and by 5.26% in 2051s (2051-2080) under RCP4.5. Under RCP8.5 climate scenarios, the mean annual streamflow will be decreased by 0.98% in 2021s and 1.43% in 2051s. The outcomes suggest that it is important to consider the influence of climate change on streamflow to frame appropriate guidelines for planning and management.

1. Introduction

Climate change is accelerating from time to time over the earth's surface due to increasing human activities. The change in climatic variables can occur in different ways, on different time scales and on different geographical scales due to internal and external forcing (Boru et al., 2019). Climate change is recognized worldwide as one of the most important environmental problems of the 21st century (Andrade et al., 2021). However, the impacts of climate change were severe in developing countries where the livelihood of the community is highly vulnerable to the risks of climate change. Changes in climate will affect human wellbeing by altering water availability, land-use management, and food production (Marin et al., 2020) and can further intensify the spatial and temporal variation of water resources through alteration of hydrological cycle (Bekele et al., 2019). The anticipated increase in global and regional temperatures due to climate change is expected to increase the evapotranspiration rate and change precipitation pattern contributing to changes in the characteristics of droughts and flood (Musie et al., 2020). Climate change leads to changes in precipitation and temperature, which have corresponding effects on river flow and sediment transport in a river basin (Ma et al., 2021).

Assessing the impacts of climate change is a current global and regional issue. Global surface temperatures show an increasing trend, and precipitation pattern variability is dynamic both spatially and temporally (Bhatta et al., 2019). According to the report of the Intergovernmental Panel on Climate Change (IPCC, 2007), all assessed emission scenarios project rising surface temperatures during the 21st century. More frequent and prolonged heatwaves are very likely, and extreme precipitation events will become more intense and frequent in many regions. The oceans will continue to warm and acidify, and global mean sea level will rise. According to this report (IPCC, 2007), the global mean surface temperature changes for the period 2016-2035 is likely to be in the range of 0.3 °C to 0.7 °C (medium confidence level). Compared to 1850-1900, the change in Earth's surface temperature is expected to exceed 1.5 °C by the end of the 21st century (2081-2100) (high confidence). The main cause of global climate change is greenhouse gas (GHG) emissions such as CO_2, CH_4, N_2O, which cause global warming (IPCC, 2013).

Human activities through the burning of fossil fuels, industrial production processes, agriculture and forestry, human society, and the use of vehicles are sources of increased GHG emissions (Hussain et al., 2018). Global warming due to increased greenhouse gas concentrations could reduce water security in the near future due to the expected decrease in rainfall, surface runoff, and actual evapotranspiration (Andrade et al.,2021). Global climate change has significant effects on the hydrological cycle and has the potential to impose additional pressures on water availability and water demand (Adem et al., 2016).

Climate change is expected to have a negative effect on economic development around the world, but the magnitude of the impact will vary from country to country. Developing countries like Ethiopia are becoming more vulnerable to climate change, which can have widespread impacts on the country for many reasons. Most notably, its economy is heavily dependent on agriculture (IPCC, 2007). A large part of the country is arid, semiarid, and very prone to desertification and drought. Rain-dominated agricultural systems are strongly affected by regional climate change. Drought events of the recent decades have demonstrated the country's vulnerability to global climate change, which is expected to exacerbate climate variability in the region (Musie et al., 2020). Climate change and its effects are therefore a concern for Ethiopia.

Blue Nile Basin or Abay Basin is one of the largest basins in Ethiopia with high population pressure, degradation of land and highly dependent on an agricultural economy and sensitive to climatic variations that affects streamflow (Ayalew et al., 2021). The increase in population growth, economic development, and climate change have been proven by IPCC (2007) to cause rise in water demand, drought or water scarcity. The limited water availability and the increasing demand for water from different sectors could contribute to the vulnerability of the Basin to water stress as the climate changes (Mengistu et al., 2021). The large population growth will increase the demand for natural resources; mainly water in the basin. Sululta Catchment is one of the catchment in the Upper Blue Nile Basin, which experiences famine due to recurrent drought, and the lack of advanced water infrastructure to use the full potential of available water resources.

Evaluation of the impact of climate change on streamflow in the catchment are limited or not addressed. Water resources planning and management in the 21st century is becoming difficult due to the conflicting demands from various stakeholder groups, increasing population, rapid urbanization, climate change producing shifts in hydrologic cycles, and the increasing incidences of natural disasters (IPCC, 2007). Sululta Catchment has observed notable spatial expansion, population growth and urbanization. Human activities in the catchment have increased over the past century and expected to grow even more rapidly in the future; hence, water management will become even more important with a changing climate.

In this study, climatic information from the Representative Concentration Pathways (RCPs) is used to predict future hydrological changes from Rossby Center Regional Atmospheric Model (RCA4) climate model. The RCA4 model is advanced from High Resolution Limited Area Model (HIRLAM), which is a numerical weather prediction (NWP) forecasting system, resulting into enhanced physical and dynamical parameterization (Ayugi et al.,2020).

Based on Coupled Model, the RCA4 model has been applied in many regions worldwide, among them (Nikulin et al., 2018; Wu et al., 2016; Collazo et al., 2018; Wu et al., 2017; Rana et al., 2020). Based on Coupled Models Inter-comparison Project phase 5 (CMIP5) which provides the most recent simulated dataset for future climate change scenarios, the IPCC has defined new RCP scenarios for climate change projection (van Vuuren et al., 2011). RCPs were developed based on varying assumptions of future greenhouse gas emissions. The RCP uses radiative forcing values ranging from 2.6 to 8.5 W/m2 in 2100 to define scenarios. The RCPs are a vital development in climate research and allow scientists to examine emission mitigation and impact analysis (Bai et al., 2019).

There are many hydrological models to understand the effects of climate change on the nature of hydrological flow and to calculate water discharge more precisely, simply and quickly than the traditional measurement method. The Soil and Water Assessment Tool (SWAT) is one of the most popular modelling programs for assessing hydrological impacts. The objective of this study was to assess the potential impacts of climate change in the Sululta Catchment 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.

2. Materials and Methods

2.1. Study Area

Sululta Catchment is located in the northern part of Addis Ababa and south of Chancho Town. The Catchment Covers an Area of 467 km^2. It is enclosed within the geographical coordinate of 9°05'01''N-9°18'45''N latitude and 38°33'15''E-38°50'45''E longitude. With respect to the main asphalt road that connects Gojjam with Addis Ababa, more proportion of the catchment lay in the western part and the rest in east direction longitudinally. The peak altitude is estimated to be about 3380 m at Ilani Welebabo Ridge and the lowest is 2542m above sea level at the mouse of the basin

(Sibilu River). The Sibilu River meanders in the flat topography of Sibilu plain. Sibilu River is the tributary of Muger River, which is one of the main tributaries of Abbay Basin (Fig. 1).

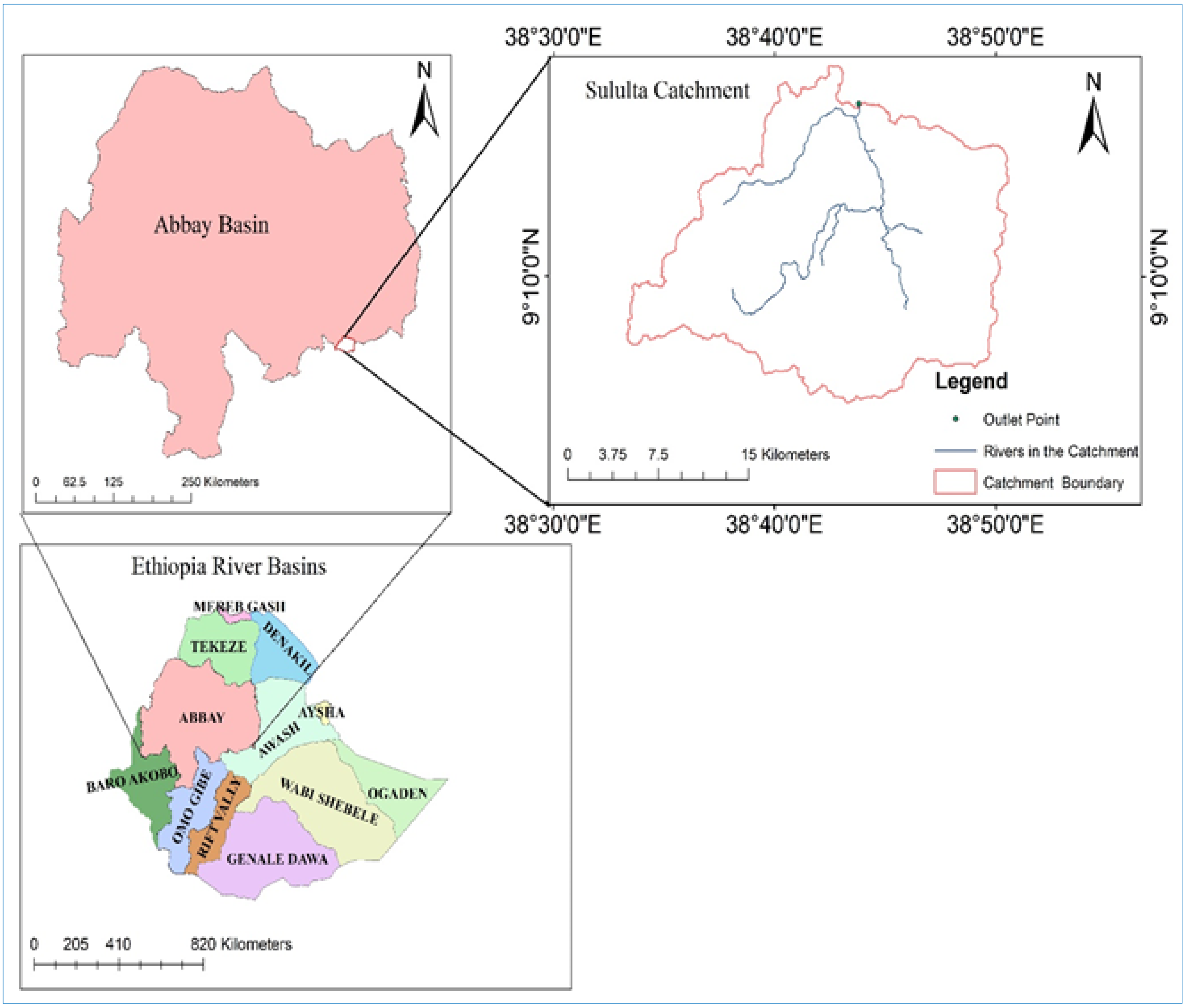

Fig. 1. Study area map

2.2. Soil and Water Assessment Tool (SWAT) Model

The SWAT model is a semi-distributed continuous hydrologic model operated in a Geographic Information System (GIS) environment (Arnold et al., 2012). SWAT model is developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time (Neitsch et al., 2005) and it is computationally efficient, uses readily available inputs and enables users to study long-term impacts.

Hydrology, plant growth, reservoir routing, land management, pesticides, and sediments are the major modules included in the SWAT model. Due to its user-friendly interface (ArcSWAT) and data requirement flexibility, SWAT has been widely used for impact assessment of climate, land use, and management practices (Bhatta et al., 2019). A SWAT model operating at daily time steps predicts land management impacts in large, complex watersheds with varying soil, land use, and management conditions. Key model components include DEM, meteorology, hydrology, soils and properties, and land management (Neitsch et al., 2011).

In SWAT, watersheds are divided into multiple sub-watersheds, which are then further divided into Hydrological Response Units (HRUs), which include uniform land use, slopes and soil properties. The hydrological component of the model is based on the water balance equation (Neitsch et al., 2011) given by *Equation 1* below. Currently SWAT is imbedded in Arc GIS interface called Arc SWAT and for this study, ArcSWAT2012 is used.

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

where SW_t is the final soil water content in mm H_2O, SW_0 is the initial soil water content on day i in mm H_2O, t is the time of days, R_{day} is the amount of precipitation on day i in mm H_2O, Q_{surf} is the amount of surface runoff on day i in mm H_2O, Ea is the amount of evapotranspiration on day i in mm H_2O, W_{seep} is the amount of water entering the vadose zone from soil profile on day i in mm H_2O and Q_{gw} is the amount of return flow on the day i in mm.

Precipitation, maximum and minimum temperatures, solar radiation, relative humidity, and wind speed are the daily values required for the SWAT model. They can be given to the model as a user defined measured time series, or they can be generated within SWAT from a monthly data and its statistics summarized over years. SWAT includes WXGEN model weather generator that can generate the above stated data or fill in gaps in measured record. The interior model is based on the contiguous U.S. states. However, it can be localized by providing a custom database (Neitsch et al., 2005).

2.3. SWAT Model Input Data

The necessary input data required for the SWAT model were DEM, land use/cover, soil data, meteorological data (precipitation, temperature, solar radiation, relative humidity, and wind speed) and hydrological data (stream flow and sediment yield) which were collated from different sources or institutions.

2.3.1. DEM

A DEM is a digital representation of a terrain surface, specifically grid or regular grid of point elevations. This is the basic input for the hydrological SWAT model to delineate watersheds and stream networks. The first step in creating the model input is the watershed delineation created using digital elevation data. A DEM is the first input to the SWAT model for delineating the watershed to be modeled. Based on the threshold specifications and the DEM, the SWAT Arc View interface was used to divide the watersheds into sub basins and divide sub basins into Hydrologic Response Units (HRUs). Shuttle radar topographic mission (SRTM) provides the DEM data having a 30 m resolution. The DEM downloaded from SRTM website has projection system of WGS 1984 UTM, zone 37N at 30m resolution. The DEM data for this Study was obtained from (www.earthexplorer.usgs.gov).

2.3.2. Land Use /Land Cover and Soil Data

SWAT requires the land use /land cover data to define the HRUs. The land use land cover map of the study area was obtained from the Ministry of Water, Irrigation and Electricity (MoWIE) GIS department. Based on this data, a SWAT land use/ land cover map was created by overlaying the land use/land cover shape file. Then, after major land use/ land cover classification was divided into subclasses mainly based on the dominant crops for cultivated land. SWAT then calculated the area covered by each land use.

It was found that 33.16% was cultivated land, 19.81% was eucalyptus forest, 38.89% was grassland, and 8.08% was shrub land. SWAT requires a variety of soil textural and physico-chemical properties such as the hydraulic conductivity, moisture content availability, physical properties, bulk density, chemical composition, organic carbon content and texture, for the different layers of each specific soil type. This soil data required by SWAT for soil database as per FAO soil group is obtained from the Ministry of Water, Irrigation and Electricity. The major soils in the study area are Chromic Luvisols (3.86%), Eutric Cambisols (28.77%), Eutric Leptosols (5.99%) and EutricVertisols (61.38%). The dominant soil type in the catchment is Eutric Vertisols, accounting for 61.38% of the land area.

2.3.3. Observed Meteorological and Stream Flow Data

The meteorological data Such as daily precipitation, maximum and minimum temperature, sunshine hour data, relative humidity, and wind speed data were collected from the Ethiopian National Meteorology Service Agency. These data were used as the input to the SWAT hydrological model for the simulation of the hydrological components. To perform hydrological analysis and simulation using data of long time series, filling in missing data is very important. The missing data can be completed using meteorological and /or hydrological stations located in the nearby, provided that the stations are located in hydrological homogeneous region.

In order to fill the missing observed rainfall and temperature data, joint application of the regression analysis and spatial interpolation techniques are used to complete short and long period breaks in data series for a given meteorological station. Such gaps in the record are filled by developing correlations between the station with missing data and any of the adjacent stations with the same hydrological features and common data periods.

In this study missing of observed rain rainfall and Temperature values were estimated using XLSTAT2018 by filling each from its neighboring stations. Data consistency was also checked by a double mass curve and found to be consistent. In this study only one station has full data. This station is Addis Ababa Observatory meteorological station. Using this station, the SWAT model generates representative weather variables for Sululta Catchment.

In this study, three stations were used to run the SWAT model. From this three stations only one of them is with full of data. Therefore, from this one station weather is generated for the rest of missing stations using the automatic weather data generator. Stream flow data were collected from MoWIE. This data is required for SWAT model calibration and validation.

2.3.4. Climate Change Scenario Data

CORDEX is a global collaborative initiative that aims to develop the knowledge of regional downscaling of global climate scenarios, and provide and develop detailed, regional climate information necessary for vulnerability, impact, and adaptation studies at local and regional levels (Obahoundje et al., 2021).

The future Scenarios were based on Representative Concentration Pathways (RCPs) radiative forcing (IPCC, 2014). RCPs are new climate scenarios based on emission pathways and greenhouse gas concentrations (Vaighan et al., 2019). RCPs explore credible future options by considering the uncertainties associated with future developments (Doulabian et al., 2021). Representative Concentration Pathways 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).

Results of CORDEX-Africa RCM simulations for the historical and future (2021–2080) climate projections under RCP4.5 and RCP8.5 with spatial resolution of 0.44° were used in this study. CORDEX-Africa gives priority to RCP4.5 and RCP8.5 scenarios, so RCP4.5 and RCP8.5 were considered in this study (Alemseged and Tom, 2015).

RCP4.5 is an intermediate-range scenario that stabilizes the radiative forcing at 4.5 W/m^2 (approximately 650 ppm CO_2 equivalent) in 2100 and does not exceed this value, although this is due to the stable climate system (Riahi et al., 2011; van Vuuren et al., 2011). RCP8.5 is the upper bound for all RCP scenarios, stabilizing radiative forcing at 8.5 W/m^2 (greater than 1370 ppm CO_2 equivalent) in the year 2100 (Riahi et al., 2011).

RCM climate data outputs based on RCP 4.5 and RCP 8.5 emissions scenarios are bias corrected for application to hydrological SWAT model for climate change impact studies. Bias corrections were considered for precipitation and minimum and maximum temperatures. Other meteorological variables such as solar radiation, relative humidity and wind speed during the base 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 (Galata et al., 2021).

This study used the Rossby Center Regional Atmospheric Model (RCA4) regional climate model obtained from (https://climate4impact.eu/impactportal/data/esgfsearch.jsp). Compared to the previous version, RCA4 is more physically consistent with improved energy flux parameterization, reduced compensating error, and better representation of the diurnal temperature cycle (Boru et al., 2019). Spatially, the RCA4 simulations cover the CORDEX-Africa domain over the period 1951–2100 with a resolution of 0.44° × 0.44° (~50km × 50km) (Alemseged&Tom,2015).

2.4. Bias Correction of Climate Model Data

Several bias correction methods are applicable to account for differences between the climate model data and the measured data (Teutschbein et al ., 2011). Often the downscaled RCPs data (RCP4.5 and RCP8.5) cannot be directly used for impact assessment as the computed variables may differ systematically from the observed ones. Bias correction is therefore applied to RCM/GCM data for climate change analysis since the data extracted from the climate models contains bias when compared to observed climate data (Teutschbein and Seibert, 2012).

In this study bias correction was carried out for precipitation and temperature by the method of power transformation (*Equation 2*) and variance scaling (*Equation 3*), respectively. From this, the comparison of the generated projection data with respect to the observed analyzed climate data (base period data) resulted in producing a similar pattern for Sululta catchment. The study by Teklay et al. (2021) also applied power transformation and variance scaling bias correction methods for precipitation and temperature, respectively. The power transformation and variance scaling can be defined as:

$$P_{cor} = a * P_{unc}{}^{b} \tag{2}$$

$$T_{Scor} = \bar{T}_{obs} + \frac{Sd_{obs}}{Sd_{mod}}(T_{mod} - \bar{T}_{mod}) \tag{3}$$

where; P_{cor} and P_{unc} are the corrected and uncorrected daily precipitation, and a and b are the transformation coefficients and T_{Scor} is the corrected temperature in the scenario period, $\bar{T}_{obs}$ is the observed mean, Sd_{obs} and Sd_{mod} are the observed and model standard deviation, respectively, T_{mod} and $\bar{T}_{mod}$ are model and model mean temperature value, respectively (Gadissa et al., 2018).

2.5. SWAT Model Set Up

The SWAT model was developed to predict the impacts of land use and management on water, sediment and agricultural chemical yields at catchment scale at daily, monthly and annual time increments (DosSantos et al., 2018). Spatial data such as land use, soil, and slope were used to create various hydrologic response units (HRUs) analysis systems.

In the SWAT model, the simulation of the hydrological process begins with watershed delineation from a DEM. Inputs entered into the SWAT model were organized to have spatial properties. Before going in hand with spatial input data, that is, the soil map, LULC map and the DEM were projected into the same projection called UTM Zone 37N, which is projection parameter for Ethiopia.

Watershed was divided into a several sub-basins, for modeling purposes. The watershed delineation process includes five main steps, DEM setup, river definition, outlet and inlet definition, watershed outlets selection and definition and calculation of sub-basin parameters. The river definition used a threshold-based river definition option to define the minimum size of the sub-basins. In SWAT, the basin is divided into sub-basins comprising a river segment and hydrological response units (HRUs), which represent areas of homogeneous land use, topography, and soil characteristics (Gassman et al., 2007).

The delineated Watershed by Arc SWAT and the prepared land cover and soil layers were overlap 100%. In addition to land use and soil, SWAT includes subdivision of HRU by slope class. A multi-slope option (an option which considers different slope classes for HRU definition) was chosen. LULC, soil, and slope maps have been reclassified to match SWAT database parameters. After reclassifying the land use, soil and slope in the SWAT database of these physical properties were overlaid for HRU definition. In this particular study, a 10% land use threshold was used to include all land uses, 20% for soil and 20% for slope were used. The HRU distribution in this study was determined by assigning multiple HRUs to each sub-basin.

2.6. Sensitivity Analysis, Calibration and Validation of SWAT Model

Determining the most sensitive parameters was an important first step in model calibration and validation. Sensitivity analysis is the process of determining the rate of change in model output to changes in model inputs (parameters) (Moriasi et al., 2007).The process required to identify the key parameters and parameter accuracies required for SWAT model calibration and validation. SWAT has a large number of flow parameters, so the most sensitive parameters must be identified to improve the calibration of the hydrological model.

After a thorough pre-processing of the required input for SWAT 2012 model, flow simulation was performed for a thirty year of recording periods starting from 1987 through 2016. The first three years of which was used as a warm up period and the simulation was then used for sensitivity analysis of hydrologic parameters and for calibration of the model.

Sensitivity analysis, calibration, and validation were performed using the SWAT-CUP (Abbaspour, 2014), which utilizes the Sequential Uncertainty Fitting (SUFI-2) algorithm. The SUFI-2 algorithm is widely used as tool combined tool for SWAT model calibration and uncertainty analysis. It accounts for uncertainties due to uncertainties in driving variables (such as precipitation), conceptual models, parameters, and measured data (Abbaspour, 2014). In the SWAT-CUP, parameter sensitivity analysis 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). To perform this, global sensitivity analysis was employed in SWAT-CUP 2012.

Calibration is the process of adjusting model parameters so that the model output matches the observed data. Calibrations are very important for parameters that were not measured and are intrinsically heterogeneous and uncertain, as it serves to optimize the unknown model parameters. Validation is used to test the calibrated model without further parameter adjustments with an independent dataset. For this catchment, observed streamflow of 1993-2011 was split into a warm-up period (1993-1995), calibration period (1996-2005) and validation period (2006-2011). A longer calibration period was used to improve the SWAT model parameterization and reduce the uncertainty in the model output (Gashaw et al.,2018).

To evaluate the SWAT model simulation outputs in relative to the observed data, model performance evaluation is necessary. There are various methods to evaluate the model performance during the calibration and validation periods. To evaluate the model performance a coefficient of determination (R^2), Nash Sutcliffe Efficiency (NSE), and root mean square error (RMSE) and PBIAS are applied. The accuracy of the simulated value when compared with the observed value is evaluated by R^2, whereas the NSE measures the goodness of fit and describes the variance between the simulated and observed values.

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(Q_i^{obs}-Q_{obs}^{mean}\right)\left(Q_i^{sim}-Q_{sim}^{mean}\right)}{\sqrt{\sum_{i=1}^{n}(Q_{i=1}^{obs}-Q_{obs}^{mean})^2}\sqrt{\sum_{i=1}^{n}(Q_i^{sim}-Q_{obs}^{mean})^2}}\right]^2 \quad (4)$$

where; R^2 is the coefficient of determination, Q_i^{obs} is the i^{th} observed flow, Q_i^{sim} is the i^{th}-simulated flow, Q_{obs}^{mean} is the observed mean flow, Q_{sim}^{mean} is the simulated mean flow and n is the total number of observed flow. It measures how well the simulated versus observed regression line approaches an ideal match and ranges from 0 to 1, with *a* value of 0 indicating no correlation (Moriasi et al., 2007).

$$NSE = 1-\frac{\sum_{i=1}^{n}(Q_i^{obs}-Q_i^{sim})^2}{\sum_{i=1}^{n}(Q_i^{sim}-Q_{obs}^{mean})^2} \quad (5)$$

where; *NSE* is the Nash-Sutcliffe efficiency. *NSE* measures the level of consistency of measured values with predicted values and is generally ranged from $-\infty$ to 1 with $NSE = 1$ as the optimal value (Moriasi et al., 2007).

$$PBIAS = \frac{\sum_{i=1}^{n}\left(Q_i^{obs}-Q_i^{sim}\right)^2 * 100}{\sum_{i=1}^{n} Q_i^{obs}} \quad (6)$$

where; *PBIAS* is the percentage deviation between observed and simulated values. *PBIAS* measures the relative percentage error between simulated and measured values (Moriasi et al., 2007). The positive value denotes underestimation; negative value indicates overestimation and zero means optimal estimation. The propagation of uncertainties in model outputs in SUFI-2, expressed as the 95% probability distribution, calculated by the 2.5% and 97.5% levels of the cumulative distributions of output variables, is considered as 95PPU (Abbaspour, 2015).

3. Results and Discussion

3.1. Sensitivity Analysis, SWAT Model Calibration and Validation

Streamflow sensitivity analysis was performed on 20 hydrological parameters using SUFI-2 global sensitivity analysis in SWAT- CUP. Eleven sensitive parameters were considered based on *t*-stat and *p* value as shown in Table 1.

Table 1. Sensitivity analysis for hydrologic parameters

Parameter	t-stat	P-value	Rank
R_CN2	5.348435899	0.000052234	1
V_ALPHA_BF	4.551513807	0.000372045	2
R_REVAPMN	-2.299283507	0.036274494	3
R_EPCO	1.964763518	0.068243406	4
R_SOL_Z	-1.854604056	0.08341677	5
R_SOL_K	-1.761745084	0.098474242	6
V_GW_DELAY	1.321659811	0.206085477	7
V_GWQMN	1.030584764	0.319067529	8
R_RCHRG_DP	0.787128391	0.343466598	9
R_HRU_SLP	-0.78347279	0.345544774	10
R_CH_N2	-0.598550096	0.458403985	11

The t-stat provides a measure of sensitivity (larger absolute values indicate more sensitivity) and the *p*-value determines the significance of sensitivity (smaller value suggest a higher level of significance) (Abeysingha et al., 2020). Initial SCS runoff curve number for moisture condition II (CN2) and base flow alpha factor (ALPH A_BF) are found to be the most sensitive parameters. Result of sensitivity analysis was used to conduct the calibration of SWAT model.

The calibration of the model was performed for a period of January 1, 1996, to December 31, 2005, using SUFI- 2 algorithm in SW AT-CUP using measured streamflow data. The model was calibrated by model parameters, and those parameters with fixed value have also been validated. Taking the first three years as a warm up period, the flow was simulated for 10 years. The automatic calibration SUFI-2 was used to calibrate the model using observed stream flow.

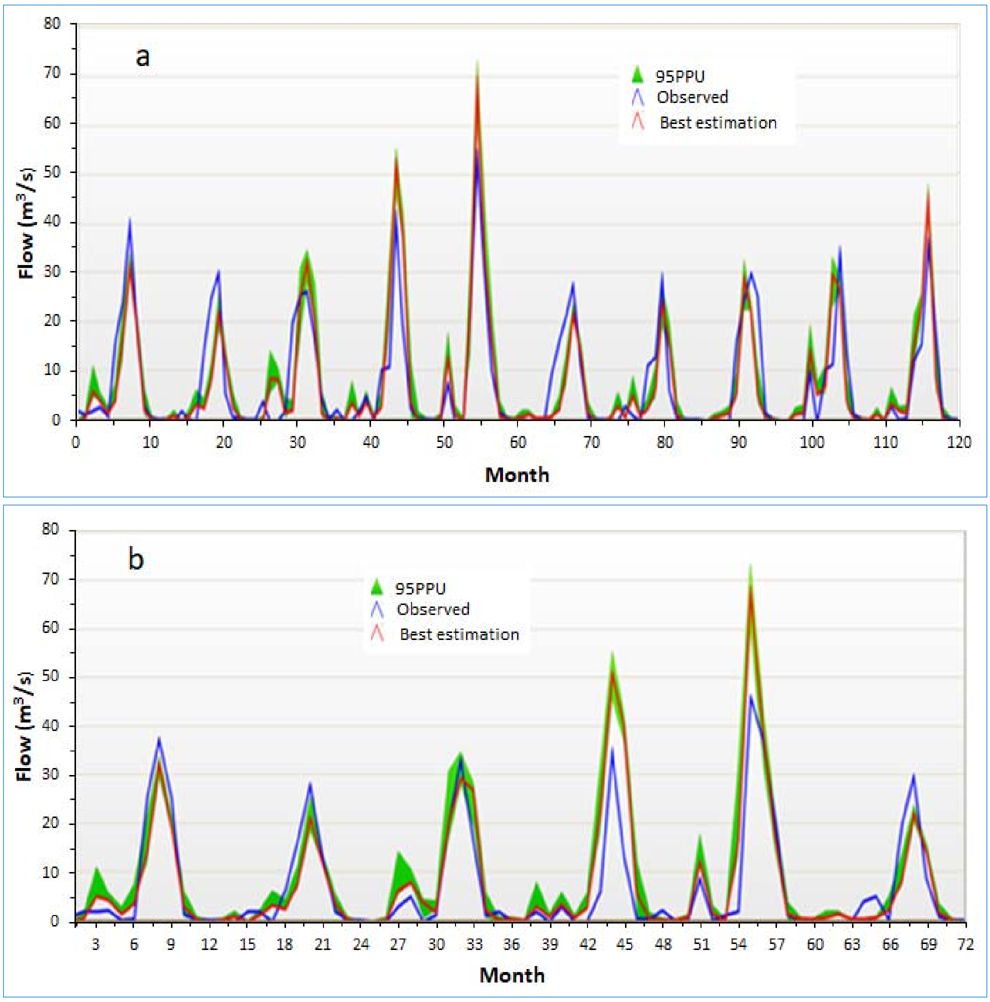

Fig. 2. Results of average monthly flows for calibration (a) and validation (b)

Observed daily stream flows were adjusted on a monthly basis, and simulations run were conducted on monthly basis to compare the modeling output with the measured daily discharge at the outlet of Sululta Catchment. The calibration results showed good agreement between the observed and simulated streamflow, with coefficient of determination (R^2) and NSE values of 0.75 and 0.71, respectively.

Model validation was carried out between 2006-2011. The validation results also showed a good agreement with coefficient of determination (R^2) and NSE values of 0.78 and 0.70, respectively.

From Table 1, R_ means an existing parameter value is multiplied by 1+a given value and V_ means the existing parameter value is to be replaced by a given Value.

The calibration and validation graph shows that, the observed streamflow slightly under estimates and over estimates, the simulated flow during calibration and validation period (Fig. 2). However, the model is good enough to simulate the streamflow and fulfills the requirement recommended by Moriasi et al. (2007). From the scatter plot of observed and simulated flow (Fig. 3), most of the scatter points are uniformly clustered during calibration and validation period indicating a good agreement between the observed and simulated flow.

3.2. Climate Change Projections under RCP Scenarios

3.2.1. Precipitation

Average monthly precipitation in the study area has been projected under RCP 4.5 and RCP 8.5 climate scenarios with reference to baseline (1987-2016) precipitation in two-time horizons, i.e. near future (2021-2050) and mid near future (2051-2080). In the RCP4.5 Scenario, average monthly precipitation decreased in almost every month except, may, June and July in the near future (2021-2050). The maximum change in average monthly precipitation is observed in October in the near future and in the mid near future under RCP8.5.

In short rainy season (February-May) and dry season (October-January), precipitation amount decreased and varies from -4.65 to -19.47% and -38.94 to -56.15% respectively, but in wet season (June-September) precipitation projected to increase and ranges from +2.54 to + 11.67%, under both RCP4.5 and RCP8.5 climate scenarios for both near future and mid near future time periods. The change in average annual precipitations increases and varies from +2.6 to + 6.48% for RCP4.5 and decreases and ranges from -2.55 to -2.83% under RCP8.5 climate scenario (Fig. 4).

This study shows that average monthly precipitation decreases highly in dry season (October-January). Similar study by Dibaba et al. (2020) using four RCMs also reported a decrease in the projected average monthly precipitation in dry season.

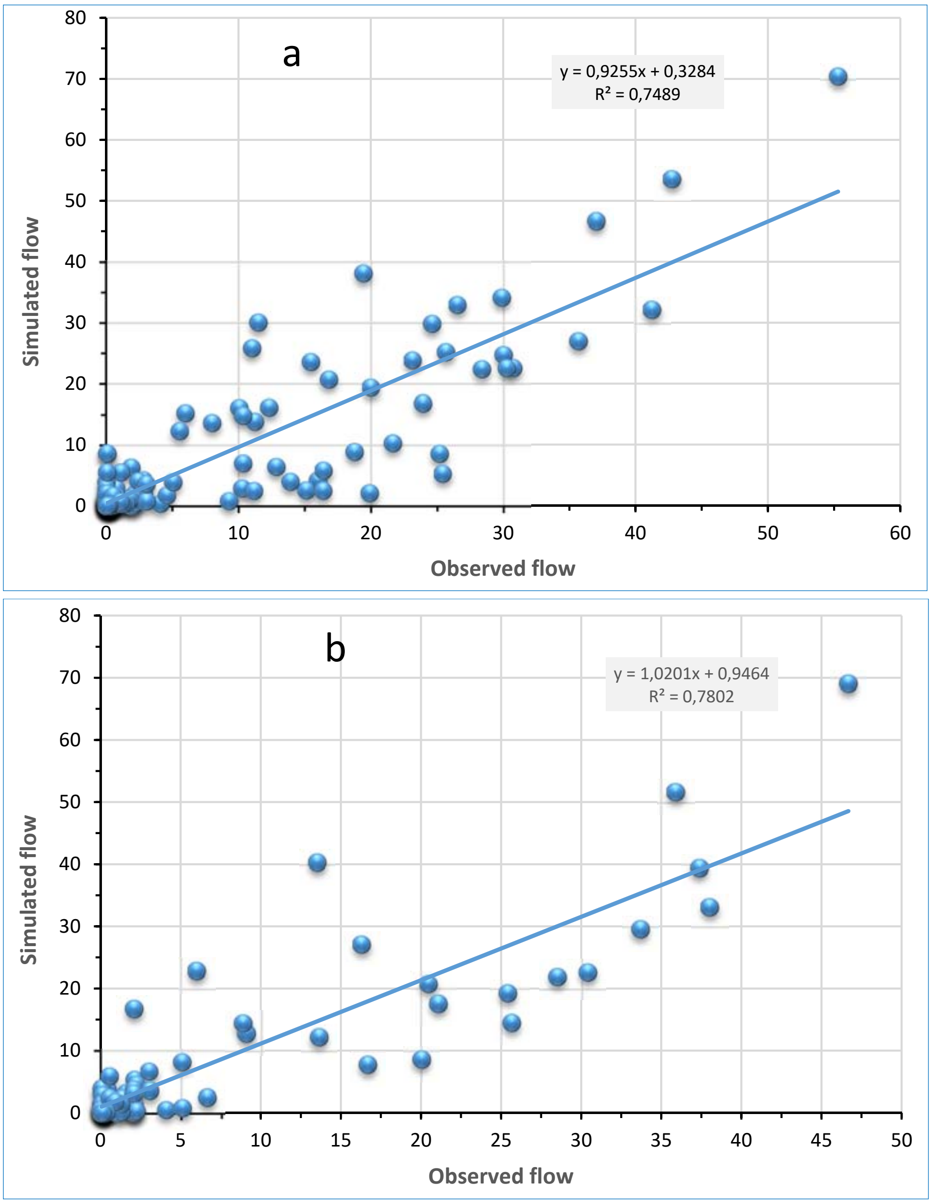

Fig. 3. Results of observed and simulated flows using scatter plot for calibration (a) and validation (b)

3.2.2. Maximum and Minimum Temperature

The study revealed future projected maximum and minimum temperature changes for both RCP4.5 and RCP8.5. The results show that the maximum and minimum temperatures increase under both RCPs during the study period. Variation in monthly mean temperature is greater for minimum temperature than for maximum temperature (Figs. 5-6).

In the RCP 4.5 scenario, the changes in average monthly maximum temperature ranges from 0.2 ℃ (June) to 1.33℃

(January) and 0.14℃ (May) to 1.43℃ (December) in 2021 to 2050 and 2051to 2080 respectively.

Under RCP 8.5, the change in average monthly maximum temperature varied from 0.37 ℃ (May) to 1.63℃ (October) and 0.56 ℃ (September) to 1.58 ℃ (November) in near and mid near future, respectively. The change in monthly average minimum temperature under RCP 4.5 varied from 0.28 ℃ (July) to 1.93 ℃ (November). For RCP8.5, change in average monthly minimum temperature varied from 1.04 ℃ (April) to 2.8 ℃ (December). The study shows that the projection of RCP8.5 is warmer than RCP4.5.

The largest temperature changes at RCP8.5 was also reported by Galata et al. (2021) using RCA4 climate model. A study by Dibaba et al. (2020) four RCMs and Galata et al. (2021) used the RCA4 climate model to reveal that the highest temperature change is observed in the RCP8.5 Scenario.

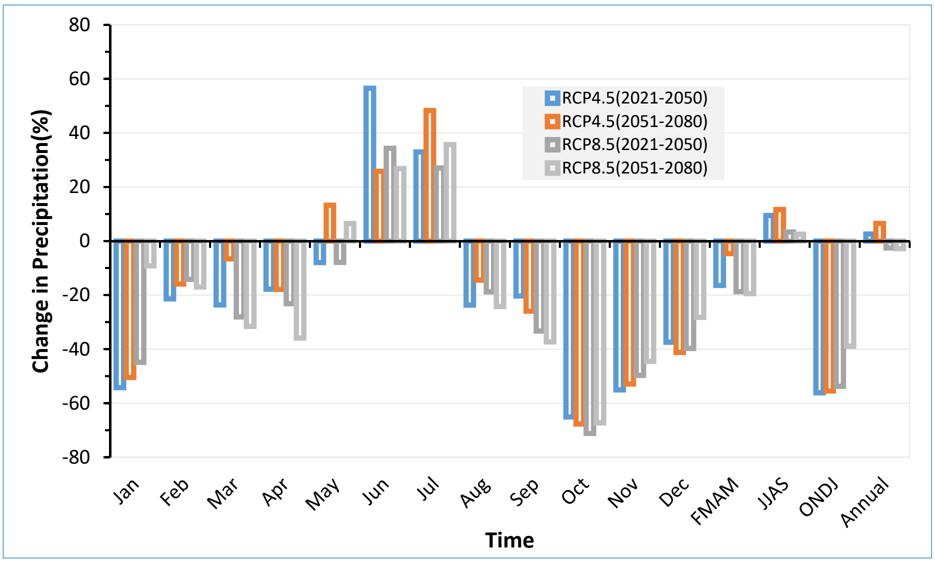

Fig. 4. Future changes in average precipitation in Sululta Catchment for 2021-2050 and 2051-2080 under RCP4.5 and RCP8.5 compared to the baseline period

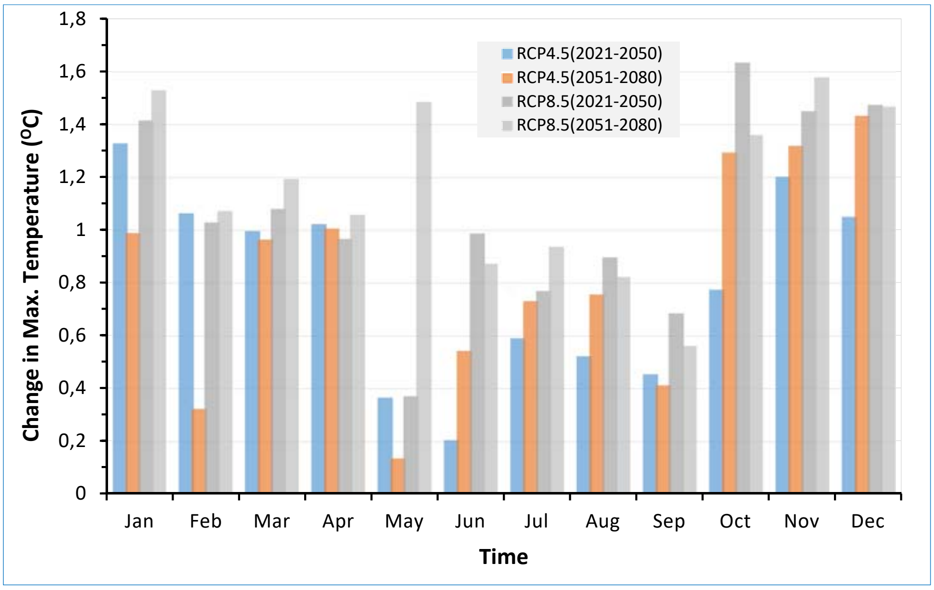

Fig. 5. Future change in average monthly maximum temperature for RCP4.5 and RCP8.5 Scenarios

3.3. Evaluating Impact of Climate Change on Stream Flow

SWAT simulations were performed against the baseline RCP4.5 and RCP8.5 to quantify the impact of climate change. Simulation results of stream flow for the two future time periods, 2021s (2021-2050) and 2051s (2051-2080) were compared with the baseline period simulation. The change in stream flow of Sululta Catchment under RCP 4.5 and RCP 8.5 scenarios shows both increasing and decreasing trends in average monthly values.

In both RCP 4.5 and RCP8.5 Scenario, the change in average monthly stream flow was found to be decreasing for all months except June and July in the near future (2021-2050) and May, June and July in the mid near future (2051-2080).

Under RCP4.5, average monthly stream flow change ranges from -39.23 to 59.07% and -38.80 to 26.85% during 2021-2050 and 2051-2080 respectively. Similarly, the change in average monthly stream flow varies from -38.80 to 26.85% for the period 2021to 2050, and from -37.44 to 32.30% over the period 2051to 2080 under the RCP8.5 Scenario (Fig. 7).

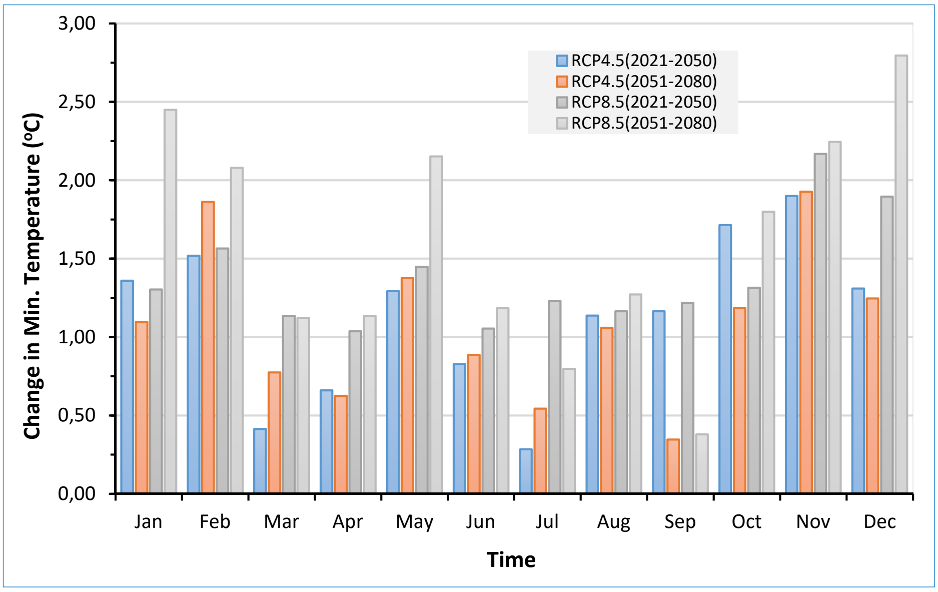

Fig. 6. Future changes in average monthly minimum temperature for RCP4.5 and RCP8.5 Scenarios

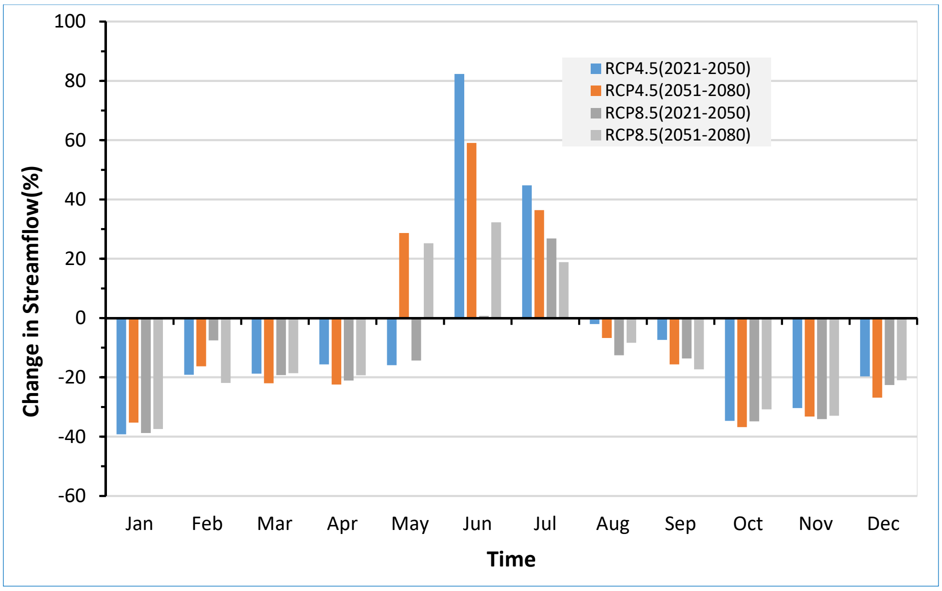

Fig. 7. Average monthly streamflow changes for RCP4.5 and RCP8.5 Scenarios

Seasonal and annual projection of stream flow showed a mixed increasing and decreasing trend even though the rate varies (Fig. 8).

In Belg season (February-May) and Bega (dry) season (October-January), stream flow will be decreased under both RCP climate scenarios of future but in Kiremt (rainy) season (June-September) change in average monthly flow will increase under both RCP4.5 and RCP8.5.

The Bega season shows larger share in decrease of flow volume in the future. The decrease may reach up to 35.84% during 2051-2080 and 34.50% at 2021-2050 for RCP 4.5 and RCP 8.5, respectively. Belg season also contributes the largest decrease in stream flow at 2021-2050 up to 17.18% and 17.77% in RCP 4.5 and RCP 8.5 respectively. But, kiremt seasons shows increase in stream flow in the future up to 17.46% in RCP4.5 and up to 2.47% in RCP8.5. The study by (Bekele et al., 2021) using four RCMs reported the projected stream flow increase in kiremt and decrease in Belg and Bega under both RCP4.5 and RCP8.5. The projected average annual stream flow increases by 11.91% during 2021-2050 and 5.26% during 2051-2080 for RCP 4.5 and decrease in annual stream flow is expected by 1.43% in RCP 8.5.

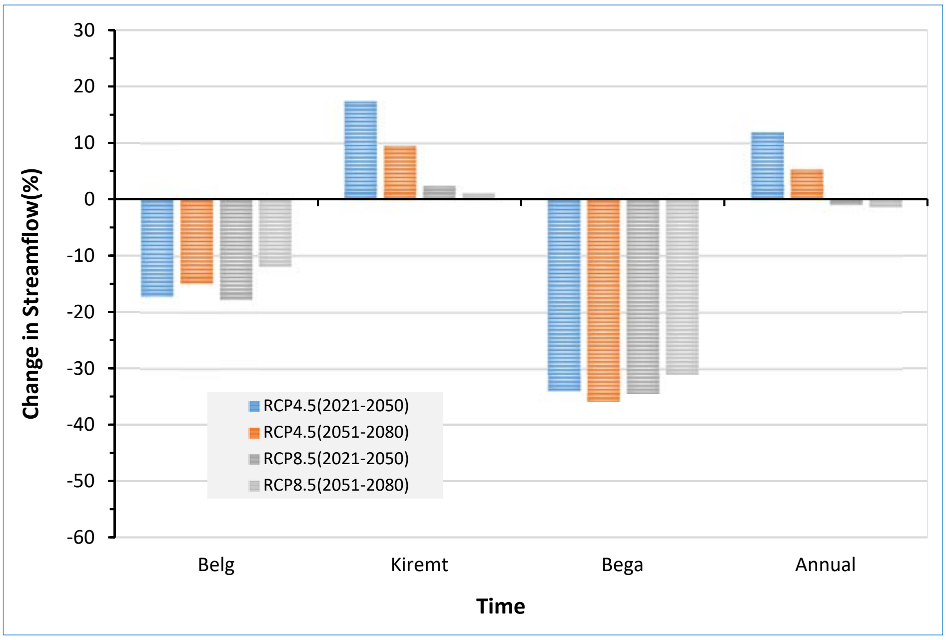

Fig. 8. Average annual and seasonal change in stream flow for RCP4.5 and RCP8.5 Scenarios

5. Conclusion

In this study, impacts of climate change on the future stream flow of Sululta Catchment has been assessed by using SWAT hydrological model on the basis of climate change forced by RCP4.5 and RCP8.5 climate scenarios of IPCC 5th Assessment (AR5) report for 2021s (2021-2050) and 2051s (2051-2080). The bias correction for downscaled RCPs data was corrected by bias correction methods successfully as the simulated climate variables produced consistent results with the historical records. The study reveals that there will be a decrease in precipitation values in dry and small rainy seasons as compared to the baseline period under both RCP4.5 and RCP8.5. However, it showed an increasing and decreasing trend in rainy season (JJAS) under both RCP4.5 and RCP8.5.

The results show that the maximum and minimum temperatures increase in both, RCP4.5 and RCP8.5 scenarios. The study also shows that the projection of RCP8.5 is warmer than RCP4.5. Seasonal and annual projection of stream flow showed a mixed increasing and decreasing trend. In Belg season (February-May) and Bega (dry) season (October-January), stream flow will be decreased under both RCP climate scenarios of future but in Kiremt (rainy) season (June-September) change in average monthly flow will increase under both RCP4.5 and RCP8.5. The projected average annual stream flow increased by 11.91% at 2021-2050 and 5.26% at 2051-2080 for RCP 4.5 and decrease in annual stream flow is observed by 0.98% in the near future and by 1.43% in the mid near future under RCP8.5.

This research will help plan sustainable management and decision-making to support future public policy in the design and implementation of various water resources programs. In this study, only two climate scenarios of RCM (RCP4.5 and RCP8.5) were used and the hydrological model did not consider land use land cover changes for different periods during the simulations. However, changes in land use and land cover can interact with climate, and different projections of future hydrological conditions are expected. Future research should therefore be conducted on related topics and should include land use and land cover change.

Data Availability Statement

All relevant CORDEX RCM data are available from an online repository or repositories. It is available from the link (https://climate4impact.eu/impactportal/data/esgfsearch.jsp).

Conflicts of Interest

The authors have no conflict of interest to declare.

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