Chapter

Evaluation of Climate Change-Induced Impact on Streamflow and Sediment Yield of Genale Watershed, Ethiopia

Tufa Feyissa Negewo and Arup Kumar Sarma

Abstract

In the 21st century, changes in induced climate can significantly affect the water resources system in the watershed. Understanding climate change disrupts hydrological processes can facilitate sustainable water resource strategies to resilient impacts of global warming. The hydrological response of watersheds will be accelerated by climate change, altering the rainfall, magnitude & timing of runoff, and sediment yield. The study investigates climate change aspects on the hydrological responses using Soil and Water Assessment Tool (SWAT) model interfaced with Geographical Information System (GIS) of Genale Basin, Ethiopia. The calibrated SWAT was applied to simulate the impact of climate, and the SUFI-II algorithm was used for parameter optimization & finalization. The change of climate scenarios was built using the outcomes bias-corrected CORDEX RCM daily precipitation, min/max temperature for Ethiopia under RCP 4.5 and RCP 8.5. The average monthly change of streamflow from −16.47% to 6.58% and − 3.6% to 8.27% under RCP4.5 and RCP8.5, respectively (2022–2080). The monthly average sediment yield change was −21.8% to 6.2% and − 5.6% to 4.66% for the RCP4.5 and RCP8.5 scenarios, respectively, over 2022–2080. It implies that the climate change-induced impacts on sediment yield are more significant than streamflow and suggest substantial adaptive management in watershed systems.

Keywords: Climate change, SWAT, Genale watershed, Sediment yield, RCM, Streamflow, Hydrological impacts evaluation

1. Introduction

Water is a unique resource given to humankind from nature impacted by induced climate change [1]. The atmospheric scientists suggest that the Earth is warming as a global temperature increase the hydrological cycle more actively. Greenhouse gases (GHGs) increase in the surroundings is a significant concern for global warming & climate changes. These changes may influence natural water resources in the catchment [2]. The Intergovernmental Panel on Climate Change (IPCC) appraisal report stated that global mean precipitation, surface temperature, droughts, and floods had changed significantly, and the changes are expected to continue [3]. Principally, developing country like Ethiopia is now facing severe climate change effects on water and agriculture sector. Currently, it is of great importance to evaluate the consequence of climate change on the regional and local water resources. The rise in surface earth air temperature and precipitation patterns are prominent features of change in climate that directly impact almost all other hydrological responses [4]. A temperate climate will accelerate the hydrological process, altering rainfall patterns and the magnitude & timing of streamflow. Climate changes are also expected to have remarkable impacts on the soil type since rainfall and runoff are the factors governing soil erosion and sediment yield/transport within landscapes [5].

The information derived from Global Climate Models (GCMs) is currently the most applicable in evaluating both past and possible future changes in climate scenarios. This climate data is then used as input to drive the hydrologic process. Long-term locally-observed climate data are also needed to validate climate model outputs to capture local settings [6]. However, direct implementation of GCM outputs to any hydrological model for subsequent evaluation of impact is despondent in climate studies because of coarse resolution issues. The simulation of GCMs runs on large scales to consider various grids across the globe, and GCM typically takes about 2.80 x 2.80 longitude and latitude resolution. To tackle the problems downscaling is assumed, a process of bringing down the climate information from GCM to regional & local hydrologic scales to produce outputs of the more acceptable resolution, which are more realistic with the local scale before estimating the risks associated with the future hydrologic scenarios [7, 8].

Different downscaling techniques have been advanced over the past two decades, deriving from two major blueprints; dynamic downscaling and statistical downscaling approaches. The dynamic approach is often viewed as a mini-GCM because it stimulates regional climate variables by decreasing the horizontal area covered (typically around 25 by 25 km) using the same boundary conditions as the evolving GCM. Because they produce high-resolution climate data, they have not been extensively accepted because of the complexities and costs involved in running this type of technique to capture regional-scale climate variables. Statistical downscaling approach, involving weather typing procedures, transfer functions, and stochastic weather generators, are the most known methods used in climate change studies nowadays [9]. They give future climate scenarios based on a statistical relationship between climate variables at one or more GCM grid points at a particular station. They are adopted because they are relatively economical to apply and give point climate data at a specific site of interest [5, 7].

The changes in streamflow and sediment yield characteristics resulting from climate change depend on individual watershed aspects. Decisive evaluations of the quantity and rate of runoff and sediment yield are needed to help decision-makers develop catchment management plans for better soil & water conservation measures [10, 11]. The SWAT-Soil and Water Assessment Tool model simulates the climate change-induced impacts for the San Jacinto River basin in Texas [12]. The effect of climate change on catchment hydrology is typically evaluated by characterizing climate change scenarios to a hydrological model based on the futuristic GHGs [1, 5, 4].

Streamflow modeling is essential to know sediment concentration in the stream, whereas peak streamflow rate is vital for hydraulic structure, watershed management practices, and flood protection. Different studies used empirical, statistical, and simulation methods to resolve the impacts of climate change on hydrological responses [13]. Recent studies recommended that SWAT is widely used as a capable model to evaluate environmental and hydrological changes with varying land types and climate conditions [14]. Additionally, the output components incorporated in the SWAT model are found to address various water-related systems in the watershed. The study highlighted that an increase in the concentration of CO_2 has a notable effect on streamflow, sediment yield, evaporation, and water yield. Carbon emission scenarios are the main driving forces in climate models. Scenarios are images or pictures of how the world is likely to emerge in the future in terms of greenhouse gasses (GHGs). In the recent study, we use the latest scenarios, called Representative Concentration Pathways (RCPs), which have rarely been applied in the study catchment. The IPCC characterizes a set of RCP scenarios (2.5, 4.5, 6.0, and 8.5) for projection of future climate based on Coupled Model Intercomparison Project (CMIP5) [15]. These four RCPs consolidate one alleviation scenario priming a low driving level (RCP2.6), two stabilization (medium) scenarios (RCP4.5 and RCP6), and one with a high GHGs emissions scenario (RCP8.5). These emissions scenarios are emerged based on the driving force such as socio-economic development, population growth, and GHGs [16]. Based on the IPCC report, by the end of the 21st century, global warming/temperature may increase by 1–5°C. Climate change scenarios for the Global Climate Model (GCM) or simple analog models are sometimes adapted to investigate climate change impacts on hydrology [17].

Nevertheless, their spatial resolutions are extremely coarse for regional climate study and need to downscale it. Therefore, either through statistical or dynamic regional climate models, the downscaling approach is required to convert GCM data into acceptable resolution before using for any hydrological study [18, 19]. Limited reports address the climate change analysis using Regional Climate Model (RCM) on streamflow and sediment concentration in the region. Nevertheless, most studies have used coarse-resolution GCM data, which are not favored for watershed hydrological modeling. The SWAT model was selected for this study because of its ability & wide range of applications, demonstrating that the model is a flexible and robust tool that can simulate various regional water flow at a watershed scale provide effective results [20].

This study contributes to investigate the effects of future climate change projection on the streamflow and sediment yield of Genale catchment using the calibrated/validated SWAT model under baseline and future two emissions and offers baseline information for adaptive soil and water resource management in a changing climate region. For the SWAT input, the future climate projection (2022–2080) statistically downscaled Regional Climate Model (RCM) Bias-corrected Coordinated Regional Climate Downscaling Experiment (CORDEX) precipitation, max/min temperature for Ethiopia, under RCP 4.5 and RCP 8.5 emissions scenario was used with historical data of (1990–2013). The climatic model data for the hydrologic modeling tool (CMhyd) is used to extract and bias-correct the climate variables obtained from RCM-CORDEX.

2. Materials and methodology

2.1 Description of the study area

The surface of the Earth has three main climate zones: tropical (hot & higher humidity zones), temperate (moderate between tropical & polar), and polar (floating and pack ice). Ethiopia is placed in the tropical climate zone lying between the Equator and the Tropic of Cancer. The latitude, longitude, & altitude of Ethiopia is given as 9^0 8′ 53” N, 40^0 29′ 35″ E, & 1343 m respectively. Based on elevation, the country has three different climate zones: Tropical zone (Dega, Weyna Dega, and Kola), with an average annual temperature of about 27°C and annual rainfall of about 510 millimeters. The study area is located on the Genale watershed with 54,941.583 Km^2 of the part of Genale Dawa River, situated in the South-Eastern part of Ethiopia and joins with Dawa River at the border with Somalia (Dolo Ado) (4° 16’N, 42° 04′E) to become the Juba River. In the Genale Basin, a total of 464 HRUs were created and scattered among 25 sub-basins. The annual mean of precipitation experienced in the area 810 mm distribution of rainfall in the watershed is 300 to 1302 mm per year. The daily max and min temperatures are 34.5 °C and 8.6 °C, respectively, with a daily average of 19 °C (**Figure 1**).

2.2 Description of the SWAT model

The SWAT was advanced in the 1990s by the United States Department of Agriculture (USDA). It is a mechanism-based and spatially semi-scattered hydrological model or flexible tool in different parts of the world, designed to calculate and route water, sediments, management practices, and nutrient-point sources of pollution from individual sub-basins through the mainstream watersheds towards its outlet resulting from changes in land use/cover in the river basins [21]. In general, SWAT simulates the hydrological cycle and water balance in the catchment using equation (1).

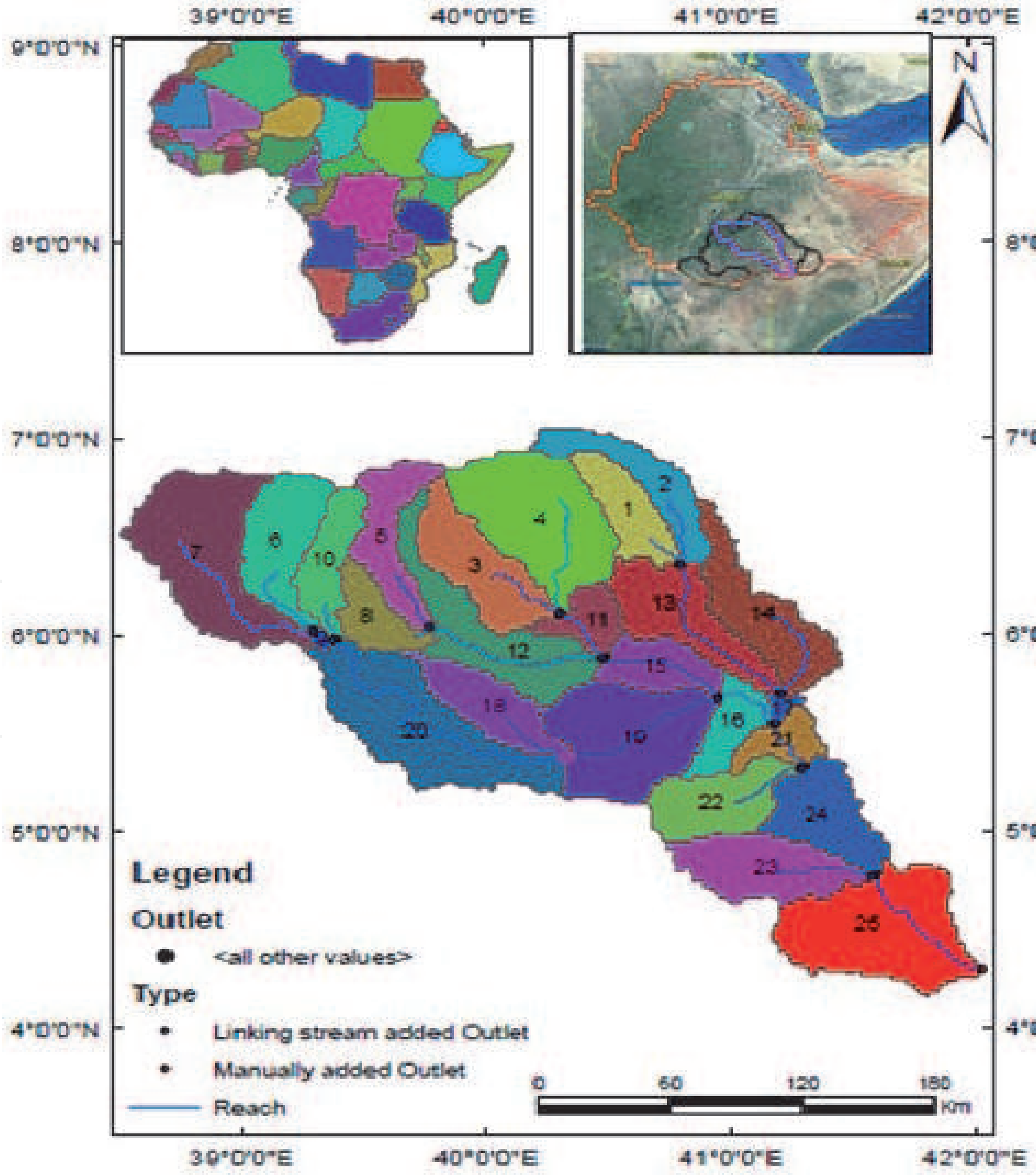

Figure 1.
Shows the delineated watershed of the study area extracted from the Africa, Ethiopia map.

$$SW_t = SW_o + \sum_{i=1}^{t}\left(R_{day} - Q_{surface} - E_a - W_{seep} - Q_{gw}\right) \tag{1}$$

Where; SWt = Final soil water content on a day i (mm/day), SWo = Initial soil water content on day i (mm/day), t = time in days, Rday = amount of precipitation on day i (mm/day),Qsurface = amount of surface runoff on day i (mm/day), Ea = amount of evapotranspiration on day i (mm/day), Wseep = amount of water entering the vadose zone from the soil profile on day i (mm/day), Qgw = amount of return flow on day i (mm/day). The SWAT uses the soil conservation service curve number (SCS-CN) approach to evaluate surface runoff, illustrating runoff to soil type, land use/cover, slope classes, and management practices, and is computationally effective [22]. The model estimates the streamflow in the sub-basins as a result of the total daily rainfall SCS- using the Soil Conservation Service curve number (CN) method as follows:

$$Q_{Surface} = \frac{\{R_{Day-0.2S}\}2}{\{R_{Day} + 0.8S\}} \tag{2}$$

The retention parameter(S) and prediction of lateral flow by SWAT model expressed as;

$$\mathrm{S} = 25.4(1000/\mathrm{CN} - 10) \tag{3}$$

Where; S = drainable volume of soil water per unit area of a saturated thickness (mm/day), CN = curve number.

The model's water yield within a watershed has been evaluated based on the equation; (Negewo & Sarma, 2021).

$$W_{YLD} = Q_{Surface} + BF - T_{Loss} = Q_{Surface} + Q_{GW} + Q_{LAT} - T_{Loss} \tag{4}$$

Where; W_{YLD} = water yield (mm), $= Q_{Surface}$ = surface runoff (mm), $+Q_{LAT}$ = lateral flow contribution to stream(mm), $+Q_{GW}$= groundwater contribution to streamflow (mm), and T_{Loss} = the transmission losses (mm) from tributary in the HRU through the bed.

For individual HRU, the sediment losses attributed to the surface runoff were evaluated based on the Modified Universal Soil Loss Equation (MUSLE) [23]. The MUSLE formula of sediment yield in the sub-basin roughly estimates the gross soil erosion caused by sheet, rill, and rain splash but does not include the erosion caused by landslides and gullies.

$$\mathrm{QSED} = 11.8 * \left(Q_{Peak} * Q_{Surface} * \mathrm{A_{hru}}\right)0.56 * \mathrm{K} * \mathrm{C} * \mathrm{P} * \mathrm{LS} * \mathrm{CFRG} \tag{5}$$

Where; QSED = Sediment loss/Sediment yield(ton/ha/day) from individual HRU, $Q_{Surface}$ = surface runoff associated to HRU (mmH2O/ha/day), $\mathrm{A_{hru}}$ = Area of HRU in(ha), Q_{Peak} = peak flow rate($\mathrm{m^3/s}$), $\mathrm{K_{USLE}}$ = soil erodibility factor, $\mathrm{C_{USLE}}$ = Cover and management practice factor, $\mathrm{P_{USLE}}$ = Conservation support practice factors of land use, $\mathrm{LS_{USLE}}$ = Topographic factor, hill slope steepness factor/the length slope factor, CFRG = coarse fragment factor.

Typically, the application of the SWAT contained five mains: (a) watershed delineation and streams network generation, (b) combination of DEM, soil data, and land use/cover data and create slopes classes, (c) creating HRU (Hydrological response unit) definition, (d) combination of climate data (e) run the simulation (**Figure 2**).

2.3 Future climate change data

The statistically downscaled Regional Climate Model (RCM) Bias-corrected Coordinated Regional Climate Downscaling Experiment (CORDEX) precipitation, min/mean/max temperature for Ethiopia, under RCP 4.5 and RCP 8.5, downloaded from(https://dataservices.gfzpotsdam.de/pik/showshort.php?id=escidoc:3124935) is provided as input data for hydrological modeling of this study. This dataset contributes bias-corrected daily precipitation, min/mean/max air temperature of ten CORDEX RCM runs covering the country of Ethiopia for historical (1970–1999) and over the 21st century for RCP 4.5 and RCP 8.5 [24]. For this study, daily rainfall and maximum & minimum temperature data of historical (1990–2013) of eight climatic stations were obtained from the Meteorological Agency of Ethiopia, and other eight climatic stations were from the global database of Climate Forecast System Reanalysis (CFSR) after filling missing data, consistency, and outlier checked [1].

Accordingly, all the bias correction has improved the simulation of precipitation and temperature before using CORDEX-RCM outputs for any climate impact modeling. The study used climate model data for hydrological modeling CMhyd to extract CORDEX-NetCDF and bias correction of precipitation, minimum and maximum temperature to predict climate change-induced temperature changes in the Genale catchment.

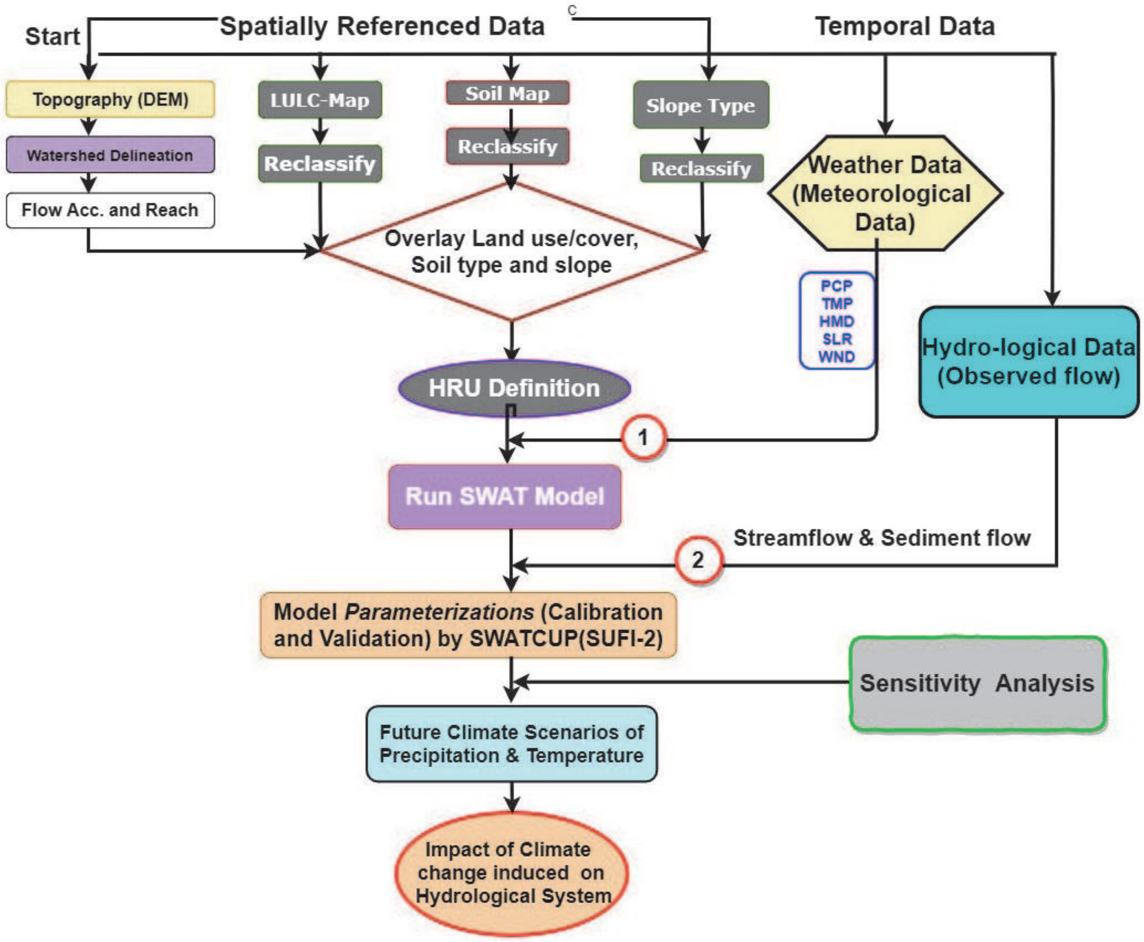

Figure 2.
Steps of the implementation of the SWAT model for the study area. Analysis of SWAT input data.

SWAT model was used to simulate water yield using the RCM under the future emission scenarios of two representative concentration pathways (RCPs) (medium emission scenario (RCP4.5) and high emission scenario (RCP-8.5)). Climate data for different periods are input into the SWAT model with the other components unchanged. The period of 1990–2013 is set as the baseline period.

Digital elevation model was downloaded from USGS Earth Explorer (http://earthexplorer.usgs. gov/) SRTM (Shuttle Radar Topography Mission) 90 m*90 m and used for watershed delineation, sub-basin, slope calculation/ classification, and extract stream networks. The spatial land use/cover collected from the Ethiopian Ministry of Water, Irrigation, and Electricity (MoWIE) GIS department of the year 2013 used for SWAT input, and the dominant land use/cover is range brushland (RNGB) accounts for about 71% of the area. This study's soil map/type is from the Food and Agricultural Organization (FAO) Digital Soil Map of the World (http://www.fao.org/geonetwork/srv/en/metadata) the scale of 1/5000000 for 2007. The soil data that integrated into the SWAT model are: the available water content, the texture, the hydraulic conductivity, the apparent density of the different soil layers, and the dominant soil type in the study watershed was Rc19-bc-204 (Calcaric Regosols), and it accounts about 40% of the catchment.

The climate data required for this paper has been taken from the National Meteorological Agency of Ethiopia, http://www.ethiomet.gov.et/etms. These data subsist of precipitation, max and min temperatures, wind energy, solar radiation, and relative humidity daily and covered the period from 1990 to 2013 for sixteen stations. The discharge data from the Ethiopian Ministry of Water, Irrigation, and Electricity (MoWIE) Hydrology department Genale @ Halwen gauging station a bit upstream of the outlet, and then transferred to the outlet, and arranged for SWAT language for the period from 1990 to 2013.

Figure 3, shows different 16 (sixteen) meteorological stations were distributed in the watershed, hydrological gauging station, watershed outlet, stream reach, and basin mark of the study area. The stations which were designated as; GMS1-Gridded Meteorological station-1, GMS2- Gridded Meteorological station-2, GMS3-Gridded Meteorological station-3, 4,5,6,7, & 8 respectively (**Figure 3**).

Figure 4 shows the distribution of rainfall in the study area for the selected different gauge stations.

From **Figure 5b**, the details of maximum, average, and minimum yearly temperature of the study area were pinpointed as 24.6, 19, & 12.93 °C, respectively, for 1990–2013 (**Figure 6**).

2.4 SWAT-CUP(SUFI-2) description

The automatic calibration and validation adjustment in the SWAT model achieved using the SWAT-CUP (SUFI-II) public user software developed by [25]. The SWAT-CUP has interfaced with five algorithms: (1) sequential uncertainty fitting (SUFI-2, (2) generalized likelihood uncertainty estimation (GLUE), (3) parameter solution (ParaSol), (4) Markov chain Monte Carlo (MCMC), and (5) particle swarm optimization (PSO) [26].

In this study, the analysis of uncertainty, calibration, validation was conducted using the SUFI-2 optimization algorithm; this algorithm needs less simulation number, faster, and one of the most used in the automatic calibration of model for several basins the semi-arid region like Genale Basin.

Assessment of performance criteria for the model is; Nash-Sutcliffe Efficiency (NSE), PBIAS, and Coefficient of Determination (R^2) has been used as the efficiency criteria to evaluate the performance of models in the Genale watershed.

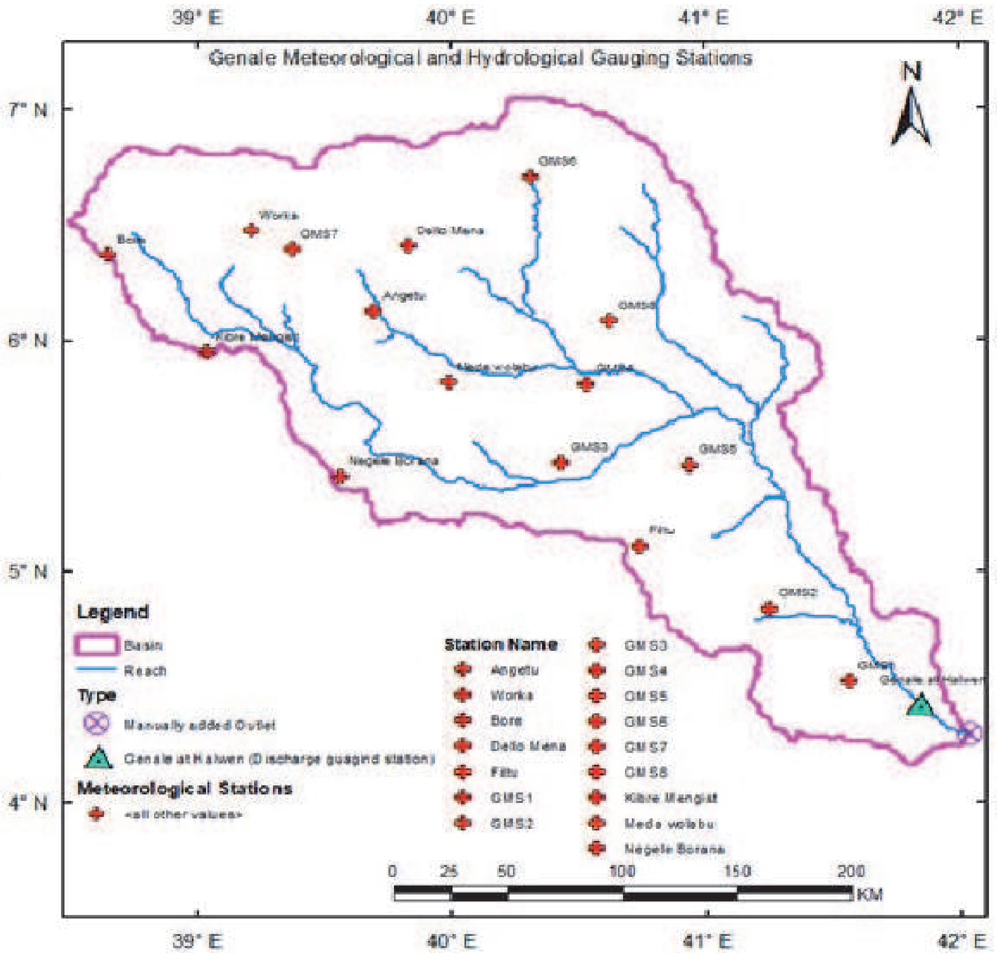

Figure 3.
Meteorological and hydrological gauging station distribution sub-basin wise for Genale River.

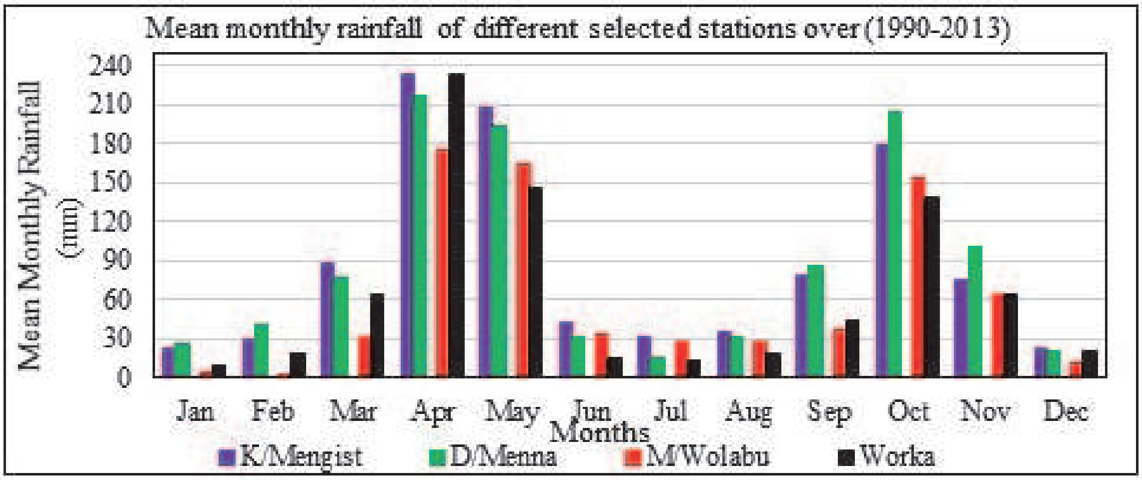

Figure 4.
Mean monthly rainfall for selected stations in the study area over 1990–2013.

The first three objective functions are mainly used for daily and monthly streamflow /sediment calibration–validation uncertainty analysis.

Coefficient of Determination (R^2)

$$R^2 = \frac{\left[\sum_{i=1}^{n}(Q_{si} - Q_{sm})(Q_{oi} - Q_{om})\right]^2}{\sum_{i=1}^{n}(Q_{si} - Q_{sm})^2 \sum_{i=1}^{n}(Q_{oi} - Q_{om})^2} \tag{6}$$

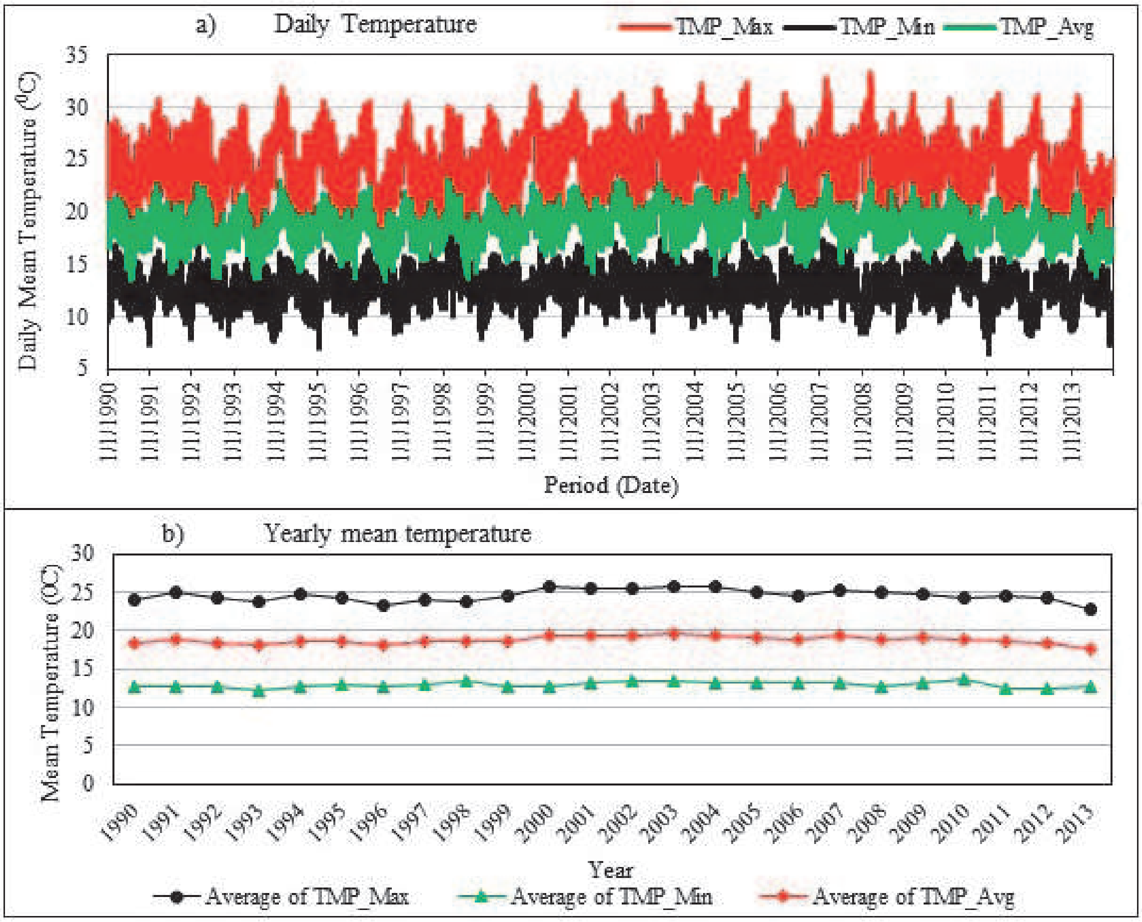

Figure 5.
Daily and yearly average maximum, minimum, and average daily temperatures in the study area, respectively.

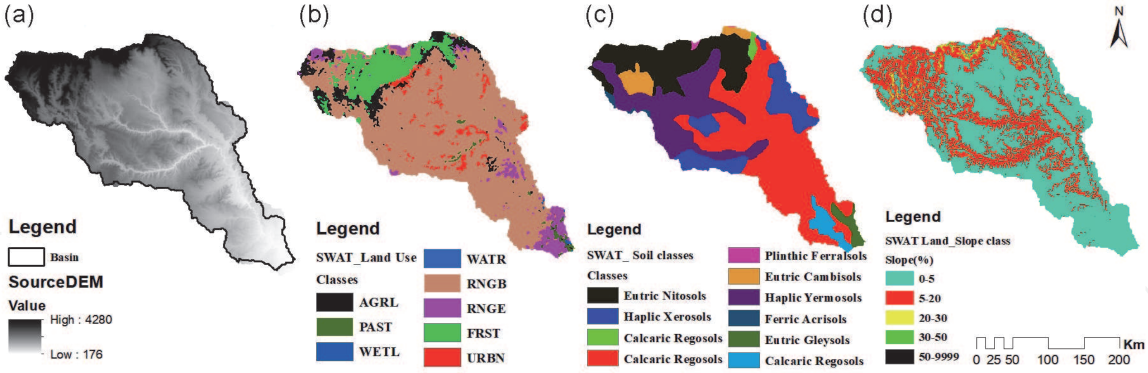

Figure 6.
DEM, LULC, soil type, and slope classes of the Genale watershed, respectively.

Where, Q_{si} is the simulated value, Q_{oi} is the measured value, Q_{om}, is the average observed value and Qsm is an average simulated value? Nash Sutcliffe Efficiency (NSE).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{oi} - Q_{si})^2}{\sum_{i=1}^{n}(Q_{oi} - Q_{om})^2} \tag{7}$$

where, Q_{oi} is the observed, Q_{si} is the simulated, and Qom is the observed discharge.

$$\text{Percent Bias (PBIAS)}; PBIAS = 100\% \times \frac{\sum_{i=1}^{n}(Q_{oi} - Q_{si})}{\sum_{i=1}^{n} Q_{oi}} \tag{8}$$

3. Results and discussions

The model was built with DEM, soil classes, land use/cover, and slope types for the Genale watershed, which contained 25 sub-basins, 464 HRUs with a catchment area 54,942Km2 at the outlet.

3.1 Model parameter sensitivity analysis

Sensitivity analysis was performed to navigate the calibration action and pinpoint parameters that significantly affect the discharge and sediment flow. In a sensitivity analysis of the model, SCS curve number (CN2.mgt), an available water capacity of the soil layer (SOL_AWC.sol), and saturated hydraulic conductivity (SOL_K.sol) are the most sensitive parameters for runoff estimation. However, model efficiency is also influenced by the reliability of spatial and temporal data.

Sediment sensitivity analysis was carried out for three years warm-up period 1987 to 1989- and 16-years calibration period 1990 to 2005- and 8-years validation period 2006 to 2013. Based on the p-value and t-stat results obtained from sensitivity analysis, the ranks of parameters were finalized. The simulated sediment was sensitive to the amount of sediment re-entrained during channel sediment routing (SPCON.bsn), (SOL_AWC.sol), CN2, etc., respectively.

A parameter with a larger absolute value of t-stat is more sensitive to flow. The p-value gives the relevance of the sensitivity. Thus, when the p-value is close to zero, then the sensitivity of the parameter is a priority (**Table 1**).

3.2 Calibration/validation

Calibrated parameters and the fitted values are final notes for the modeler from the calibration process used for the required objectives. Calibration of discharge and sediment flow was performed with several iterations of 500 simulations number; each was carried out for the calibration period of 1990–2005 monthly.

Validation is required to verify whether the calibrated parameters also work for other data of different years within the watershed. Validation time (2006–2013) results revealed a satisfactory performance, as statistical measures are in the acceptable range for discharge and sediment. **Table 2** shows the acceptable range for the model's performance in light of the calibration and validation process.

The results show satisfactory and well responded to calibration and validation process (**Table 3**).

The calibration was done from 1990 to 2005 & the validation period from 2006 to 2013, and the model performance shows satisfactory agreement between the observed and simulated flow (**Figure 7**). The calibrated/validated model also responded to the rainfall with the respective months.

As indicated, the simulated and observed sediment load agreed and showed a satisfactory performance during the calibration and validation action (**Figure 8**).

3.3 Impact of climate change in the watershed

3.3.1 Climate change impacts on temperature and precipitation

The climate change impact on hydrology was evaluated by driving the calibrated/validated SWAT model with the bias-corrected RCM-CORDEX weather corresponding to the present-day historical data and future emission scenarios. The analysis was executed on a monthly basis for streamflow and sediment yield.

Process	Parameter name	Description of the parameter	Range value	Fitted value	p-value	t-stat	Rank
Streamflow	CN2.mgt	SCS runoff curve number	35–98	−0.17	0.0	−42	1
	SOL_AWC.sol	Available water capacity of the soil layer	0–1	1.0	0.004	2.9	2
	SOL_K.sol	Saturated hydraulic conductivity	0–2000	0.566	0.12	−1.5	3
	SOL_BD.sol	Moist bulk density	0.9–2.5	0.984	0.20	1.2	4
	ALPHA_BF.gw	Baseflow alpha-factor (days).	0–1	0.570	0.21	−1.2	5
	REVAPMN.gw	Threshold depth of water in a shallow aquifer for “revap” to occur (mm)	0–500	408.6	0.308	−1.0	6
	GW_REVAP.gw	USLE support practice factor	0–1	1.2	0.49	−0.6	7
	ESCO.hru	Soil evaporation compensation factor	0–1	0.27	0.65	−0.4	8
	HRU_SLP.hru	Average slope steepness	0–1	0.578	0.72	0.34	9
	SURLAG.bsn	Surface runoff lag time	0.05–24	0.072	0.96	−0.05	10
Sediment	SPCON.bsn	The max amount of sediment that can be retrained during channel routing.	0.0001–0.01	0.0002	0.0	−29.5	1
	SOL_AWC(.)sol	Available water capacity of the soil layer	0–1	0.639	0.0	14.2	2
	CN2.mgt	SCS runoff curve number	35–98	−0.24	0.0	−10	3
	SOL_K(..).sol	Saturated hydraulic conductivity	0–2000	0.845	0.0	7.18	4
	SPEXP.bsn	Exponent parameter for calculating sediment retrained in channel sediment routing.	1–1.5	1.156	0.0	−5.63	5
	CH_COV1.rte	Channel erodibility factor.	−0.05-0.6	0.78	0.145	−1.44	6
	USLE_K(..)sol	USLE equation soil erodibility (K) factor.	0–0.65	0.012	0.57	−0.6	7
	USLE_P.mgt	USLE equation support parameter	0–1	0.029	0.73	0.35	8

Table 1.
Fitted values and rank of parameters used in the SWAT model calibration/validation (1998–2012).

The statistically downscaled Regional Climate Model (RCM) Bias-corrected Coordinated Regional Climate Downscaling Experiment (CORDEX), precipitation, min/mean/max temperature for Africa-Ethiopia, under RCP 4.5 and RCP 8.5. The average annual rainfall in the study climate stations during the baseline 24-years period (1990–2013) was 810 mm, and the maximum and minimum yearly rainfall accounts were 1,303 mm and 300 mm, respectively.

The monthly temperature of the catchment varies from 14.5°C to 24.6°C, with an average of 19.5°C. We predicted the long-term average precipitation with the historical data for two climate emission scenarios. As shown in **Figure 9**, significant changes occur in the dry season (December, January & February).

p-factor	r-factor	R2	NSE	PBIAS		RSR	Rating
				Flow	Sediment		
0.7–1	<1, (close to 0)	0.75–1	0.75–1	<±10%	<±15%	0–0.5	very good
		0.65–0.75	0.65–0.75	±10–15%	±15–30%	0.5–0.6	good
		0.5–0.65	0.5–0.65	±15–25%	±30–55%	0.6–0.7	satisfactory
Close to 0	>1, (infinite)	<0.5	≤0.5	> ± 25%	> ± 55%	>0.7	unsatisfactory

Table 2.
SWAT statistical performance index acceptable range [25, 26].

Types of assessment		p-factor	r-factor	R2	NSE	PBIAS	RSR	Rating
Flow	Calibration	0.51	0.78	0.87	0.81	−2.1%	0.50	good
	Validation	0.54	0.86	0.85	0.78	−0.5%	0.52	good
Sediment	Calibration	0.48	0.37	0.84	0.79	3.8%	0.61	satisfactory
	Validation	0.43	0.39	0.82	0.75	3.9%	0.67	satisfactory

Table 3.
Actual index value for SWAT output during calibration/validation process (1990–2013).

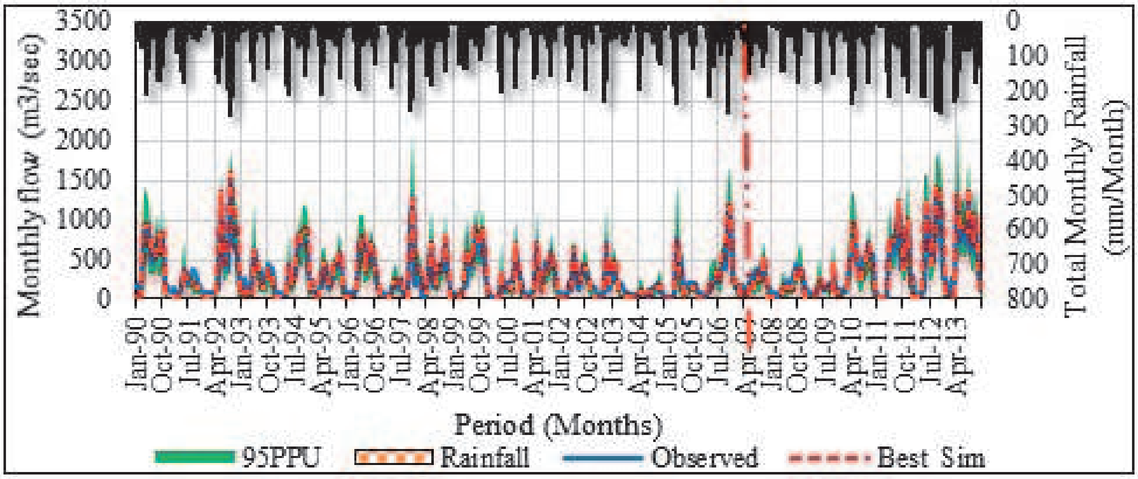

Figure 7.
Monthly calibration and validation of streamflow (1990–2013) for Genale River basin at Genale Halwen.

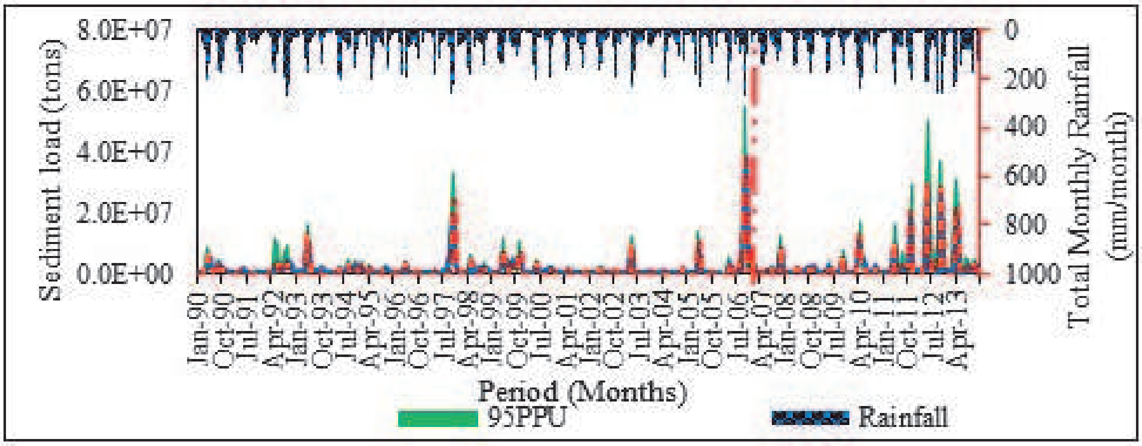

Figure 8.
Monthly observed and simulated sediment load plots for the calibration (1990–2005) and validation (2006–2013).

Figures 9 and **10** show the climate changes in the average monthly precipitation and the maximum and minimum air temperatures over the catchment between the historical and future periods (2022–2080) for the two emission scenarios. Generally, the climate change over the Genale basin will likely become warmer, especially in autumn and spring, considering the higher emission scenario (**Figure 10**).

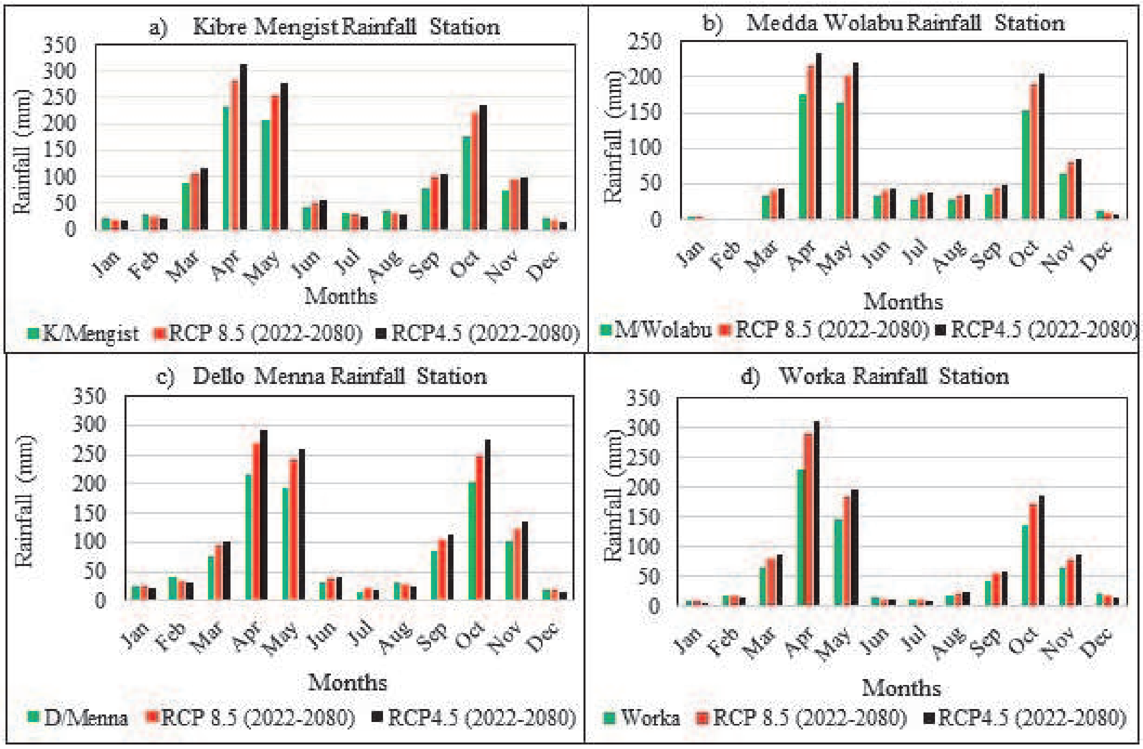

Figure 9.
Comparison of average observed monthly precipitation for baseline condition, RCP4.5, & RCP8.5 scenarios of four stations in the catchment.

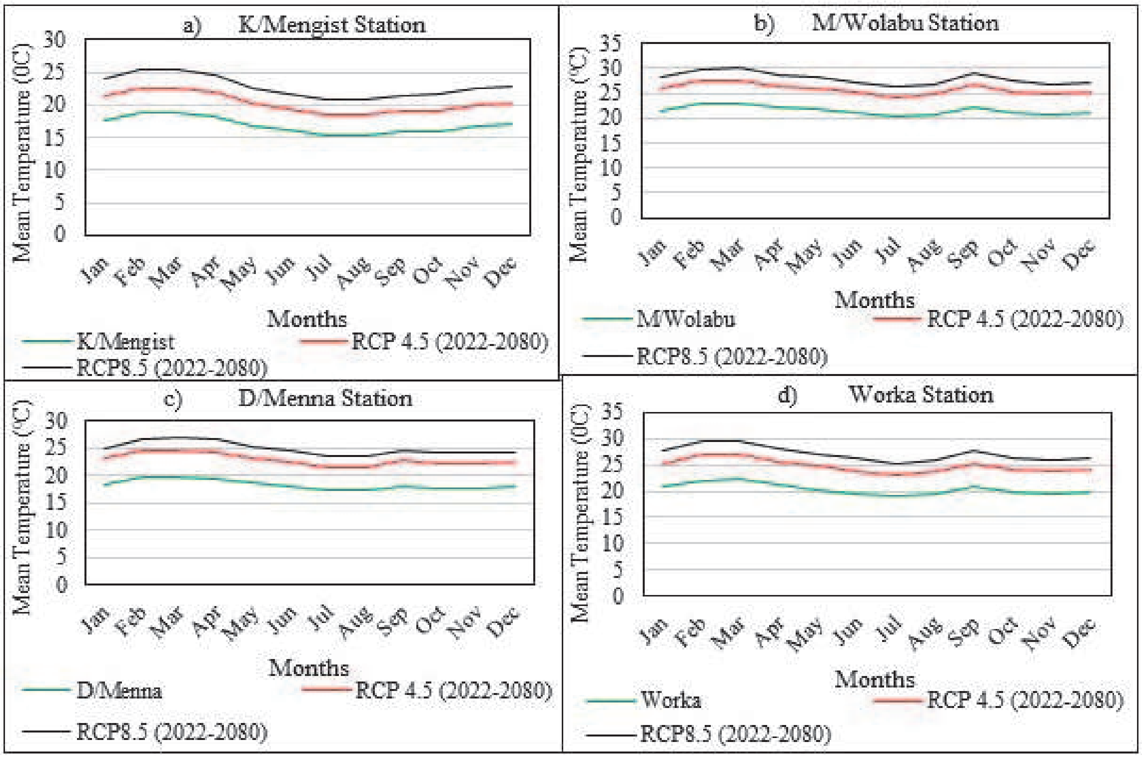

Figure 10.
Comparison of mean temperatures for historical data, RCP4.5, & RCP8.5 scenarios of four stations in the catchment.

Indistinct, the maximum temperature increase is somewhat higher than that of the minimum temperature in the region.

Figure 10 shows an average of mean monthly changes in temperatures in the study watershed, and it is increasing under emission scenarios of RCP4.5 and RCP8.5.

3.3.2 Climate change impact on streamflow and sediment

The bias-corrected rainfall and maximum/minimum temperature outputs were used as inputs to the calibrated/validated SWAT model to examine the Genale catchment streamflow and sediment yield responses in the future years. The climate-induced discharge changes are understood by assessing differences produced by the SWAT model when driven by future scenarios and present-day climates. A similar study by Negewo & Sarma (2021) for the Genale watershed revealed that the mean annual quantity of water resources is possible to increase under RCP4.5, but variations are substantial for individual sub-basins and HRUs. The study results reflected that climate change might increase the high flows in the catchment in the Autumn season (April, May, June) and Spring season (September, October & November) (**Figure 11**).

Monthly discrepancy showed that the increase in discharge is more pronounced in March, April, May, August, September under RCP4.5, and the decrease is more pronounced in the same months under RCP8.5 scenarios (**Figure 11**). The average monthly change of streamflow for the RCP4.5 and RCP8.5 was running from −16.47% to 6.58% and − 3.6% to 8.27%, respectively, of 2022–2080(**Figure 12**).

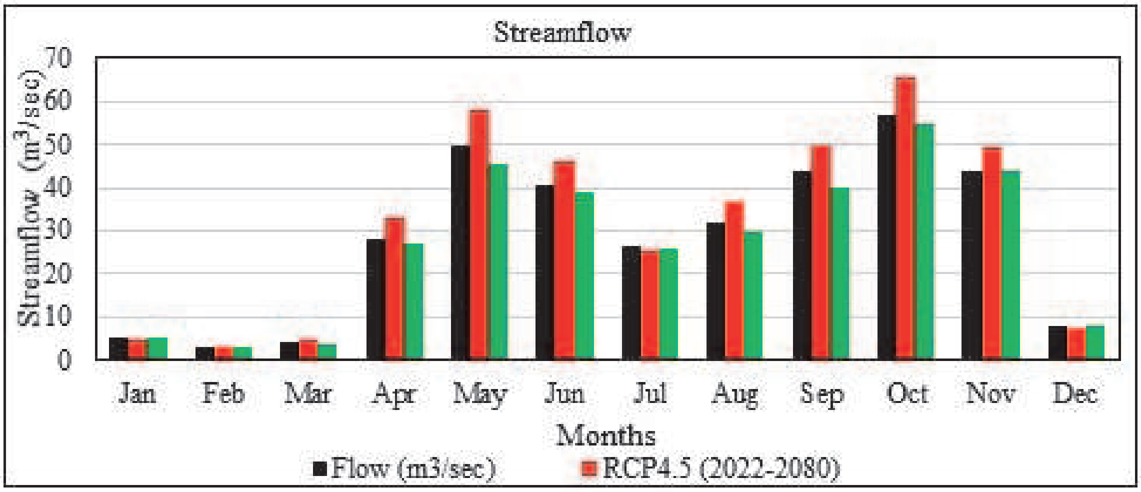

Figure 11.
Streamflow variations under historical data and two emissions scenarios.

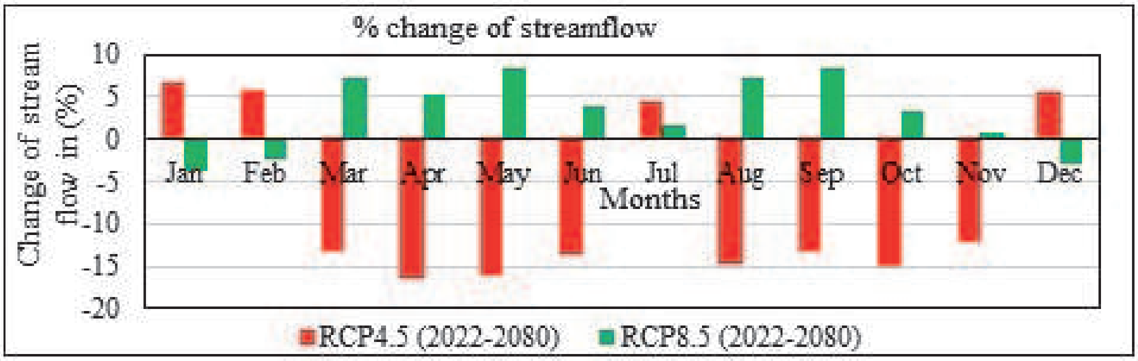

Figure 12.
Predicted relative changes (percent of baseline levels) in monthly streamflow by RCP4.5 & RCP8.5.

The change in monthly streamflow is consistent with the predicted changes in rainfall and temperature patterns in the future period.

The change patterns of sediment yield follow that of streamflow in the region.

Prediction of RCM showed an increase in sediment yield for RCP4.5 and slightly decreased for the RCP8.5 scenario (**Figure 13**). Monthly variation showed that the magnitude changes in sediment yield in March, April & June was the highest with values of −21.8%, −15.0%, −15.0% and − 13.7% respectively for RCP4.5 scenario, and slightly lower in January, March, November, September & December with values of −3.5%, 1.5%, 2.1%, 2.1% & 2.2% respectively for RCP8.5 scenario (**Figure 14**). It should be recognized that the maximum increase in heavy rainfall and extreme events was also predicted in the respective months. Hence, the corresponding change predicted by the model is reasonable. The monthly average changes in sediment yield for the RCP4.5 and RCP8.5 scenarios were − 21.8% to 6.2% and − 5.6% to 4.66%, respectively, over 2022–2080 (**Figure 14**).

The increase in change (percentage) of sediment yield is more significant than discharge, implying that the sediment concentration in the Genale catchment will likely increase in the future periods under the RCP4.5 scenario.

From the spatial distribution of the sediment yield for the baseline & two emissions scenarios periods (**Figure 15**), the high-sediment-yield regions are mainly

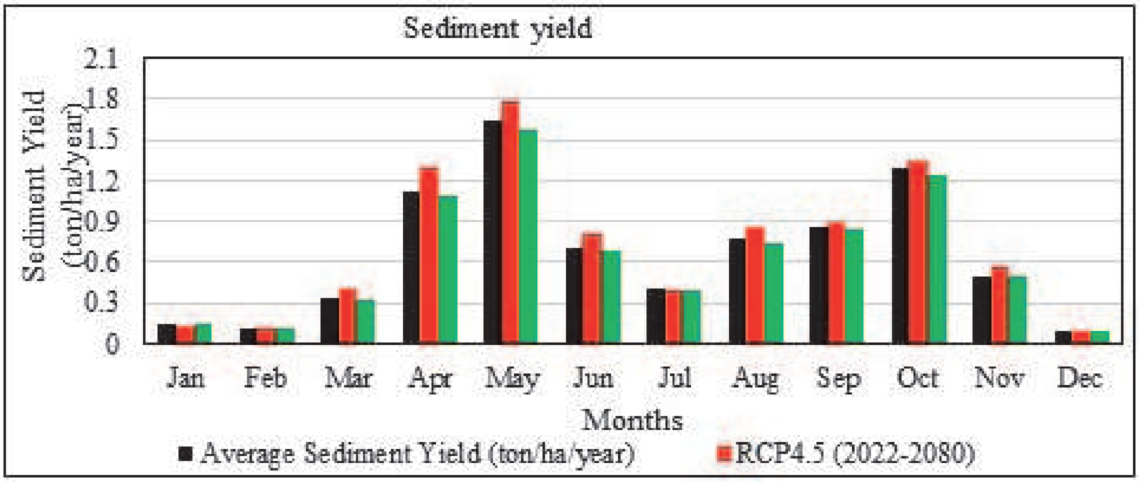

Figure 13.
Sediment yield variations for baseline and two GHGs scenarios.

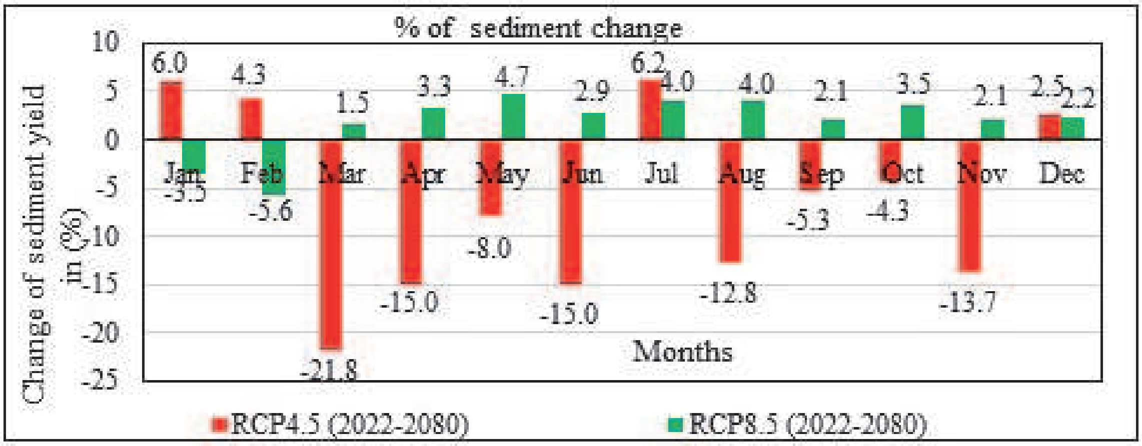

Figure 14.
Predicted relative monthly changes in sediment yield in future periods for two emission scenarios compared to baseline.

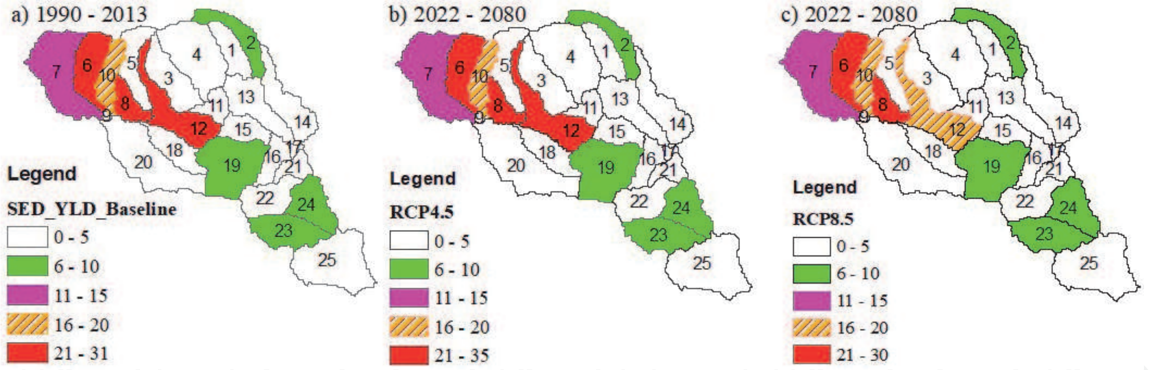

Figure 15.
Annual average spatial distribution of sediment yield (ton/ha/year) at sub-basin scale in historical data & future periods under baseline, RCP4.5& RCP8.5.

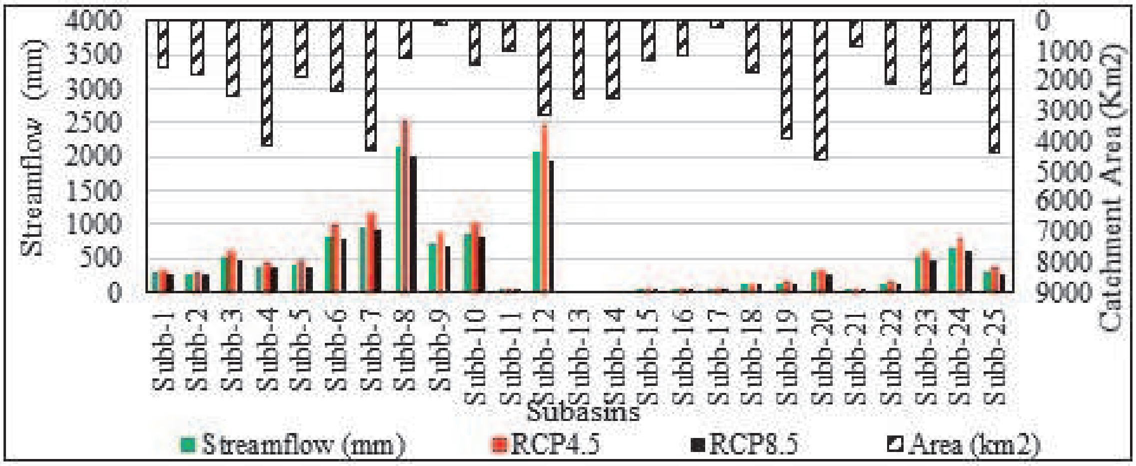

Figure 16.
Annual average spatial distribution of streamflow (mm) at sub-basin scale in historical data & future periods under baseline and two emission scenarios.

located in the upstream regions of the catchment for all cases, in which the sediment yield varies from 0 to 31 (baseline condition), from 0 to 35 (under RCP4.5) & from 0 to 30 (under RCP8.5) over 1990–2013, 2022–2080, 2022–2080 respectively.

Irrespective of the catchment area, the spatial distribution of streamflow at the sub-basin level follows the trend of sediment yield patterns in historical data (1990–2013) and future periods (2022–2080) under baseline conditions & two emissions scenarios (RCP4.5 & RCP8.5) (**Figure 16**).

From the results, a comparison of monthly stream discharge & sediment yield predictions for 2022–2080 indicated that the impact of climate changes induced on sediment yield is more significant than on streamflow under the two emission scenarios.

4. Conclusions

The study evaluated the impact of climate change-induced on the sediment yield and streamflow of the Genale catchment, Ethiopia, for the medium-future period 2022–2080 under the RCP 4.5 and RCP 8.5 emission scenarios. The SWAT hydrological model was applied to simulate discharge and sediment yield, and the SUFI-2 algorithm technique in the SWAT-CUP tool was used for parameterization. The process of uncertainty analysis, calibration (1990–2005), & validation (2006–2013) for both discharge and sediment were satisfactory. The sensitivity analysis enabled that the SCS curve number (CN2.mgt), an available water capacity of the soil layer (SOL_AWC.sol), and saturated hydraulic conductivity (SOL_K.sol) are the most sensitive parameters for runoff estimation.

The study used the change of climate scenarios built up using the outcomes bias-corrected CORDEX RCM daily precipitation, min/mean/max temperature for Ethiopia under RCP 4.5 and RCP 8.5 emission scenarios and fed them into the validated SWAT model to simulate future changes in streamflow and sediment yields due to change of climate. The average monthly change of streamflow for the RCP4.5 and RCP8.5 was running from −16.47% to 6.58% and − 3.6% to 8.27%, respectively, of 2022–2080. The monthly average changes in sediment yield for the RCP4.5 and RCP8.5 scenarios were − 21.8% to 6.2% and − 5.6% to 4.66%, respectively, over 2022–2080. The monthly average discharge varies significantly throughout the year and relatively high in March, April, May, August, September, and October. The monthly streamflow and sediment yield variations were more during the wet seasons (Autumn and Spring). The results revealed that the impact of climate changes induced on sediment yield is more significant than streamflow under the two emission scenarios for 2022–2080.

The results revealed that regional decision-makers and other stakeholders are helpful for the effective adaptive strategy, plan & management practices of soil and water resources improvement under changing climate.

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Conflict of interest

The authors declare no conflict of interest.

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