MAJOR PROJECT REPORT

ON

Assessment of climate change impact on streamflow variability in Upper Narmada River Basin using SWAT Model

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Submitted by

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DECLARATION

I, Shivangi Lakhera, RollNo.2K20/ENE/12 student of M.Tech (Environmental Engineering), hereby declare that the project Dissertation titled "Assessment of climate change impact on streamflow variability in Upper Narmada River Basin using SWAT Model" which is submitted by me to the Department of Environmental Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of and Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: **Delhi** **Shivangi Lakhera**

Date:

CERTIFICATE

I hereby certify that the Project Dissertation titled "Assessment of climate change impact on streamflow variability in Upper Narmada River Basin using SWAT Model" which is submitted by Shivangi Lakhera, 2K20/ENE/12, Department of Environmental Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi **Prof. S.K. Singh**

Date: **Head of Department**

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ABSTRACT

A wide range of hydrological processes in different spatiotemporal dimensions can be simulated using SWAT being a physical model. This study uses the Soil Water Assessment Tool (SWAT)model to analyse the possible effect of climate change on the future streamflow of the Narmada River watershed, a sub basin of the Narmada River, India. The model was calibrated for 1988-2007 and validated for 2008-2015 using monthly discharge data at the watershed outlet. Calibration and validation of the SWAT model were carried out in SWAT-CUP using the SUFI-2 algorithm. The coefficient of determination (R2) and Nash Sutcliffe efficiency (NSE) were 0.87 in calibration, whereas in validation was 0.85 each. The outcome indicates that the simulated and observed flow have a good match. The calibrated model was then run for the future (2025-52) using climate model output. The study of climate change is completed using the Representative Concentration Pathway RCP4.5 and 8.5 scenarios from three different GCM. The downscaled output of these GCM from CORDEX has been used in this study after bias correction. The study aims to provide an understanding of applicable methodologies, for future streamflow implications from climate change, and worldwide strategies to reduce prediction uncertainty. Future research directions in SWAT modelling are also discussed.

KEY WORDS: *SWAT; Hydrological modelling; Climate change; Streamflow*

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ABBREVIATIONS

ArcSWAT	ArcGIS interface Soil and Water Assessment Tool
AR5	Assessment Report- 5
ASTER	Advance Space–borne Thermal Emission and Reflection Radiometer
CMIP5	Coupled Model Intercomparison Project-5
CORDEX	Coordinated Regional Climate Downscaling Experiment
CWC	Central Water Commission
DEM	Digital Elevation Model
ECP	Extended Concentration Pathway
ET	Evapotranspiration
GCM	Global Climate Model
GIS	Geographical Information System
HRU	Hydrologic Response Unit
LULC	Land Use Land Cover
NSE	Nash Sutcliff coefficient
PRECIP	Precipitation
RCP	Representative Concentration Pathway
RMSE	Root Mean Square Error
RS	Remote Sensing
SURQ	Surface Runoff
SWAT	Soil and Water Assessment Tool
WYLD	Water Yield

CHAPTER 1

INTRODUCTION

1.1 Background of the study

The changing climate has become an important topic of discussion in the last few decades. The accelerating increase in global temperatures is linked to the greenhouse effect and known as global warming (IPCC 2013). As per the reports, published by Intergovernmental Panel for Climate Change (IPCC 2013) eleven of the twelve years (1995-2005) rank among the twelve warmest years in the instrumental record of global surface. Over the past 50 years (1956-2005), the linear warming trend has doubled than that for 100 years (1906-2005). The changes in climate resulting in the change in rainfall pattern may adversely affect the future water resources availability in basins (Harmsen et al., 2007).

Direct or indirect changes in air temperature and precipitation impacts the hydrologic cycle further effecting the water resources. Change in climate alters the characteristics of precipitation, such as amount and intensity as well as the rate of evapotranspiration. This leads to considerable significant changes on the hydrological regimes by affecting the volume, peak rate, and timing of river flow (Thin et al., 2020). Evaluation of changes in river flow due to changing climate is essential in the field of water resource management and decision making related to water resource availability. The assessment of climate change impact on streamflow is one of the most important issues in hydrological research (Myanmar Climate Change Alliance). Simulation and quantification of the responses of regional hydrological and/or water quality processes to anthropogenic and natural causes, as well as different management techniques, is a typical use of hydrological and ecohydrological models. (Ogden, 2021; Sood and Smakhtin, 2015; Sood and Smakhtin, 2015). Input data, climate models, and hydrological or ecohydrological models, on the other hand, are all key sources of uncertainty in current hydro-climatic modelling frameworks (Kundzewicz et al., 2018).

The water balance of the natural catchment has changed substantially and significantly due to anthropogenic involvement such river regulation. This has led the researcher's inclination towards studies which utilizes a modelling approach to help in better understanding of complex watershed processes and their interactions with topography, land use management, soils and climate help in the evaluation of key water balance components, surface runoff, groundwater, and evapotranspiration being the major ones. Climate and land use lead to changes in hydrological components and are significant factors which lead to the amplification of hazards such floods, droughts and pollutant transportation (Lee and Kim, 2017). The Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC 2014) emphasizes water resources availability, which states that streamflow in rivers is going to change significantly because of the changes in precipitation and temperature (IPCC 2014). Unplanned anthropogenic activities in the name of development have altered the atmospheric gas composition, causing the climatic parameters to change, along with several other adverse effects which in turn have prominent effects on the water resources locally as well as on a global scale. This calls attention to understand the hydrologic variability with respect to potential climatic changes.

The Soil Water Assessment Tool (SWAT) is a basin-scale continuous model that evaluates the effects of various management techniques on watershed-related factors (Swain, 2017). It's a grey-box, physical, semi-distributed (in terms of space) model (Setegn et al., 2010). SWAT is widely used for assessment and evaluation of hydrological impacts, such as estimation of streamflow, analysing the impact of changing climate on water resources, water quality assessment and flow simulation-based flood warning systems. Various studies conducted have identified SWAT as an efficient and potential model for the purpose of simulation and projection of hydrological parameters in a watershed. The main aim of this paper is to comprehensively review the application of hydrological model SWAT for streamflow simulation and forecasting in changing climate scenarios. Furthermore, this paper also aims to discuss current challenges met and corresponding required future research directions in this area for a better and more comprehensible framework that will facilitate enhanced SWAT modelling in scenarios of changing climate.

1.2 Impact of climate change on water resources

Climate change is an unavoidable process that has brought the Earth from an ice age to the present. Many studies and investigations have been conducted around the world to determine the impact of future climate changes on human activities and the natural world. It was also frequently associated with the identification and evaluation of potential human adaptive responses to a changing climate. Water is most essential topographical agent that adjusts the surface morphology of the planet on an exceptionally great scale (Singh & Manaan, 2017). Proper water management practices are necessary to contribute to the area's socioeconomic growth. Freshwater "inadequacy" and security have been identified as the most pressing worldwide environmental issues of the twenty-first century. These resources will be lost if they are not properly managed, which will have a negative impact on both our lives and the environment. Climate change will result in significant changes in the hydrological cycle's geographical and temporal pattern variation. This will result in water shortages, floods, droughts, and environmental deterioration, among other things, and is particularly noticeable in semi-humid and semi-arid regions.

Climate change is a worrying event, according to numerous studies (for example, increase in temperature results in increase in evapotranspiration, and decrease in the amount of available water). This needs ongoing monitoring and quantification of climate change impacts. According to IPCC reports, observational data and climate projections show that freshwater supplies are particularly sensitive to climate change, which has far-reaching effects for human civilizations and ecosystems. Climate change has an impact on the operation and functionality of existing water infrastructure, such as hydropower, structural flood defences, drainage and irrigation systems, and water management practises.

During the last few decades, the water resources are facing tremendous pressure dramatic change in climatic conditions and uneven rainfall pattern inducing problems of droughts and floods (Shan et al., 2020). By 2050, more than a billion people in Asia could be affected by a decrease in freshwater availability, particularly in large river basins. The Himalayan glacier melt, which is expected to increase flooding and rock avalanches, will have adverse impacts on water resources over the next two to three decades. The receding glaciers will eventually cause a decrease in river flows in future time periods. Increased flooding from the sea and, in some cases, river floods will put coastal areas, particularly densely populated mega-delta regions, at risk.

In the recent years, the number and intensity of natural hazards has increased significantly around the world which has become an issue of global concern has raised the awareness about the changing climate of the earth in the global community. Climate change has proven to show adverse significant impacts on all realms of the hydrological cycle. Many researches and scientists have carried out studies to comprehend the situation of changing climate and its impact on hydrological systems. Evaluation of future streamflow under changing climate scenarios requires certain tools such as hydrological models, outputs from climate models, methods for downscaling and bias correction. Different combinations of RCP scenarios and

Global climate Models can be used to obtain results of the studies. The GCM model outputs are able to simulate complex climate aspects and are tested against historical observations and hence are commonly used by researchers. Numerous modelling studies have used hydrological model, SWAT along with climate models to assess and evaluate the impacts of climate change on streamflow in different regions (Tehrani et al., 2019).

The studies involving climate change impact assessment on water resources thus becomes important for better water management practices in the near future to combat the adversities of changing climate.

1.3 Objectives of the study

The objectives of the thesis are:

1. To setup SWAT hydrological model for Upper Narmada River Basin and to simulate streamflow at a specified location on the river basin.
2. To prepare GIS inputs of the study area required by SWAT model
3. To calibrate and validate the model using SWAT–CUP
4. To assess and generate climate change impact on future streamflow and hydrological scenario including major water balance component (Precipitation, surface runoff, evapotranspiration, water yield) using CORDEX climate data in the SWAT model of Upper Narmada watershed.

CHAPTER 2
LITERATURE REVIEW

2.1 DESCRIPTION OF THE SWAT MODEL

2.1.1 General Concepts

The Soil and Water Assessment Tool (SWAT) is a semi-distributed, continuous time watershed modelling system (Jain et al., 2017) to model the runoff from snowmelt and rainfall. It is a physical model based on daily time step working mechanism. SWAT is integrated into GIS environment as a free additional extension ArcSWAT for ArcGIS to make it capable of simulating a high level of spatial detail by allowing the division of a watershed into a large number of sub-basins (Gassman et al., 2003). SWAT is also capable of predicting the impact of land cover changes and water management practices on the characteristics of a specified catchment. Evaluation of sediment and agricultural yields in watersheds of varying sizes and type of soils is another area of application of SWAT model. Separating and evaluating the effects of a single variable is preferrable in SWAT since it is a deterministic model, and it is easy for comparison of the relative effects from one variable to another. In SWAT model, the watershed is divided into multiple subbasins and further into hydrological response units (HRUs) to incorporate hydrological modelling. HRUs are spatial objects possessing unique land use, management, and soil attributes. SWAT simulates surface runoff in a watershed by considering a number of different physical processes, which includes evaporation, runoff, infiltration process, potential and actual evapotranspiration, lateral flow and ground water contribution. Analysing long-term impacts is computationally efficient for users using SWAT by incorporating readily available inputs (Neitsch et al., 2011; Arnold et al., 2012; Hasan and Pradhanang 2017; Duan et al., 2018). The SWAT model is operated in two different phases simultaneously. The first phase is the land phase. It deals with various processes that occur in each sub-watershed. The other phase happens to be the routing phase, which evaluates the network through which water from each sub-watershed reaches the watershed's final exit (Swain, 2017). The basic equation that replicates the water balance in each sub-watershed follows a standard technique, in which the difference between inflow and outflow represents changes in moisture content (Swain, 2017).

$$SWt = SW_0 + Rd - Qs - Ea - Ws - Qg \qquad ....(1)$$

This equation represents the water-balance in SWAT model, where SWt is the moisture content of soil at time t (mm), SW_0 is the initial moisture content (mm), t refers to time (days), Rd is the rainfall that has occurred on the particular day (mm), Qs indicates the runoff (surface flow) on corresponding day (mm), Ea refers to evapo-transpiration on that day (mm), Ws is the quantity of water that seeps into the soil leading to percolation on that particular day (mm) and Qg indicates return flow on the day (mm) (Swain, 2017). Different equations such as SCS-CN equation and Green-Ampt-Mein- Larsen equation is used for computation of runoff in SWAT. For evapotranspiration estimation, Penman-Monteith equation is commonly used in SWAT. Apart from Hargreaves and Priestly-Taylor methods. The SWAT model's principal uses lies in hydrological processes within watersheds, particularly in land-use and climate change (Gassman et al., 2016). However, it is affected by a significant amount of uncertainty, just like other hydrological models (Ma et al., 2019). Certain softwares have been created to help lessen these uncertainties. SWATCUP (Calibration and Uncertainty Program) is one such example, which addresses the inverse model using a set of procedures for calibrating and validating models, including PSO (Particle Swarm Optimization), GLUE (Generalized Likelihood Uncertainty Estimation), ParaSol (Parameter Solution), MCMC (Markov Chain Monte Carlo), and SUFI2 (Sequential Uncertainty Fitting Ver. 2), among others (Abbaspour et al., 2017).

2.1.2 Input Data

For the simulation of hydrological processes in a basin system, SWAT requires a Digital Elevation Model (DEM), a land use map, a soil map, and daily-scale climate data (Tan et al; 2021). There is an urgent need for the best datasets, particularly climate data, to ensure that the model performance replicates observed streamflow as accurately as possible (Abbaspour et al., 2017). As a result, before developing and applying a specific SWAT watershed model, it is crucial to evaluate the available climate data sources. Climate data including daily precipitation data and minimum and maximum temperatures are usually available from local meteorological and/or hydrology agencies and are easy to obtain. Local climate datasets, on the other hand, can be expensive and difficult to obtain for model users. Daily time step working for SWAT simulations demands climatic data such as precipitation, maximum and minimum temperature, and solar radiation data. Optional input data includes relative humidity and wind speed (Arnold et al., 2012b). These data can be generated internally using SWAT or taken from observed and measured records. Solar radiation, relative humidity, and wind speed are generated as monthly values that are tabulated for 13 different climate factors, although precipitation and temperature inputs are normally derived from collected data (Arnold et al., 2012b). Long-term weather records are used in creating these tables which can be standard data sets within SWAT or must be developed from measured data for a specific research region (Tan et al., 2021). SWAT employs only the Penman-Monteith (Monteith, 1965) and Priestly-Taylor (Priestley and Taylor, 1972) potential evapotranspiration (PET) methodologies (Arnold et al., 2012b). The Green-Ampt infiltration method (Green and Ampt, 1911) necessitates the use of sub-daily precipitation inputs, which can be measured or generated. Also, the wind speed data also becomes necessary only if the Penman-Monteith option is selected for application in SWAT. Temperature data is required by a variety of algorithms, such as daily soil and water temperature calculations, crop growth, snowfall, and the Hargreaves PET method. Neitsch et al. (2011) and Arnold et al (2012b) provide additional explanations of how climate data are used in SWAT.

2.1.3 Calibration and validation

The calibration process of SWAT model requires the comparison of results of simulations with the values measured in the field (e.g., rainfall, discharge, etc.) in order to minimise the differences between them (Abbaspour et al., 2017). It is important to note that some parameters (such as snow-melt parameters and canopy storage) require prior calibration during the calibration process (Abbaspour et al., 2017). As a result, these parameters must be fitted and fixed first before being deleted from the second calibration (Abbaspour et al., 2017). In order to substantiate the calibrated findings, the process of validation is preformed (Abbaspour et al., 2017). Apart from the accuracy of the input data (Meaurio et al., 2015), the time interval used to perform the calibration and validation stages can influence model performance (Amatya and Jha, 2011) and hence it is strongly advised to choose the time interval accordingly. The SWAT model's performance must be assessed not only for analysing the model's ability to recreate hydrological processes within watersheds, but also for the support it provides in improving and refining the modelling process through parameter changes. (Krause and colleagues, 2005). Krause et al. (2005) also suggested using a variety of associated statistical measures to analyse model performance scientifically. NSE, PBIAS, and RSR are the most closely related statistical indices for evaluating hydrological models (Moriasi et al., 2007). For measuring the accuracy of SWAT predictions, the root mean square error (RMSE), coefficient of determination (R2), Nash-Sutcliffe Efficiency (NSE), percent bias (PBIAS), Kling-Gupta Efficiency (KGE), and various other statistics have been published in the literature. (Krause et al., 2005; Moriasi et al., 2007; Moriasi et al., 2015; Tan et al., 2019a). The R2 and NSE are the most commonly utilised statistics to assess the correctness of SWAT model output (Gassman et al., 2007;

Gassman et al., 2014; Tan et al., 2019b, 2020). For satisfactory NSE and R2 streamflow prediction outcomes, a requirement of 0.5 and 0.6 was proposed, along with stringent statistical criteria for "excellent" and "very good" streamflow simulation results (Moriasi et al., 2007, 2015). Most of the studies reviewed here cited Moriasi et al. (2007) and/or Moriasi et al. (2015), according to the statistical results reported in the respective analyses, and references to the criteria of satisfactory or unsatisfactory results in the remainder of this discussion are implicitly based on the Moriasi et al. (2007, 2015) criteria.

2.2 Global Climate Models

Climate change research has been well supported since the early 1980s by the development of General Circulation Models (GCMs). GCMs are the most advanced and readily available tools for simulating the response of the Earth's climate to changing atmospheric composition. GCMs are numerical models coupled with ocean models, land-use models, economic and future development models, and provide an arena for the study of climate change impacts on different processes involved in the atmosphere (Fowler et al., 2007).

2.2.1 Representative Concentration Pathways (RCPs)

RCPs are "time series of emissions and concentrations of the whole suite of greenhouse gases (GHGs), aerosols and chemically active gases, as well as land use/land cover," according to the EPA (Moss et al., 2008). There are four RCPs that are created using Integrated Assessment Models found in the literature. These RCPs are available in AR5 Chapters 11 to 14 of the "Fifth IPCC Assessment" as a basis for climate forecasting and projection. The following are four RCP scenarios:

- **RCP2.6**

The radioactive forcing peaks at almost 3 W m-2 prior to 2100, then falls with constant emissions after 2100, assuming continuous emissions.

- **RCP4.5 and RCP6.0**

In these scenarios, the corresponding ECPs assume constant concentrations after 2150 for two intermediate stabilisation pathways in which radiative forcing is stabilised at approximately 4.5 W m-2 and 6.0 W m-2 after 2100.

- **RCP8.5**

The related ECP assume continuous emissions after 2100 and constant concentrations after 2250 for a high route in which radiative forcing reaches 8.5 W m-2 by 2100 and continues to rise for some years.

2.2.2 Bias Correction

The correction of daily projected raw GCM output is simply characterised as the bias correction approach. In this method, the difference in mean and variability between GCM and observation in a reference period is used. The output we get from GCM or RCM outputs is usually biased and hence there is a requirement to modify these outputs before using them in regional impact analyses (Ahmed et al., 2013).

Following methods and approaches can be used for Bias correction:

- Variance scaling (VARI)
- Linear Scaling (LS)
- Distribution Mapping (DM)
- Local Intensity Scaling (LOCI)
- Power transformation (PT)
- Quantile Mapping (QM)
- Delta Change Approach etc. (Fang, Yang, Chen & Zammit, 2015)

2.3 Studies on Impacts of Climate Change on Streamflow in Asia

Different studies have projected varying streamflow conditions under changing climate scenarios for different regions. Both positive and negative changes in streamflow have been projected. Studies conducted in India have shown different projections for streamflow under climate change. A study carried out on the Upper Sind River Basin calculated the average annual streamflow to increase by 16.4 and 93.5% over the mid-century and end-century, respectively (Narsimlu et al., 2013). Another study conducted in the Bhakra- Satluj River Basin projected an increase in mean annul streamflow by 12.8 % over mid-century and by 19.4 % for end century under A1B scenario (Hamid et al., 2017). Similar study conducted on the Upper Indus Basin projected showed increase in flow by 19.24% and 16.78% for mid and late century, respectively for RCP 4.5 scenario and increase of 20.13% and 15.86% during mid and late century, respectively for RCP 8.5 scenario (Shah et al., 2020). Some studies conducted in the Himalayan watershed also projected prominent changes in streamflow for the future climate scenarios. The Upper Beas Basin situated in the Western Himalayas is expected to see a rise (0.31% to 14.18%) in mean annual streamflow. However, a decrease is expected in the latter half of the century due to reduction in snow cover as a result of increasing temperatures (Rani and Sreekesh., 2019). Similar to India, in Thailand, one study conducted in the Nong Han Lake Basin**,** calculated higher streamflow than the baseline period (Supakasol et al., 2020). The study resulted in a significant increase of 41.9% in streamflow in the Chao Phraya basin. SWAT model has also been used in Iran to study the streamflow variability due to climate change. Halilrood River Basin in Iran is expected to see a slight increase in future streamflow, mainly due to increase in precipitation as result of changing climate (Mehmoodli et al., 2021). A climate modelling study in Vietnam over the Dakbla river basin used the SWAT model to study the impact of climate change on future stream flow in the basin. The results indicated an overall average annual increase of stream flow by 40% and risks of flooding (Raghavan et al., 2014). Assessment of climate change impacts on streamflow through SWAT modelling in Kabul River basin, Afghanistan showed an increase in future streamflow during most of the months (Aawar and Khare, 2020). The El Kalb River basin, Lebanon is predicted to have a decrease of 28-29% in the average annual discharge during the 2021-2040 period and up to 45% decrease in streamflow under RCP 8.5 scenario for 2081-2100 period (Ghanimeh et al., 2021). In China, the Lake Dianchi was studied for future streamflow assessment under A2 and B2 climate scenario and the outputs revealed that the annual average streamflow would decrease in the future by the declination of -7.12 to - 21.83 % and -6.34 to -17.09 % under A2 (B2) scenarios (Zhou et al., 2015). Jianzhuangcuan catchments were also studied to quantify the impacts of climate change on streamflow (Huo and Li., 2013). The study revealed an increase in streamflow of up to 3.67 percent under 2020 and 2030 scenarios. The Yellow River Basin in Tibetan Plateau was also studied to assess the impact of future climate change on this region's hydrological components for the period of 2013–2042 under three emission scenarios A1B, A2 and B (Zhang et al., 2015). The results showed that A1B and B1 scenarios were characterised by an increasing streamflow trend in future while a decrease in streamflow was projected for A2 scenario. The future climatic projections also show an increase in streamflow in the Miyun Reservoir Basin on the basis of CMIP5 models (Yan et al., 2019). For the study of the impact of changing climate on the Huangnizhuang catchment (HNZ) in China, six GCMs were employed under RCP2.6, RCP4.5 and RCP8.5 scenarios. The results revealed an increase in precipitation in the middle and end of twenty-first century over the HNZ, but a declining streamflow ranging -6.9 to 0.8 %, mainly due to an increase of evapotranspiration, as air temperature increases for all the GCMs and RCPs (Lü et al., 2015).

Table 2.1: Summary of reviewed publications assessing climate change impacts on streamflow in Asia

Region	Climate Model	Down scaling method/ Bias Correction	Country	Key Findings	Reference
Subernarekha River basin	4 RCMs (RCP 4.5, RCP 8.5)	Bias Correction using IMD gridded data	India	Increase in streamflow with maximum increase under RCP 8.5 scenario	Gaur et al. (2021)
Mun River Basin	34 GCMs (RCP 2.6, RCP4.5, RCP8.5)	Delta method for downscaling	Thailand	Increase in streamflow by 10.5%-23.2% during 2020-2093	Fang and Li (2021)
Halilrood Basin	11 G-RCMs (RCP4.5, RCP8.5)	Bias correction using linear scaling and distribution mapping method	Iran	Higher precipitation intensity resulted in minor increase of streamflow in the months of January and March	Mahmoodli, et al. (2021)
El Kalb River Basin	GCM (RCP 2.6,4.5, 8.5)	Statistical downscaling using REMO 2009	Lebanon	28%, 28% and 45% decrease in average annual streamflow for RCP 2.6, 4.5, 8.5 respectively during 2081-2100	Ghanimeh et al. (2021)
Laixi River Basin	GCM (RCP2.6, RCP4.5, RCP8.5)	Downscaling using SDSM	China	RCP2.6 scenario resulted in , greater increase of streamflow in the 2050s than 2080s, and opposite under RCP4.5 and RCP8.5.	Gao et al. (2021)
Nong Han Lake Basin	PRECIS RCM (A2 and B2)	Bias correction by Change Factor Method	Thailand	Calculated runoff was higher than the baseline period.	Supakasol, et al. (2020)
Upper Indus Basin	RCM (RCP 4.5 & RCP 8.5)	The historical modification approach for downscaling	India	RCP4.5 showed increase in flow by 19.24% and 16.78% for mid and late century, respectively. Increase in flow was 20.13% during mid and 15.86% during late century for RCP 8.5.	Shah et al. (2020)
Vaksh River Basin	5 GCM (RCP 4.5, RCP 8.5)	Downscaled using Climate change toolkit (CCT)	Tajikistan	Streamflow is predicted to increase by 2099	Gulakhmadov et al. (2020)

				from 17.5% to 52.3% under both RCP scenarios	
Tamor River Basin	4 RCMs (RCP 4.5 and RCP 8.5)	Linear Scaling method	Nepal	Decrease of over 8.5% in streamflow during the twenty-first century under RCP8.5 scenario	Bhatta et al. (2019)
Upper Beas River Basin	Non parametric methods (Mann-Kendall test and Sen Slope estimator)	Synthetic method for developing climate change scenarios	India	A rise (0.31% to 14.18%) in mean annual streamflow	Rani and Sreekesh (2019)
Miyun Resevoir Basin	21 GCMs (RCP 4.5, RCP 8.5)	Bias-Correction Spatial Disaggregation (BCSD) method	China	Increase in streamflow during 2021-2035 period	Yan et al. (2019)
Wardha Region	RCM (RCP 4.5 & RCP 8.5)	The historical modification approach for downscaling	India	A decrease in future streamflow is expected	Sowjanya et al. (2018)
Satluj River Basin	GCM (A1B)	The use of PRECIS RCM for downscaling purpose	India	Increase in mean annul streamflow by 12.8 % over mid-century and by 19.4 % for end century	Hamid et al. (2017)
Yellow River Basin	GCM (A1B, A2, B1)	BCSD approach	China	Tangnaihai gauge reported an increase in streamflow under A1B and B1, while declining trend is witnessed in A2 scenario	Zhang et al. (2015)
Koshi River Basin	2 RCM (A1B scenario)	Bias corrected	Nepal	Monthly streamflow reduced by 30% in the dry months and increased by 25% in the high flow months	Devkota and Gyawali (2015)
Lake Dianchi	7 GCMs (A2 and B2 scenario)	SDSM model	China	Decrease in annual average streamflow in the future by -7.12 to -21.83 % under A2 and -6.34 to -17.09 % under B2 scenarios	Jing Zhou et al. (2015)
Huangnizhuag catchment	6 GCMs (RCP 4.5, RCP RCP 8.5)	Bias correction by Change Factor Method	China	Streamflow showed a decline,	Lü et al. (2015)

				by 6.9 to 0.8 % in the future	
Dakbla River Basin	3 GCMs (A2)	WRF model for downscaling	Vietnam	40% increase in streamflow with risk of flooding	Raghavan et al. (2014)
Upper Sind River Basin	GCM (A1B)	The use of PRECIS RCM for downscaling.	India	Increase in average annual streamflow by 16.4 and 93.5% over the mid-entury and end-century, respectively	Narsimlu et al. (2013)
Jianzhuangcuan River Basin	14 GCMs (A1B, B1)	Delta Method of downscaling	China	Monthly streamflow increases upto 3.67 % for 2030 scenario	Huo and Li (2013)

2.4 A General Global Review

The SWAT model applied on Volta River Basin in West Africa projected that river flow will decrease up to 40% in future period (Sood et al., 2017). Another study conducted in Africa in Lake Tana Basin integrated SWAT model and an ensemble of nine GCMs under A1B, B1 and A2 scenario to forecast the future streamflow. The results revealed five of the nine models indicating a significant reduction in annual streamflow over the period of 2080-2100 (Setegn et al., 2011). The Zambezi River Basin showed a similar trend of increasing streamflow under RCP 8.5 scenario. However, a slight decrease in annual streamflow of less than 3% under RCP 4.5 was projected by the model (Ndhlovu and Woyessa, 2021). The White Volta and Pra Basin in Ghana however showed a trend of decreasing streamflow for future periods (Kankam-Yeboah et al., 2017). A study conducted in Kalihi and Nuuanu watersheds in Hawaii also used seven GCMs to project the future streamflow and revealed that there was a general overall decline in the daily streamflow, with reduced extreme peak and low flows (Leta et al., 2018). Impacts of changing climate were also studied in The Shell Creek and Logan Creek Watersheds of Nebraska, a state in USA under A1, B1 and A1B scenario. The results indicated a general increase in streamflow for both watersheds, however the increase was more prominent and larger for Logan Creek Watershed (Liew et al., 2012). Another study was conducted in USA on the Alabama River Basin using GCMs under RCP 4.5 scenario. The monthly streamflow under RCP 4.5 scenario increased by as high as 300% for months of summer and spring but decreased for the winter months (Quansah et al., 2021). Aparicio et al., (2017) evaluated changes in streamflow under RCP 4.5 and RCP 8.5 climate change scenarios in Segura River Basin, Spain. The river basin is expected to witness a general decrease in seasonal streamflow for both the scenarios. On corelating with the baseline period (1971–2000), future streamflow in the Headwaters of the Segura River Basin will experience a considerable change due to changing temperature and precipitation. During 2041–2070 time period, a high variability in the streamflow was observed under both the scenarios. Maximum variations of about 33%-54% decrease in streamflow is projected under RCP8.5 for 2071–2100 period. Various studies have also assessed the changing hydropower potential due to change in streamflow under different climate change scenarios. Thau and the Chiba catchments, located in Southern France and North-eastern Tunisia, respectively were also studied to model the climate change impacts on hydrological parameters. The projected magnitude of changes indicated a decreased streamflow owing to increasing temperature and decreased rainfall in the future periods (Sellami et al., 2015). The changing streamflow and hydropower potential in Grande River Basin, Brazil under various RCP scenarios was studied by the researchers. The results showed significant reduction in the mean monthly streamflow during the time period (2007–2040) under RCP 4.5 for both RCMs, while the largest reductions were observed during the third time period (2071–2099) under RCP 8.5 (Oliveira et al., 2017). It is quite evident from the reviewed studies that there exist many discrepancies in the projected streamflow and clear trend for a particular country or region is difficult to assess under scenarios of changing climate.

Table 2.2: Summary of reviewed publication assessing climate change globally

Region	Climate Model	Down scaling method/ Bias Correction	Country	Key Findings	Reference
Alabama River Basin	GCMs (RCP 4.5)	Statistical downscaling	USA	Increase in streamflow for spring and summer months and decrease for winter months	Quansah et al. (2021)
Zambezi River Basin	6 GCMs (RCP 4.5, RCP 8.5)	Delta change method	Africa	Increased streamflow under RCP 8.5 scenario	Ndhlovu and Woyessa (2021)
Awash River Basin	GCM (RCP 2.6, RCP 4.5, RCP 8.5)	Statistical downscaling	Ethiopia	Increase in streamflow by more than 34%	Gebrechorkos et al. (2020)
Kalihi and Nuuanu watersheds	7 GCMs (RCP 4.5 and 8.5)	Bias corrected	Hawaii	An overall decline in the daily streamflow values, extreme peak and low flows	Leta et al. (2018)

White Volta and Pra River Basins	Two GCMs (A1FI)	A stochastic weather generator LARS-WG	Ghana	Decrease in mean annual streamflow by 22% in 2020s and 50% in the 2050s for White Volta Basin. 22% and 46% decrease in the 2020s and 2050s for Pra Basin	Kankam-Yeboah et al. (2017)
Segura River Basin	2 RCMs (RCP 4.5, RCP RCP 8.5)	Bias correction using distribution mapping approach	Spain	General decrease in streamflow	Aparicio et al (2017)
Grande River Basin	2 RCM (RCP 4.5, RCP RCP 8.5)	Bias Correction	Brazil	Reduced streamflow, with largest reduction in (2071-2099) time period under RCP 8.5 scenario	Oliveira et al. (2017)
Volta River Basin	One RCM, boundary condition from one GCM (A1B)	Dynamic downscaling (COSMO-CLM).	West Africa	River flow will decrease up to 40%.	Sood et al. (2017)
Thau and Chiba Catchments	4 Climate models (A1B)	Multi Fractal approach and spatial interpolation	Southern France and North-eastern Tunisia	Projected decrease in streamflow with more pronounced changes in Chiba catchments	Sellami et al. (2016)
Zenne river basin	RCMs (A2, B2)	CCI-HYDR perturbation tool	Belgium	Increase of 109 % in extreme flows 109% under the wet summer scenario.	Olkeba & Willy (2013)
Shell and Logan Creek Watershed	RCMs (A2, A1B, B1)	Statistical Downscaling Method	USA	Overall increase in streamflow for both watersheds	Liew et al. (2012)
Lake Tana Basin	Ensemble of nine GCMs (A1B, B1, A2)	The historical modification approach for downscaling	Ethiopia	Five of the nine models indicate significant reductions in annual streamflow	(Setegn et al. 2011)

CHAPTER 3
METHODOLOGY

3.1 Assessing climate change impact on streamflow: Framework

Climate change has proven to show adverse significant impacts on all realms of the hydrological cycle. Numerous modelling studies have used SWAT to assess and evaluate the impacts of climate change on streamflow in different regions (Tehrani et al., 2019). The first step involves the streamflow simulation of a particular region in SWAT model by utilizing the climate and meteorological data. The accuracy of the simulated streamflow is checked by calibration and validation process for the SWAT model using historical observed data. A climate model, generally a GCM (General circulation model) is further selected to evaluate climate change impacts for current and future time periods. After this, an emission scenario is selected to study impacts of climate change on the desired region. Application of bias correction along with methods for downscaling data from climate model is the next step which is done to so that projections from GCMs can be translated to regional scale for the assessment of desired study area. After using methods for downscaling of the GCM data, a simulation model is used to obtain river runoff and flow conditions for the study area (Tehrani et al., 2019). Land use patterns changes, changes in river morphology, anthropogenic activities and reservoir construction and working are some of the designed scenarios which can be used to analyse results.

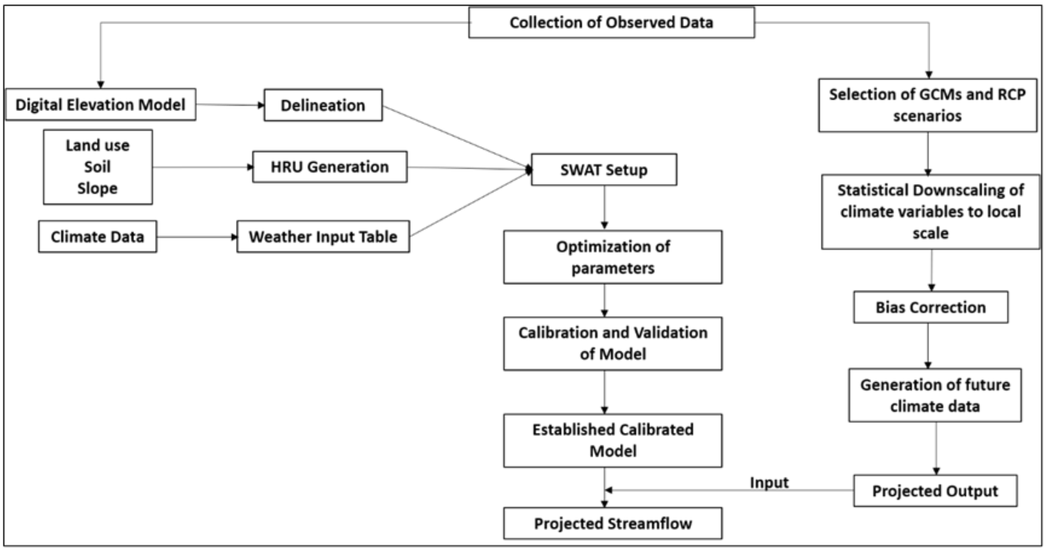


Figure 3.1: Graphical representation of framework for climate change impact on streamflow using SWAT

3.2 Study Area

3.2.1 Location

The Narmada, also known as the Rewa, is the longest river in Central India and the sixth largest in the Indian subcontinent. It is the third longest river entirely in India after the Godavari and the Krishna. It is the historic boundary between northern and southern India, which flows 1,312 km westward via the Gulf of Khambhat and empties into the Arab Sea. Along with the Tapti River & Mahi River, it is one of just three major rivers running from East to West in the peninsula of India (longest west flowing river). At an altitude of 1068 metres above sea level on the Amarkantak plateau of the Maikala River in the Shahdol area of Madhya Pradesh, the river rises at 23°45' latitude north and 80°35' longitude east. The river runs 1,212 kilometers into the Arabian Sea in the Cambayan Gulf near Bharuch, Gujarat. The first 1,085 kilometers of its trip are home to Madhya Pradesh. For the next 40 kilometers the river marks the boundary between the states of Madhya Pradesh and Maharashtra. It then defines for the next 42 kilometers the boundary between Maharashtra and Gujarat. The last 165 kilometers of the course are located in Gujarat. This study simulates the water resources of the upper Narmada basin, which drains 44,548 km2 from the basin's most eastern end to the downstream gauging station at Hoshangabad. Figure 3.2 shows the location map of Upper Narmada Basin w.r.t. India.

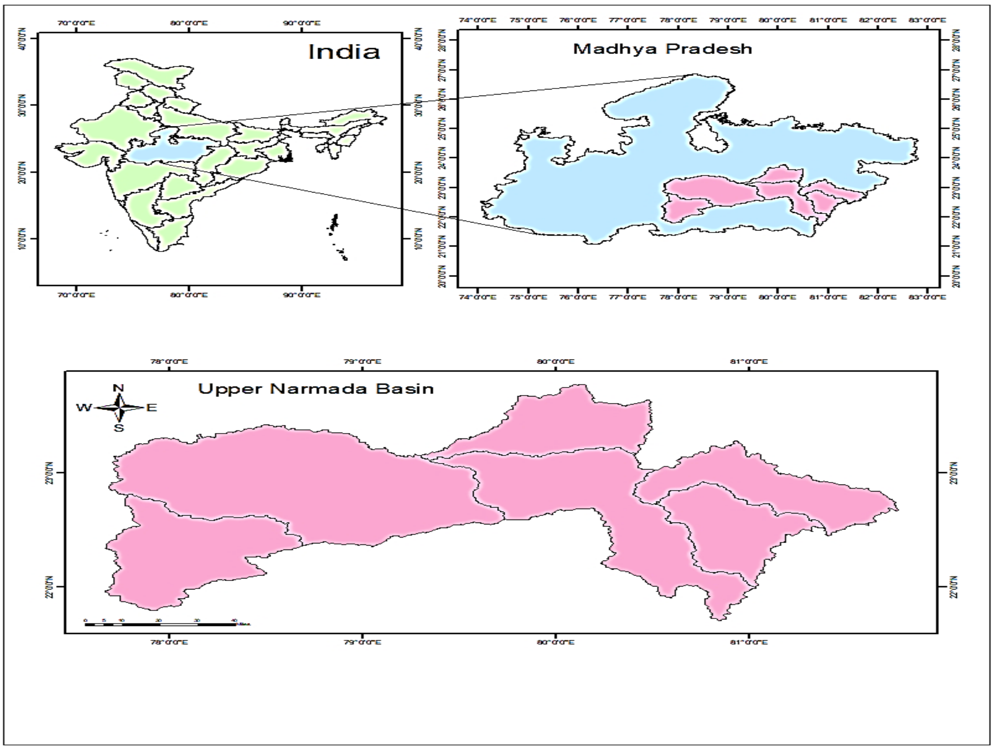


Figure 3.2: Upper Narmada Basin depicted on map

3.2.2 Climate

The Narmada basin is subject to a tropical monsoon climate. The basin's climate is humid and tropical, while extremes of heat and cold are common in some areas. The basin has four distinct seasons throughout the year, (i) winters, (ii) summers, (iii) south west monsoon, and (iv) post monsoon. The typical yearly temperature varies from 17˚5 C to 20˚C in the winter and from 30˚C to 32˚5C in the summer. Temperatures in the monsoon range from 27o 5 C to 30o C. Temperatures range from 25 to 27.5 degrees Celsius during the post-monsoon season. During the five monsoon months of June to October, the basin receives over 90% of its rainfall. In the months of July and August, around 60% of the total is received. The high mountainous and upper plains parts of the basin receive a lot of rain. It gradually reduces as you get closer to the lower plains and lower hilly sections, before increasing again towards the coast and the basin's southwestern extent. The annual rainfall in the upper hilly areas is generally greater than 1400 mm (55"), but it can reach 1650 mm (65") in some places. The upper plains however receive rainfall ranging from 1400 mm (55") to less than 1000 mm (40").

3.3 Data sources and input data

For analysis, SWAT hydrological model requires physiographical data input like Land use land cover data, digital elevation model, weather data and soil data. The sorces of various input data is shown in Table 3.1

Table 3.1: Sources and description of the input data for SWAT

Data	Source
Land use land cover	ORNL DAAC-NASA (https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1336)
Soil Map	FAO (https://data.apps.fao.org/map/catalog/srv/eng /catalog.search#/metadata/446ed430-8383-11db-b9b2-000d939bc5d8)
Digital Elevation Model	ASTER 30m (https://search.earthdata.nasa.gov/search)
Meteorological Data	IMD grided data (https://www.imdpune.gov.in/Clim_Pred_LRF_New/ Grided_Data_Download.html)
River Discharge Data	India–WRIS (https://indiawris.gov.in)
CORDEX Climate Data	CCCR-IITM Pune (http://cccr.tropmet.res.in/home/cordexsa_datasets.jsp)

3.3.1. Digital Elevation Model (DEM)

A DEM is created to describe the geography and characterizes the rise of each point in a given district at a predefined spatial goal. Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is one of five sensors on board of Terra satellite launched by NASA. The ASTER DEM is available freely for users to download and use. ASTER V3 data used in this study is latest in this series made available in 2019 for public use. It has a spatial resolution of 30m. The DEM was utilized to delineate the basin using the ArcSWAT GIS interface's analytic approach, as well as to provide topographical parameters for each catchment of the basin, such as overland slope, stream network, and slope length. The DEM of the study area used as the SWAT input is shown in the figure 3.3.

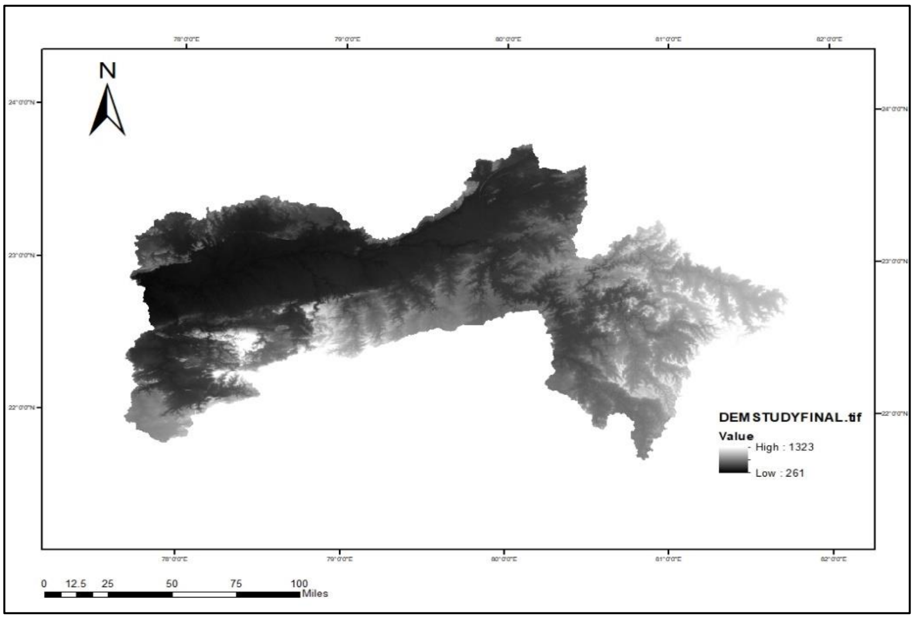


Figure 3.3: DEM of Upper Narmada Basin

3.3.2. Land use land cover map

In a watershed, land use is one of the most important elements influencing runoff, soil erosion, and evapotranspiration. In the present study, LULC of India was obtained from The Oak Ridge National Laboratory Distributed Active Archive Center (ORNLDAAC) available at 100m resolution for India. The LULC map for the required study area was extracted from the map of the India in the ArcGIS interface using shapefile of the study area. India. Figure 3.4 shows the land use map of the study area. The data is originally classified in International Geosphere-Biosphere Programme (IGBP) classification scheme which was later classified in SWAT format.

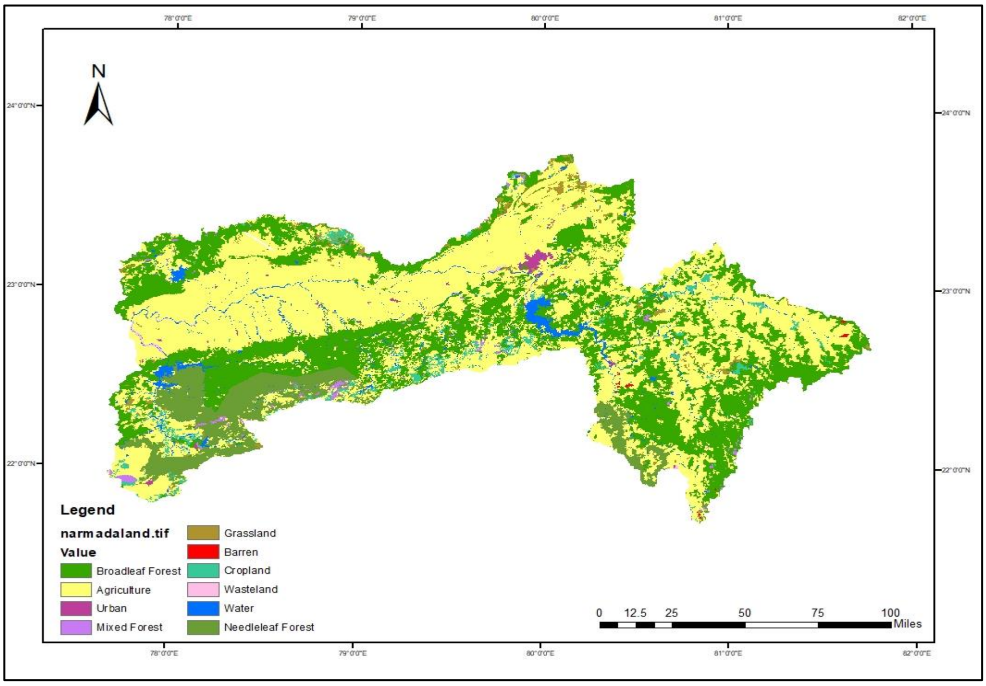


Figure 3.4: Land use map of Upper Narmada Basin

3.3.3. Soil Map

The SWAT model requires varied soil textural and physicochemical properties for multiple levels of each soil type, such as soil texture, hydraulic conductivity, organic carbon content. Soil map data is taken from Food and Agriculture organization (FAO) soil database. Figure 3.5 shows soils in the study area with different FAO soil codes. Almost 5000 soils are present in SWAT's database. In this database soils are differentiated at a spatial resolution of 10 kilometres.

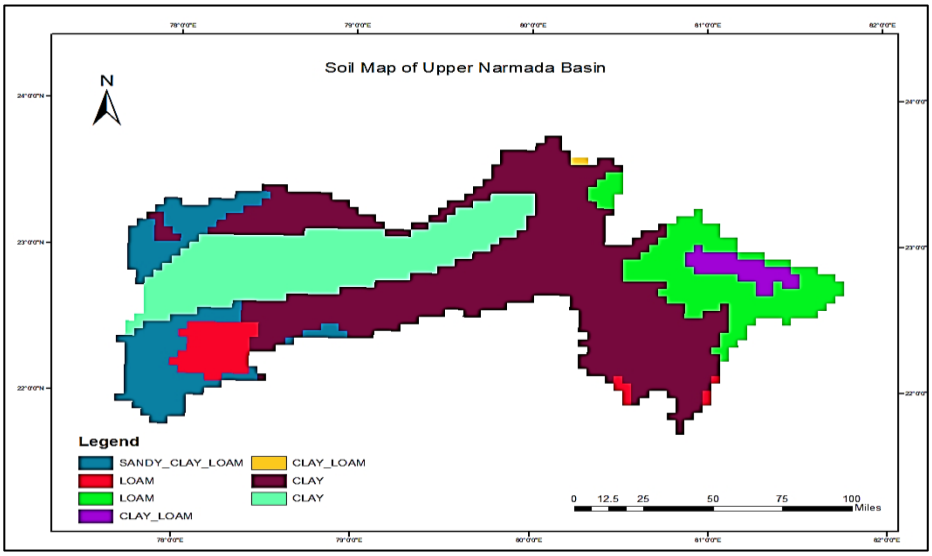


Figure 3.5: Soil Map of Upper Narmada Basin

3.3.4. Meteorological Data

SWAT model requires meteorological datasets of having one day temporal resolution. Indian meteorological department provide free grided data for whole India. Rainfall data are provided at high resolution of 0.25˚ x 0.25˚ while max. and min. temperature are provided at 1˚ X 1˚ resolution. Daily precipitation, maximum and minimum temperature were obtained from this data base for a time of 30 years (1985–2015) and utilized in the SWAT hydrological model.

3.3.5 River discharge data

Information regarding the water resources of the country in the is one of the most important components of water resource management. The fulfilment of this criteria is an initiative of the India-WRIS Project with the purpose of disseminating data in the public domain. This data base was initiated through MoU signed between CWC, ISRO and Ministry of Jal Shakti and is managed by National Water Informatics Center (NWIC)**.** It has continuous data for period (1988-2015) without any missing value. This daily data was downloaded and used for calibration and validation of SWAT model.

3.3.6 CORDEX Climate Data

The output of multiple CMIP5 models is used to address current and future climate challenges in the context of global climate change. For the purpose of this study, CORDEX downscaled climatic data were received from the Indian Institute of Tropical Meteorology's Centre for Climate Change Research in Pune (CCCR-IITM). The resolution of CORDEX data is 0.44° × 0. 44°. In this study, GCM downscaled on IITM-RegCM4 RCM has been used (Giorgi et al., 2012) since its performance is satisfactory in the Indian subcontinent (Dubey et al., 2020; Mall et al., 2018; Singh & Saravanan, 2020). It can simulate current climate features throughout the study region (Gao & Giorgi, 2017). In this study, IITM-RegCM4 (CCCMA-CanESM2), IITM-RegCM4 (NOAA-GFDL-ESM2), IITM–RegCM4 (CNRM-CM5) has been used, shown in Table 3.2, which are especially downscaled for the Asian region by the Indian Institute of Tropical Meteorology (IITM-India).

Table 3.2: Climate models used in the study

RCM	Driving GCM	GCM modelling organization
IITM-RegCM4	CanESM2	Canadian Centre for Climate Modelling and Analysis (CCCma), Canada
	GFDL-ESM2M	National Oceanic and Atmospheric Administration (NOAA), Geophysical Fluid Dynamics Laboratory (GFDL), USA
	CNRM-CM5	Centre National de Recherches Me´te´orologiques (CNRM), France

3.4 SWAT Model Setup

The first step in setting up a SWAT project requires the reprojection of the input raster data UTM projection. All the input data was hence cross checked to be in UTM projection. The study area was identified to be in WGS1984 zone 44 Northern Hemisphere. Further processing of the SWAT model requires four major steps-

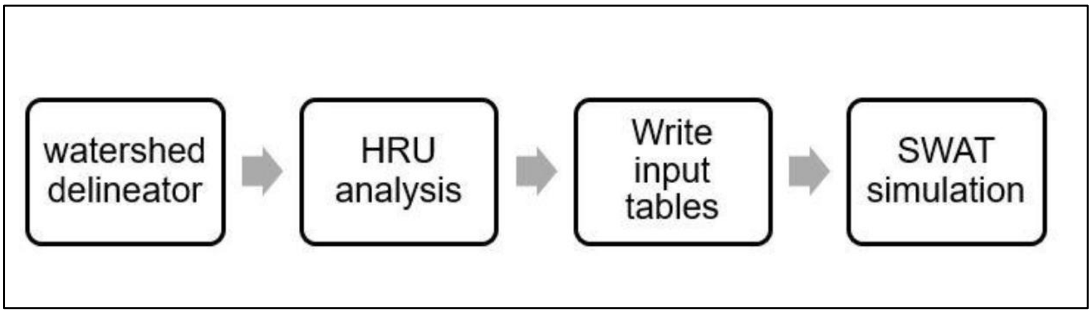


Figure 3.6: SWAT Model setup flow diagram

3.4.1 Watershed Delineator

ASTER DEM of the study area was used to delineate the watershed. In SWAT, each watershed is divided into HRU and each of them is a unique combination of land use, slope and soil (Neitschetal.,2011). Watershed delineator is incorporated in SWAT toolbar with the help of which watershed was delineated from DEM (Figure 3.7). CWC gauge station Hoshangabad was used as outlet point to delineate watershed (Table 3.3). Following steps were used in watershed delineation window.

1. In DEM projection setup option, setting Z unit to m

2. Clicking flow direction and accumulation
3. Giving minimum area value
4. Clicking create streams and outlet (Figure 3.8)
5. Removing all automatically generated outlet point
6. Clicking ‘Add’ in manual edit option to add Hoshangabad (CWC gauge station) as outlet
7. Clicking delineate watershed to generate watershed

Table 3.3: CWC Gauge Station Details

Outlet Station	**Location**
Hoshangabad	Latitude: 22.4230 Longitude: 77.4420

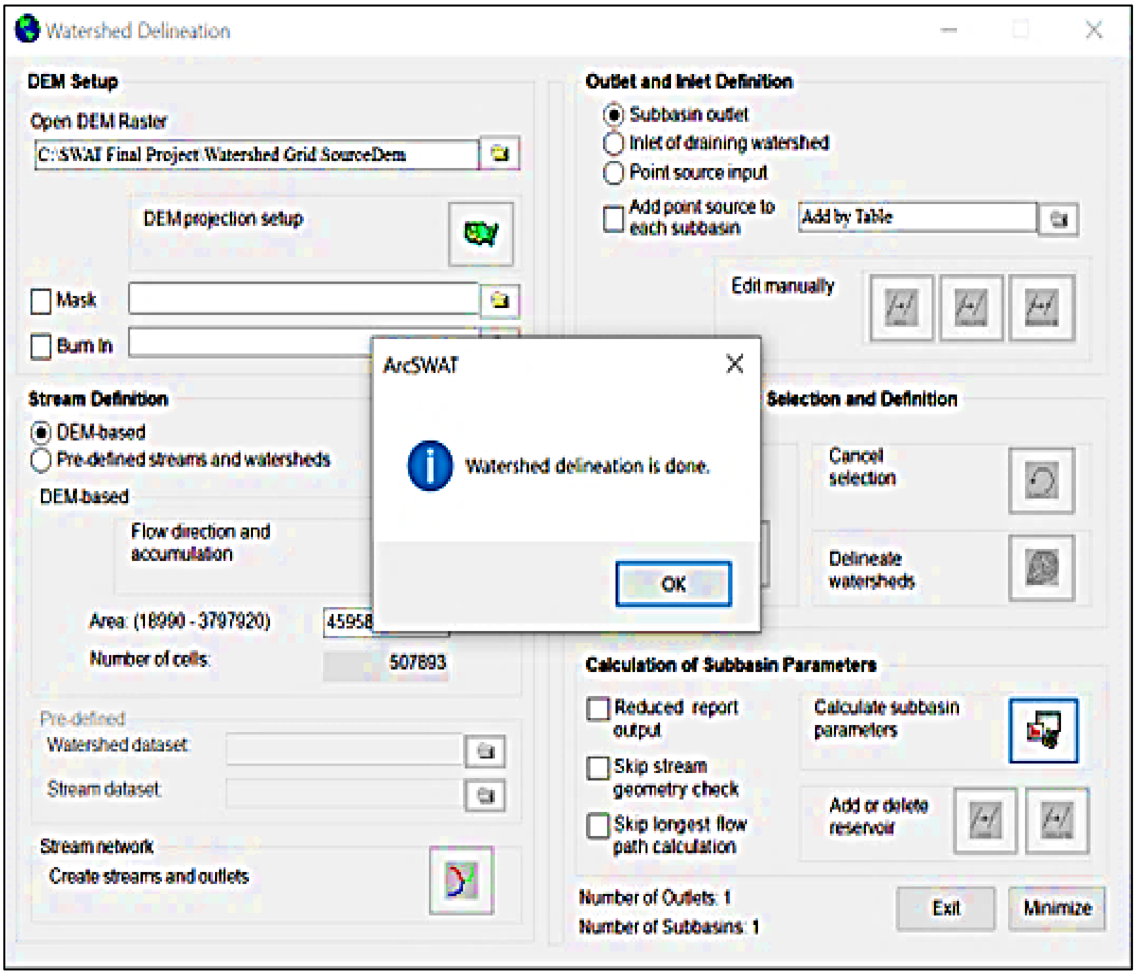


Figure 3.7: Watershed delineation window in ArcSWAT Interface

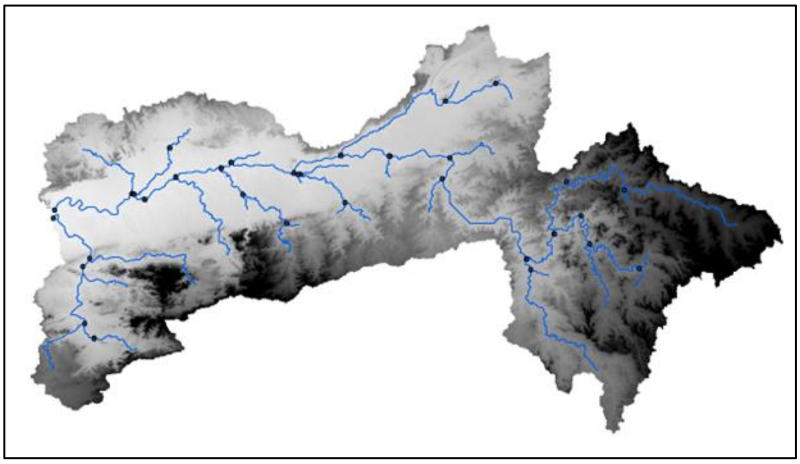


Figure 3.8: Reach and outlet map of study area

3.4.2 HRU Analysis

In SWAT, each watershed can be divided into sub watershed and each sub watershed is divided into HRU (hydrological response unit). Each HRU is a unique combination of land use, slope and soil (Neitschetal.,2011). To conduct HRU analysis we need to provide land use data, soil data and slope definition and overlay. First step is providing LULC map for the watershed which was utilized after reclassifying the SWAT Format with help of lookup table (Figure 3.9).

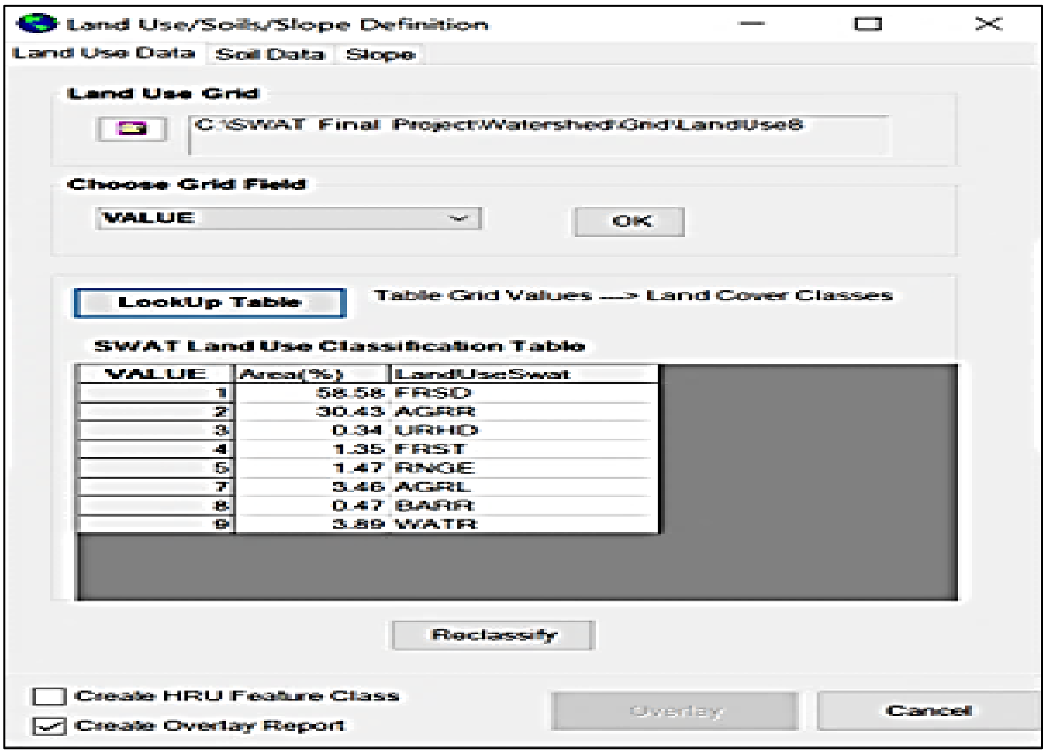


Figure 3.9: Land use Definition window in ArcSWAT interface

After adding soil data, slope classes are added (Figure 3.10). It is up to user how many slope classes to add. In this study we have taken 5 slope classes. After overlaying all classes, we need to give HRU definition. HRU thresholds needs to be define by user, it merges the lower classes with upper one in generated HRU. Lower value gives us lower classes and larger value give us more classes but it does not impact on streamflow or discharge result. As our study area is small threshold value for land use, soil and slope were given as 5%, 10% and 5%. After giving HRU definition land use, slope and soil map of watershed get generated. Total 29 HRUs were generated for Narmada River watershed.

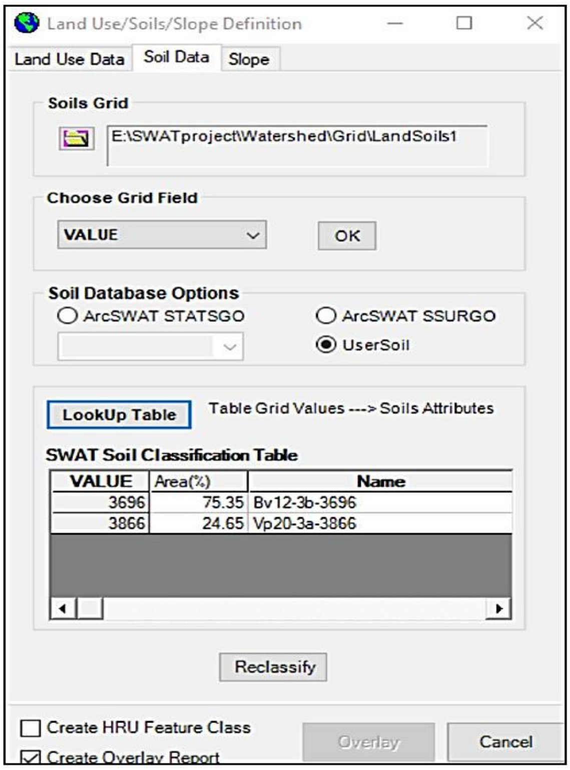


Figure 3.10: Soil data definition window

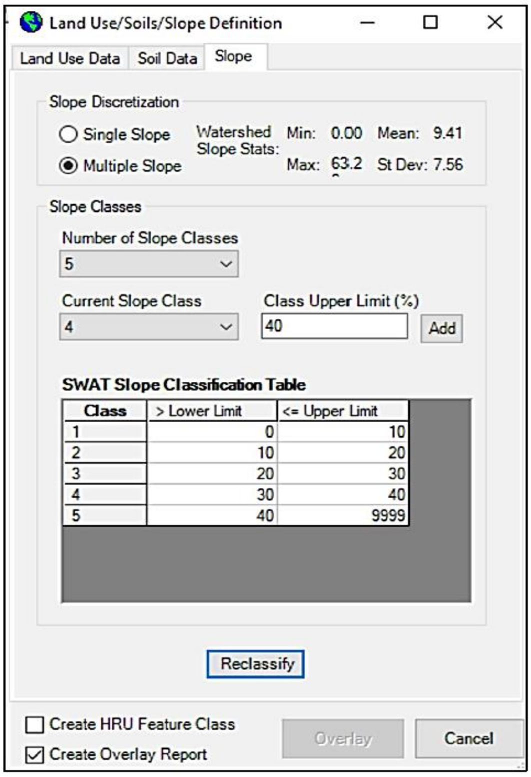


Figure 3.11: Slope definition window

After adding land use, second step is to add soil map. Already prepared and projected soil map of district was added as soil data. After adding soil data, slope classes are added (Figure 3.11). It is up to user how many slope classes to add. In this study we have taken 5 slope classes. After overlaying all classes, we need to give HRU definition. HRU thresholds needs to be define by user, it merges the lower classes with upper one in generated HRU. Lower value gives us lower classes and larger value give us more classes but it does not impact on streamflow or discharge result. As our study area is small threshold value for land use, soil and slope was given as 5%, 10% and 5%. After giving HRU definition land use, slope and soil map of watershed get generated. Total 29 HRUs were generated for Upper Narmada watershed.

3.4.3 Creating Input Table and Weather data setup

This stage entails reading weather data as well as creating input tables. Selecting weather station files such as rainfall data, temperature data, and the weather generator file allows the basin's weather data to be defined. The rain gauge sites are shown in the rainfall data definition tab (Figure 3.12). The SWAT-acceptable format for the rain gauge locations table was used. The daily time step precipitation data for all of the sites was stored in distinct text files that the SWAT database automatically chose from their location. In the temperature data tab, the temperature locations table was similarly submitted. The (0.25ox0.25°) grid sites in the basin were used to determine the precipitation and for temperature (1ox1o) grid sites were used. IMD provides only daily rainfall and temperature data. So other data (solar radiation, relative humidity, windspeed) were generated using SWAT weather generator during simulation. SWAT weather generator uses climate data file containing average climate data of 83 years from WGEN user to calculate this missing value. For India it is provided on SWAT official website (https://swat.tamu.edu/data/india-dataset/).

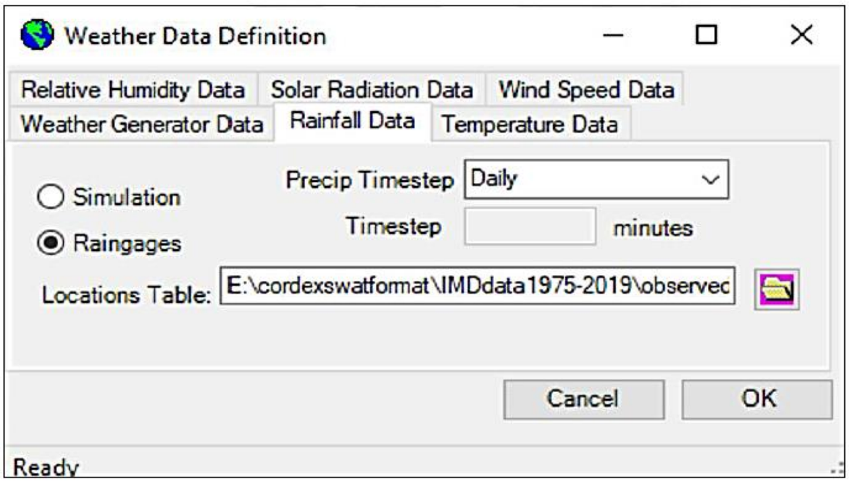


Figure 3.12: Weather data definition form

The next step is the write SWAT input tables which writes the database table into the main SWAT database and the project database. The tables need to be written in a specific sequence so that some of the related tables could be written. All tables need to have a status of ‘Completed’ before the SWAT project can be setup and run as shown in figure 3.13.

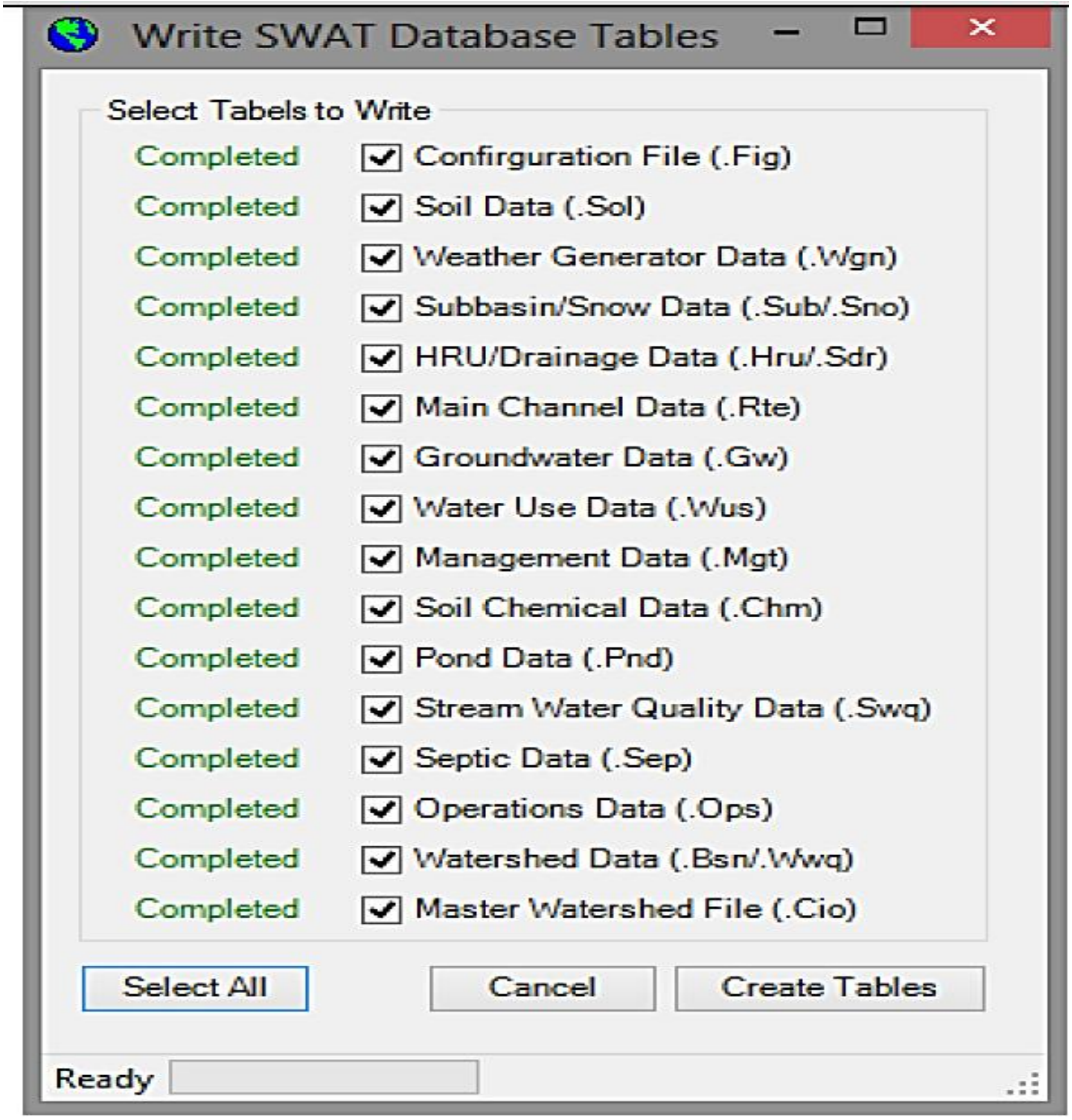


Figure 3.13: The completed SWAT database tables form

3.4.4 SWAT Simulation

The final step is the setup and run SWAT model simulation. The period of simulation was taken for six years from January 2000 to December 2005 for which the observed data was sufficiently available. One year of warm up period was given to the model so that it could better simulate the results. The model is run for the entire duration of six years but the warm up period is not shown in the results. The setup of SWAT Run (Figure 3.14) is necessary before the final SWAT Run could be made. The setup generates the final input files for the period of simulation.

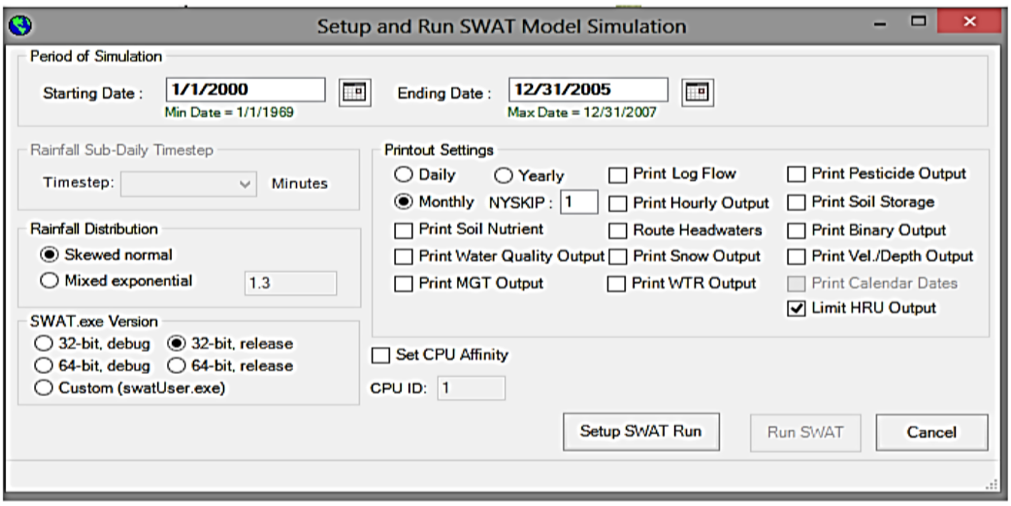


Figure 3.14: SWAT setup and Run form

After the successful SWAT Setup, the Run SWAT button becomes active. The final SWAT run is allowed which takes time in processing all the information and the message of successful model run appears (Figure 3.15).

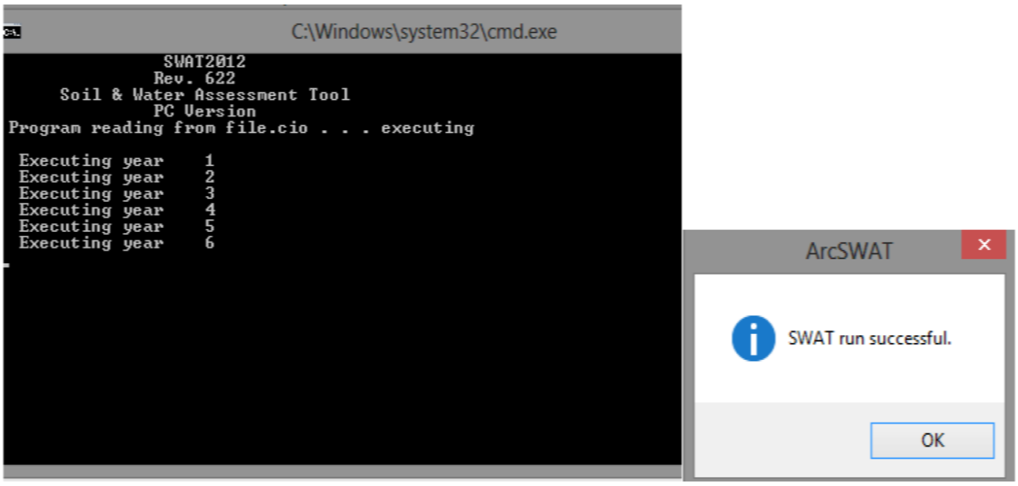


Figure 3.15: Model execution window

3.4.5 SWAT Output

The output of the SWAT model is in the format of database files which need to be imported to the main SWAToutput.mdb file in the SWAT database (Figure 3.16). These output files can be exported into a spreadsheet for further analysis and plotting. For the analysis of the entire basin flow, the sub-basin at the outlet is identified and the flow from that sub-basin is plotted and checked with the observed flows of the basin.

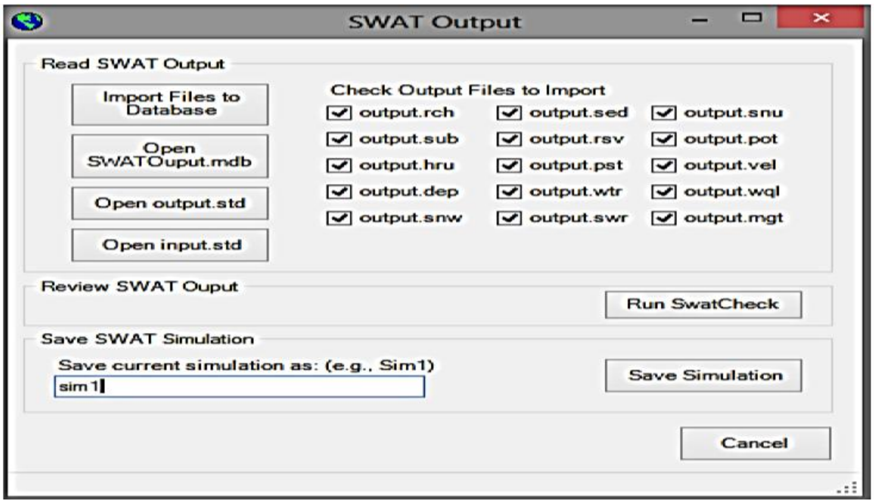


Figure 3.16: SWAT Output Form window

The current simulation can be saved with a suitable name and made as the default simulation. The first simulation was run for (1975–2015) with first three years as warm up period. This time period was chosen as for this period continuous streamflow data was available without any missing value.

3.5 Calibration and sensitivity analysis

The simulated results of the model were checked with the observed streamflow discharge. The SWAT model calibration, validation and sensitivity analysis were performed in SWAT- CUP, open-source software using the SUFI-2 algorithm (Abbaspour et al., 2004). In SUFI-2 algorithm, parameter uncertainty accounts for all uncertainties (conceptual model, input, etc.) (Abbaspour et al., 2004). Sensitivity analysis is a method for determining how altering input parameters affects model outputs.

To calibrate streamflow, we need to convert observed daily data downloaded from WRIS – India website to monthly data as monthly streamflow calibration is found to happen best in SWAT-CUP (Srinivasan et al., 2010). It was done using Pivot table in excel. After converting to monthly data, it needs to be formatted into form suitable for SWAT – CUP. In order to see the impact of parameter on model result 500 simulations were performed for Hoshangabad gauging station.

3.5.1 Parameters

Global Sensitivity Analysis is used to determine the sensitivity of the parameters utilised in the calibration operation in SWAT model. To determine the parameters' sensitivity, a multiple regression system is used to regress Latin hypercube generated parameters against the objective function. P-value and t-stat were utilised as statistical metrics. A t-stat is the ratio of a parameter's coefficient to its standard error. It's a scale that indicates how accurate the regression coefficient is measured. As a result, the parameter is sensitive when the coefficient is greater than the standard error. A p-value is produced using the values calculated for the t-stat for a parameter and the t-distribution student's table, where a greater value indicates less parameter sensitivity and vice versa. (Abbaspouri 2015).

In this study total 14 parameters were selected on basis of sensitivity analysis and literature review (Jayanthi & Keesara,2019; Mishra & Lilhare, 2016; Pandeyetal., 2019; Rickardsetal., 2020) shown in table 3.4.

Table 3.4: Maximum, minimum and best fitted values of parameters

S.No.	Parameter	Change type	Fitted value	Min value	Max value
1	CN2.mgt	Relative	−0.05	−0.1	0.1
2	ALPHA_BF.gw	Replace	0.57	0.5	0.85
3	GW_DELAY.gw	Replace	367.05	30	450
4	GWQMN.gw	Replace	0.29	0.1	1
5	ESCO.bsn	Replace	0.21	0.1	0.7
6	EPCO.bsn	Replace	0.11	0.1	0.7
7	GW_REVAP.gw	Relative	0.04	0.02	0.2
8	REVAPMN.gw	Replace	228.88	120	250
9	SOL_K.sol	Relative	−0.04	−0.1	0.2
10	OV_N.hru	Replace	0.15	0.01	0.2
11	SOL_AWC.sol	Replace	0.26	0.1	0.8
12	CANMX.hru	Replace	34.55	20	80
13	CH_N2.rte	Replace	0.01	0.01	0.4
14	HRU_SLP.hru	Relative	−0.17	−0.5	1

3.5.2 SWAT Model Performance

The SWAT model performance in this study is determined using the Nash–Sutcliffe Efficiency (NSE), coefficient of determination (R2), and percent bias (PBIAS) as shown below in table 3.5 (Nash and Sutcliffe 1970; Gupta et al. 2009). For flow simulation model performance is considered very good if 0.75<NSE<1 and 0.75<R2<1 (D.N. Moriasietal.,2007).

Table 3.5: SWAT Model performance parameters

Formula	Name of indicator
$R^2 = \frac{(\Sigma[X_i - X_{av}][Y_i - Y_{av}])^2)}{\Sigma[X_i - X_{av}]^2 \Sigma[Y_i - Y_{av}]^2}$	regression coefficient
$NSE = 1 - \frac{\Sigma[X_i - Y_i]^2}{\Sigma[X_{av} - Y_{av}]^2}$	Nash–Sutcliffe efficiency coefficient

where X_i is the observed data, Y_i is the simulated data, Y_{av} is mean of simulated data and X_{av} is the mean of observed data, i is the *i*th measured or simulated data.

3.6 Selection of climate models and Bias correction

Assessment of the impact of climate change on the hydrologic response of the study area, involves subjecting the calibrated SWAT model of the study area to synthetic climatic data predicted by downscaled climate models. Therefore, selection of appropriate climate models marks an important step in the assessment.

For the present study, six GCMs were evaluated for the study area. IITM-Regcm4 RCM has data available for six GCM. In this study, top three climate models among six, NOAA-GFDL-ESM2, CNRM-CM5 and CCCma-CanESM2, having the highest R2 and Nash and Sutcliffe efficiency coefficient (NSE) with observed temperature and precipitation for the historical period, most accurately representing the study area were chosen for future simulation in SWAT. The performance criteria of the GCMs is shown in table 3.6

Table 3.6: Performance evaluation of climate model data

Climate model	Maximum Temperature		Minimum Temperature		Precipitation	
	R^2	NSE	R^2	NSE	R^2	NSE
CCCma-CanESM2	0.87	0.86	0.93	0.93	0.52	0.45
NOAA-GFDL-ESM2	0.87	0.87	0.93	0.93	0.61	0.52
CNRM-CM5	0.90	0.89	0.94	0.94	0.60	0.53
MPI-ESM-MR	0.86	0.86	0.93	0.93	0.47	0.38
IPSL-CM5A-LR	0.87	0.88	0.93	0.93	0.45	0.32
CSIRO-Mk 3.6	0.87	0.86	0.94	0.94	0.41	0.30

3.6.1 Bias Correction

Temperature and precipitation simulations from climate models often exhibit significant biases due to systemic model errors, limiting the usage of data as direct input for hydrological models. On a daily time, step, bias correction procedures are used to reduce the difference between observable and simulated climate variables (Teutschbein & Seibert, 2012). In this study, CMhyd (Climate Model data for hydrologic modelling) tool is used to bias correct RCM data (Rathjens et al., 2016). This tool has different methods embedded in it to perform bias correction. Among them, distribution mapping is found better in studies as compared to other methods for removing biases for both temperature and precipitation (Teutschbein & Seibert, 2012). Moreover, distribution mapping has performed well in different studies (Jayanthi & Keesara, 2019; Pandey et al., 2019; Smitha et al., 2018). CMhyd tool interface is shown in figure 3.17

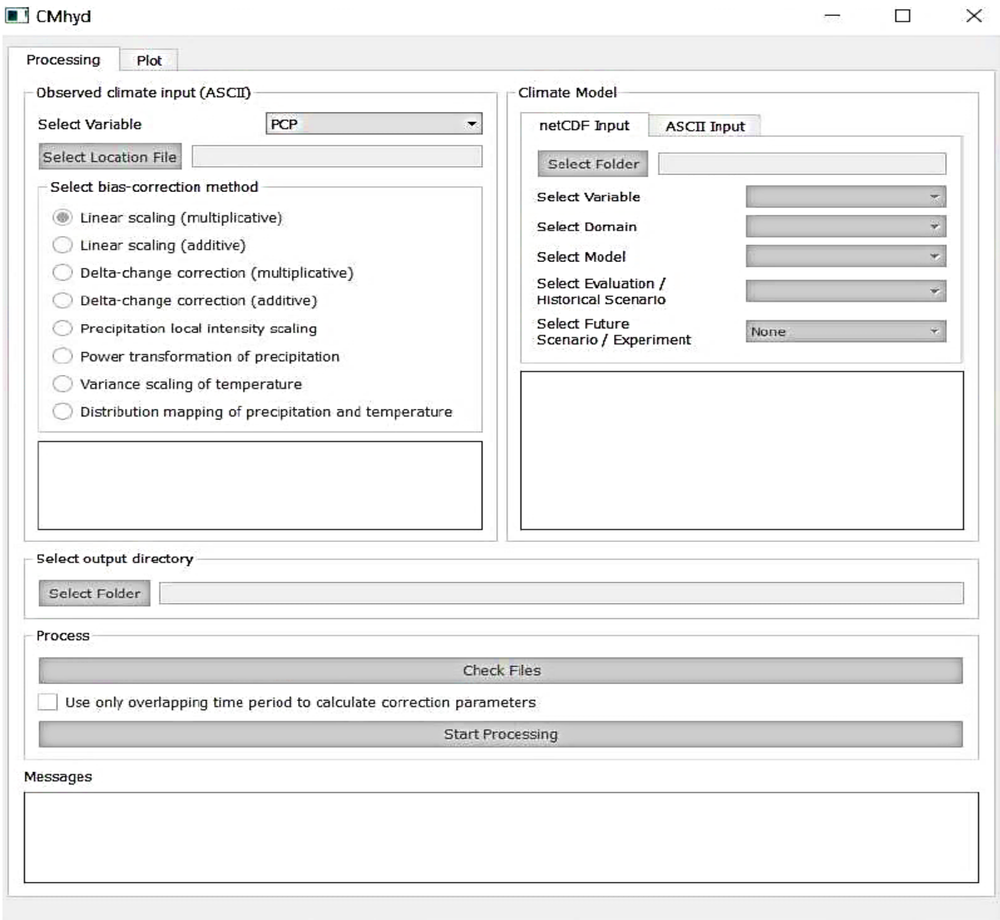


Figure 3.17: CMhyd tool interface

The basic idea behind distribution mapping is to create a transform function to conform the distribution function of raw environment variables (RCM data) to the observed distribution function of observed data (Tarekegn et al., 2021; Teutschbein & Seibert, 2012). In this study, thirty-year simulated historical data of climate model (1975-2005) was overlapped with IMD observed data of the same period for evaluating biases and creating transform function. CMhyd tool perform this task and apply same transform function to correct historical and future simulations of RCM. For evaluating bias-corrected model performance, NSE and R2 have been used in this study.

In the present study, the R2 and NSE for maximum temperature ranges from 0.81 to 0.6 and 0.79 to 0.83 respectively. For minimum temperature R2 ranges from 0.88 to 0.90 and NSE from 0.89 to 0.92. This signifies that monthly maximum and minimum temperature has very good correlation with IMD data for all six-climate models. However, the precipitation does not correlate that well. It varies from 0.33 to 0.58 for R2 and NSE from 0.30 to 0.49. Out of three selected models, the performance of NOAA-GFDL-ESM2 and CNRM-CM5 is satisfactory for precipitation and for CCCma-CanESM2 is low compared to these two. In previous studies, it is also seen that regardless of GCM/RCM selection, most of the models fails to capture the observed trend of precipitation for the historical period (Mishra & Lilhare, 2016).

The whole process of the selection of climate and simulation can be summarised as;

1. Find the existing anomalies between historical observed data and modelled data (CMIP5).

2. Do the bias correction using CMhyd tool to minimise the anomalies for all the selected models.

3. Select the model showing the best fit or minimum anomalies.

4. Do the future projections based on this model using Representative Concentration Pathways (RCP4.5) scenario.

3.6.2 RCPs Scenarios (RCP8.5 and RCP4.5)

Both RCP8.5 and RCP4.5's anticipated increases in climate variable (precipitation) were compared to the baseline (observed) and climatic dataset (precipitation). Following that, the bias-corrected dataset was used as an input into a hydrological model to forecast probable daily stream flows in the Upper Narmada River watershed for the RCP8.5 and RCP4.5 scenarios.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Calibration and Validation of SWAT model

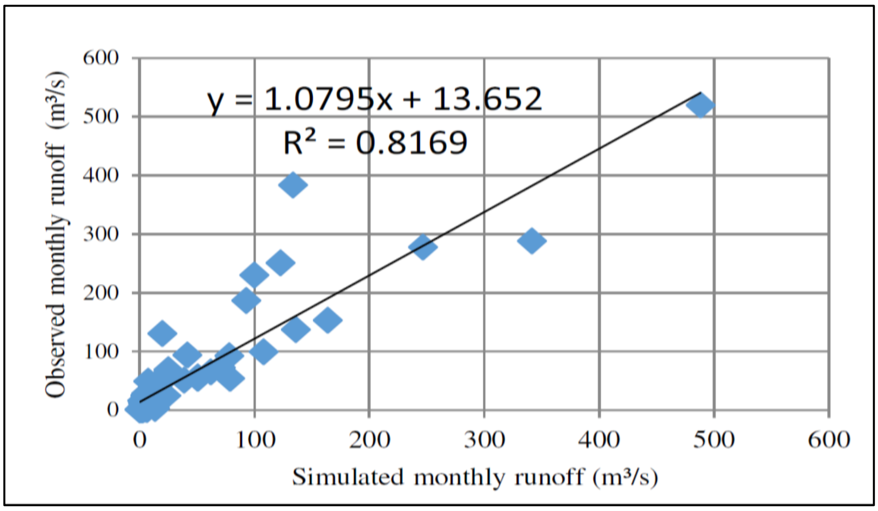
The SWAT model calibration was performed on a monthly basis in SWAT - CUP. Hoshangabad station of Narmada watershed has continuous discharge data available till 2015. So whole period was divided into calibration (1988-2007) and validation period (2008-2015). An initial model was set up from 1985 to 2015. The first three years (1985-1987) were considered as a warm-up year. Table 3.7 shows the outcome of the calibration and validation process. Fig.4.1 shows correlation between observed and simulated flow and fig.4.2 represents the relation graphically.

During calibration (1988-2007) R2 value for streamflow is 0.82 and NSE is 0.78. For validation (2008-2015) R2 and NSE obtained are 0.79 and 0.76 respectively. This shows very good performance of SWAT model. For flow simulation model performance is considered very good if 0.75 < NSE <1 and 0.75 < R2 < 1. Thus, calibrated model can be used for future climate change impact studies.

Table 3.7: Evaluation of SWAT Model Performance

Station	Calibration		Validation	
	R^2	NSE	R^2	NSE
Hoshangabad	0.82	0.78	0.79	0.76

(a)



(b)

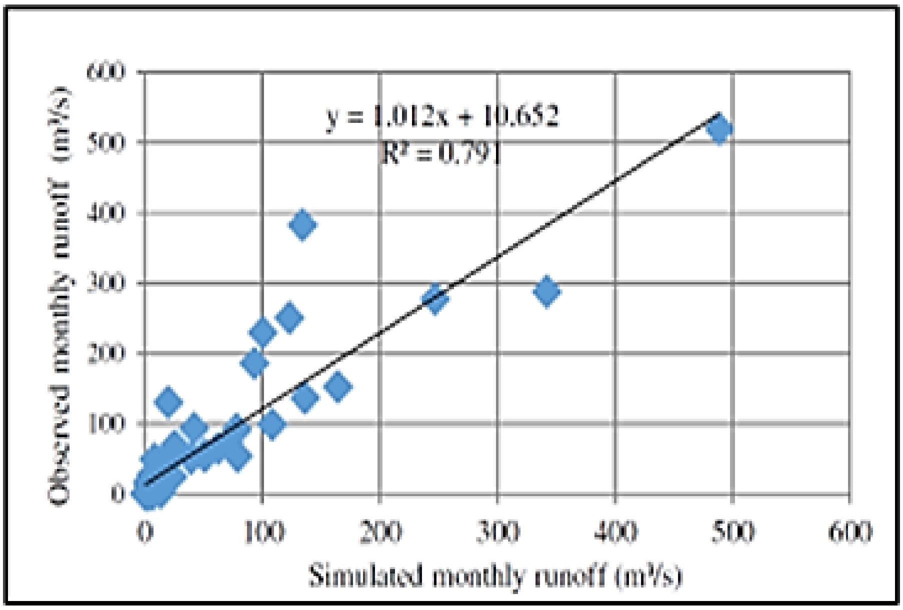


Figure 4.1: Correlation between monthly observed and simulated streamflow of Narmada River in (a) calibration (1988-2007) and (b) validation (2008-2015)

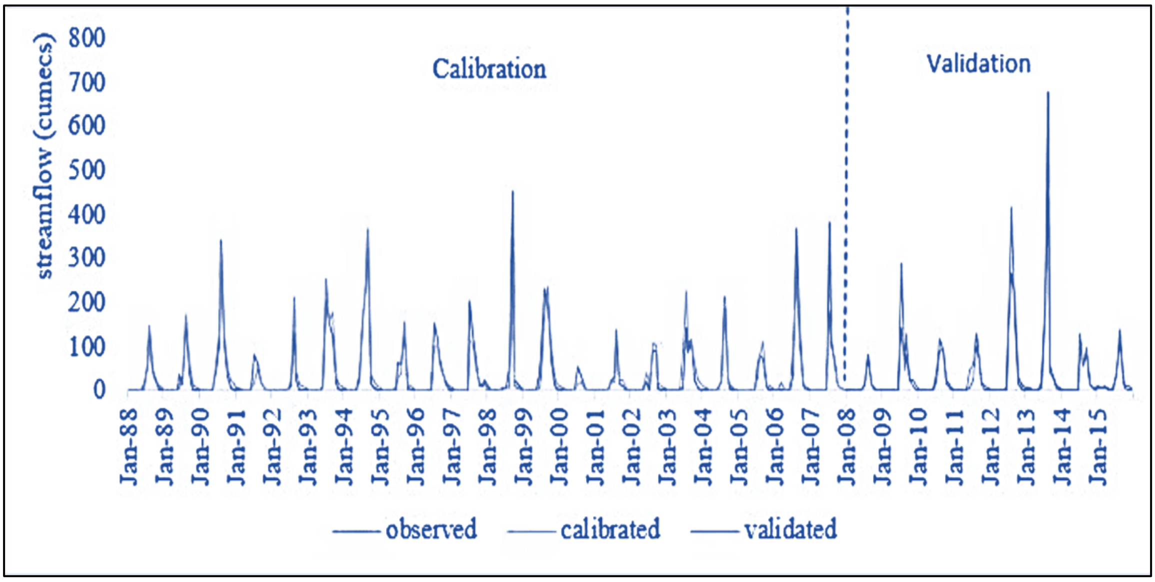


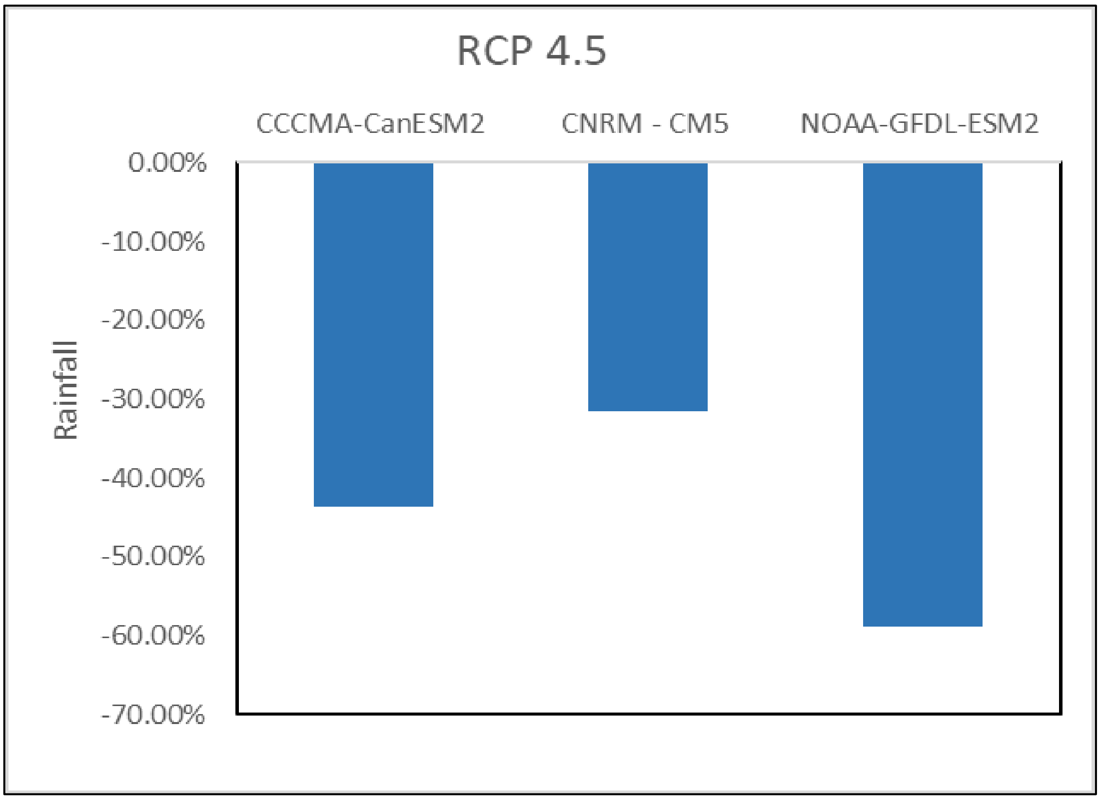
Figure 4.2: Graphical representation of observed streamflow with SWAT simulated streamflow for calibration (1988-2007) and validation (2008-2015) period

4.2 Projected change in precipitation and temperature

Upper Narmada Basin receives rainfall only in summer monsoon (June to Sept) (Figure 4.4), which is also the case for other watersheds in the Narmada basin. Changes in the future period

(2025-2052) rainfall and temperature were calculated relative to baseline (1988-2015) data. Analysis indicates a decrement in average annual rainfall of watershed in both RCP scenarios for all climate models (Figure 4.3). The decrease in rainfall is more significant in RCP 4.5 than 8.5. The percent change in average annual rainfall is shown in figure 6.3 for both RCP scenarios. Under RCP 4.5 scenario, NOAA-GFDL-ESM2 shows highest decrement of 58.83%, followed by CCCMA-CanESM2 (43.69%) and CNRM - CM5 (31.58%). In RCP 8.5 scenario, decrement ranges from 22.67% to 44.52%. CCCMA-CanESM2 shows highest decrement of 37.64%, followed by NOAA-GFDL-ESM2 (29.59%) and CNRM-CM5 (24.83%).

NOAA-GFDL-ESM2 in RCP 8.5 scenario shows a significant increase in precipitation for summer (Jan to May) and winter months (Oct to Dec) compared to other models and baseline data (Figure 4.4). In summer, the precipitation increased by 63.5% and 48% in winter compared to the baseline.



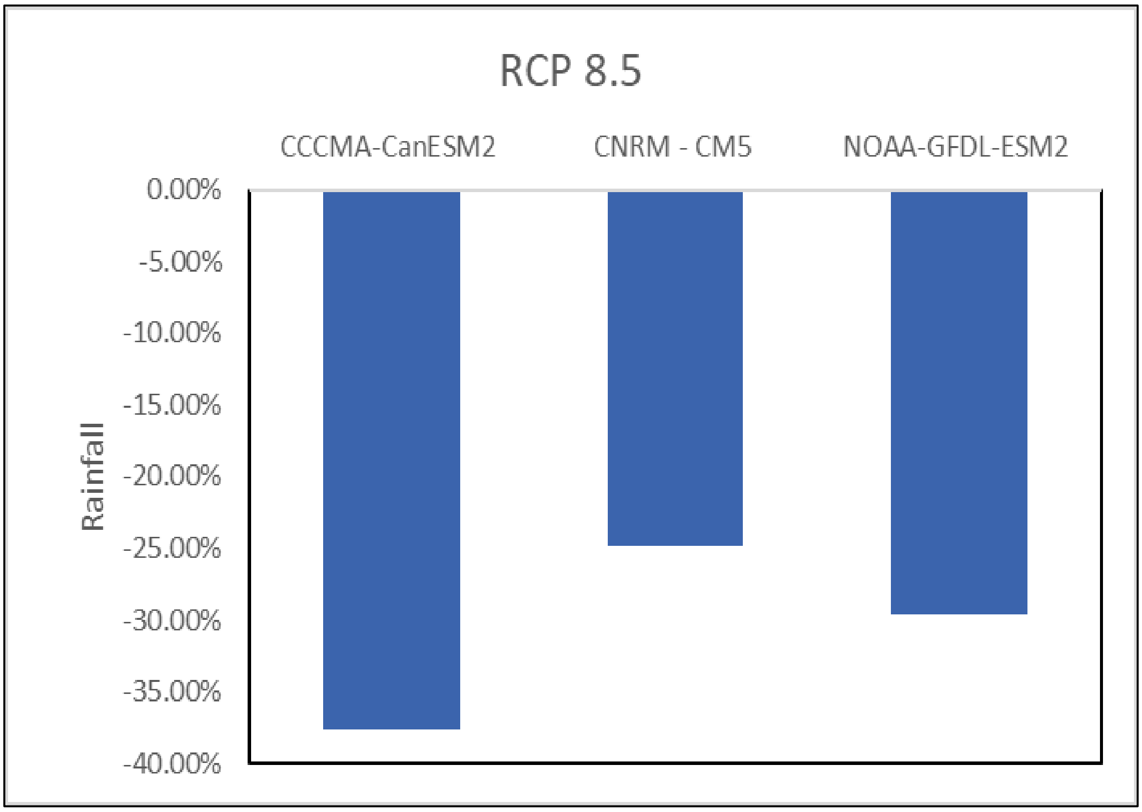
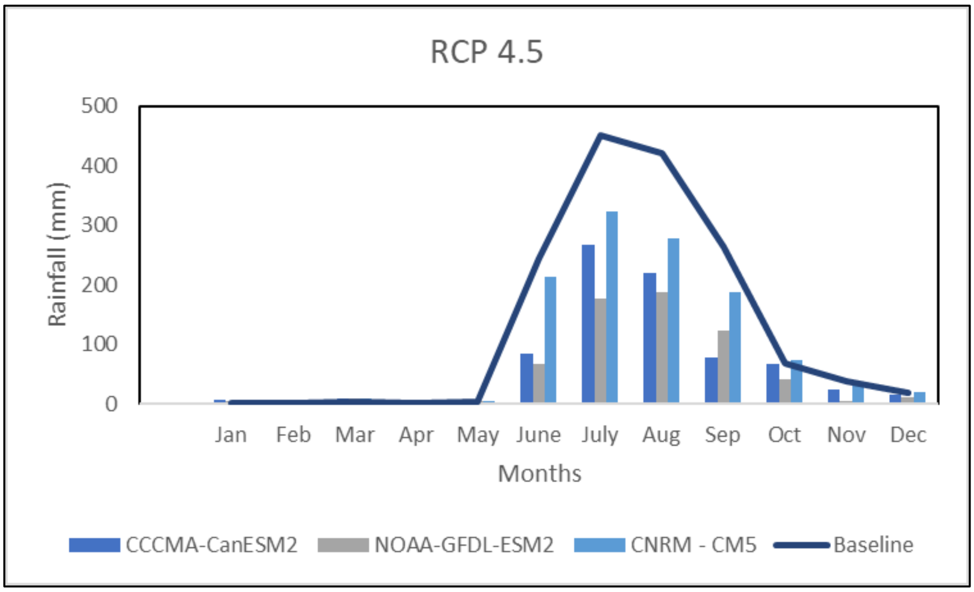


Figure 4.3: Average annual rainfall comparison with baseline rainfall for Narmada watershed for (a)RCP 4.5 (b) RCP 8.5



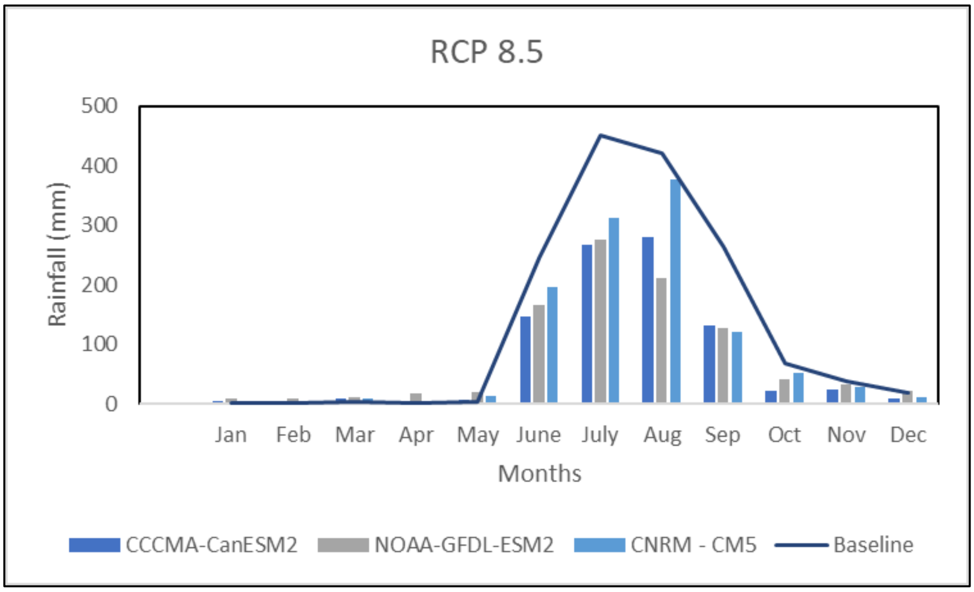
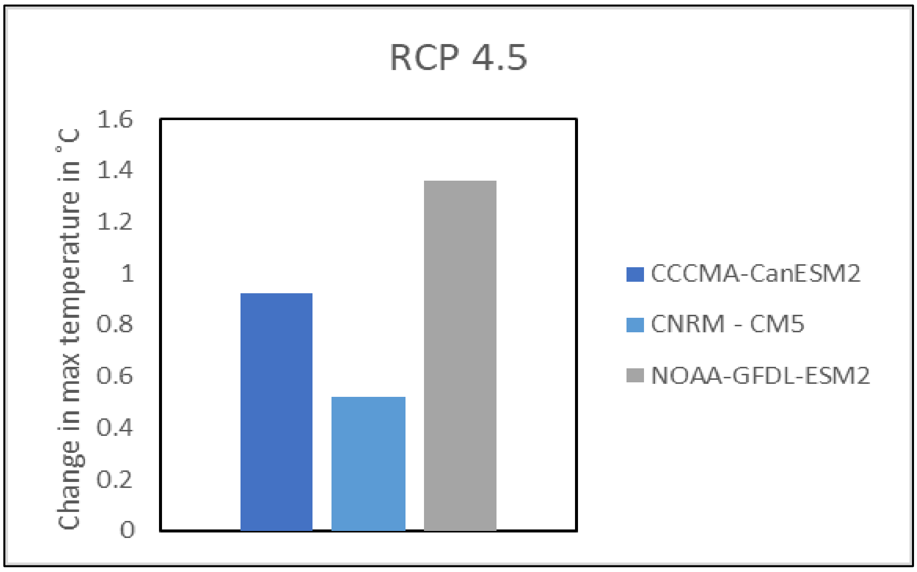


Figure 4.4: Average monthly rainfall comparison with baseline rainfall for Upper Narmada Basin for (a)RCP 4.5 (b) RCP 8.5

The average annual temperature for both scenarios show an increment in future across all models (Figure 4.5 and 4.7). In their annual cycle, both maximum and minimum temperatures have two maxima (Figure 4.6 and 4.8). In maximum temperature, first peak was observed in the month of May where the temperature reaches around 40˚C, before arrival of monsoon and the secondary peak is observed in October, after monsoon has passed. Under RCP 4.5, highest increase in maximum temperature is predicted by NOAA-GFDL-ESM2 of +1.31˚C while under RCP 8.5 CCCMA-CanESM2 shows highest increase in maximum temperature of +1.62˚C. CCCMA – CanESM2 and CNRM- CM5 shows + 0.92˚C and +0.53˚C increase under RCP 4.5. Under RCP 8.5 NOAA-GFDL-ESM2 and CNRM-CM5 shows increment of +1.41˚C and +0.82˚C (Figure 4.7)

For minimum temperature both scenario shows increasing trend. RCP 8.5 shows more increment in minimum temperature than RCP4.5. For RCP 4.5 increase in minimum temperature ranges from +0.73 ˚C to +1.62 ˚C. CCMA-CanESM2, CNRM-CM5 and NOAA-GFDL-ESM2 predict increment of +1.62 ˚C, +0.73 ˚C and +1.16 ˚C. Under RCP 8.5 increase in minimum temperature for CCCMA-CanESM2, CNRM – CM5 and NOAA-GFDL-ESM2 are +1.86 ˚C, +1.24 ˚C and 0.73 ˚C (Figure 4.7).



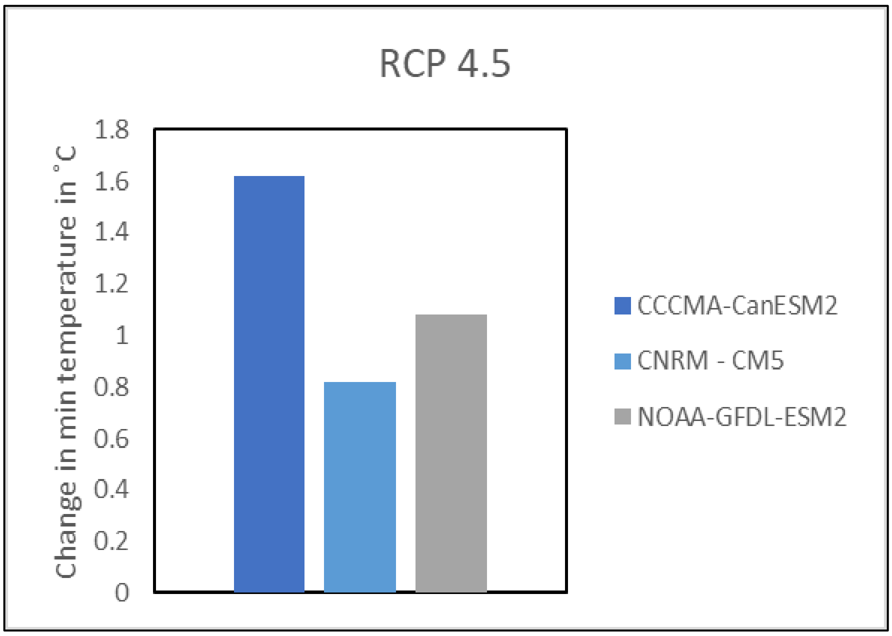
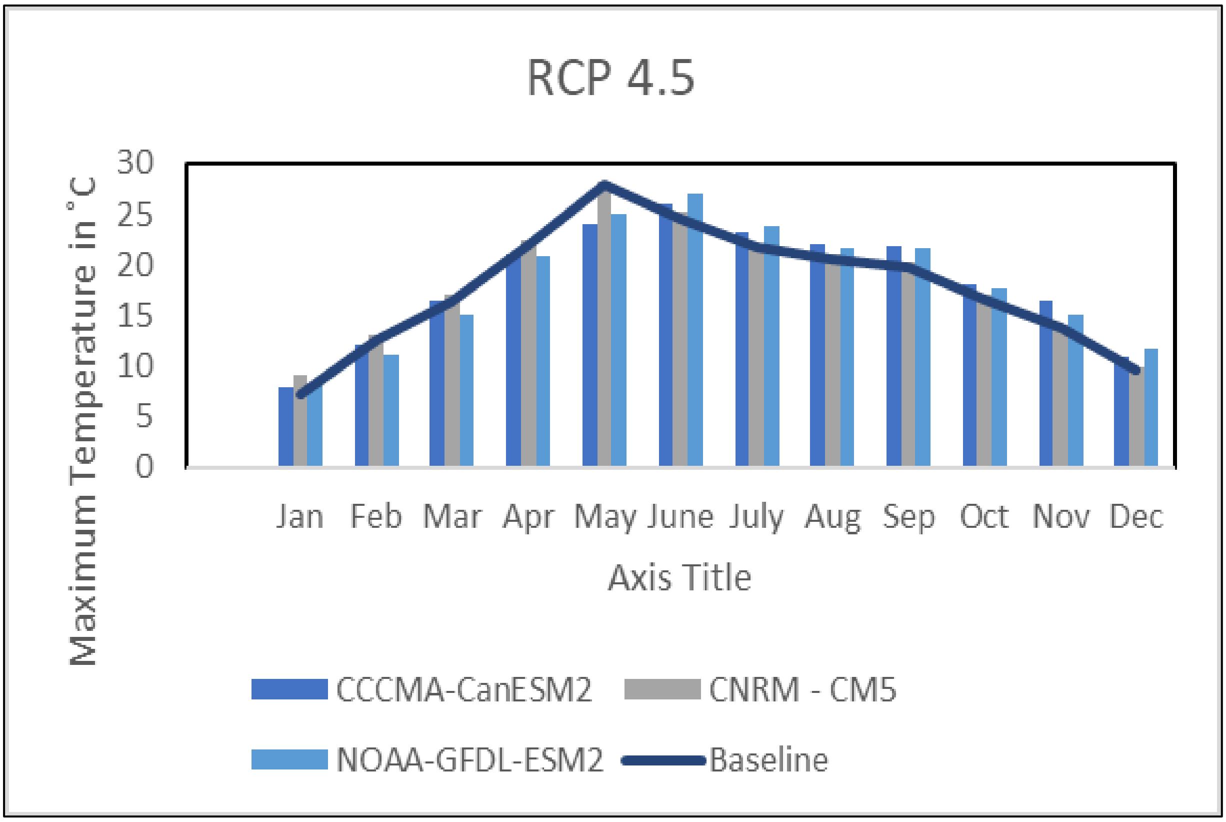


Figure 4.5: Change in average annual (a) maximum and (b) minimum temperature as compared to baseline period for RCP 4.5



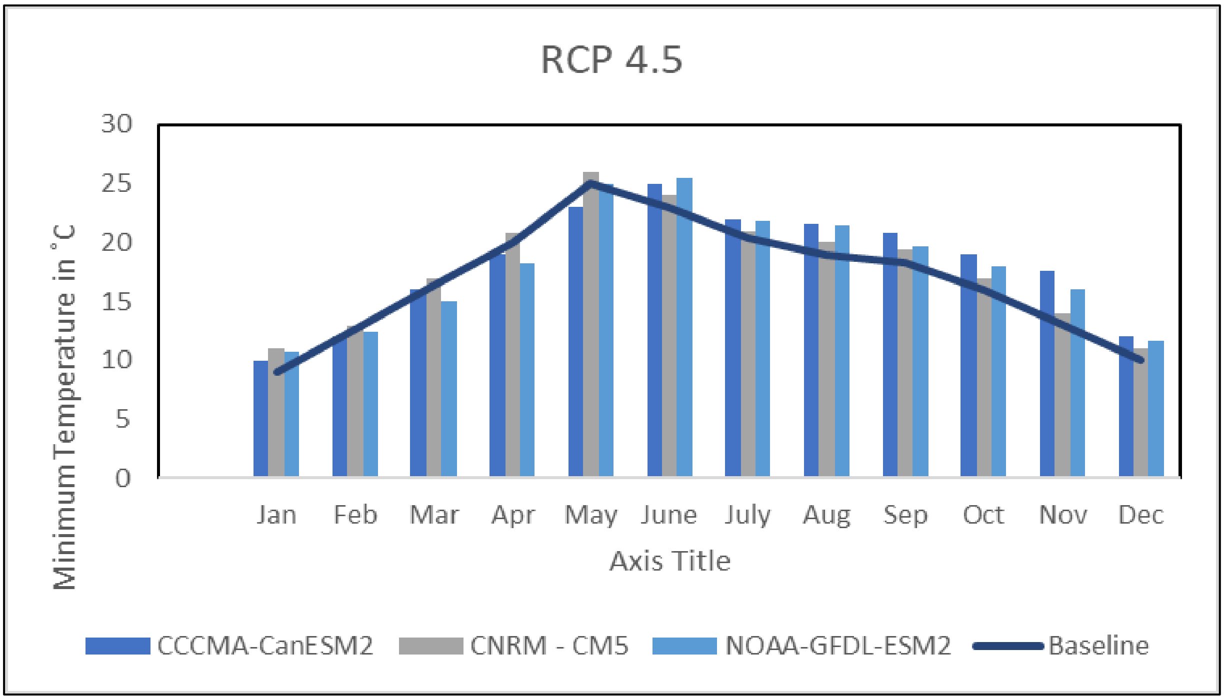
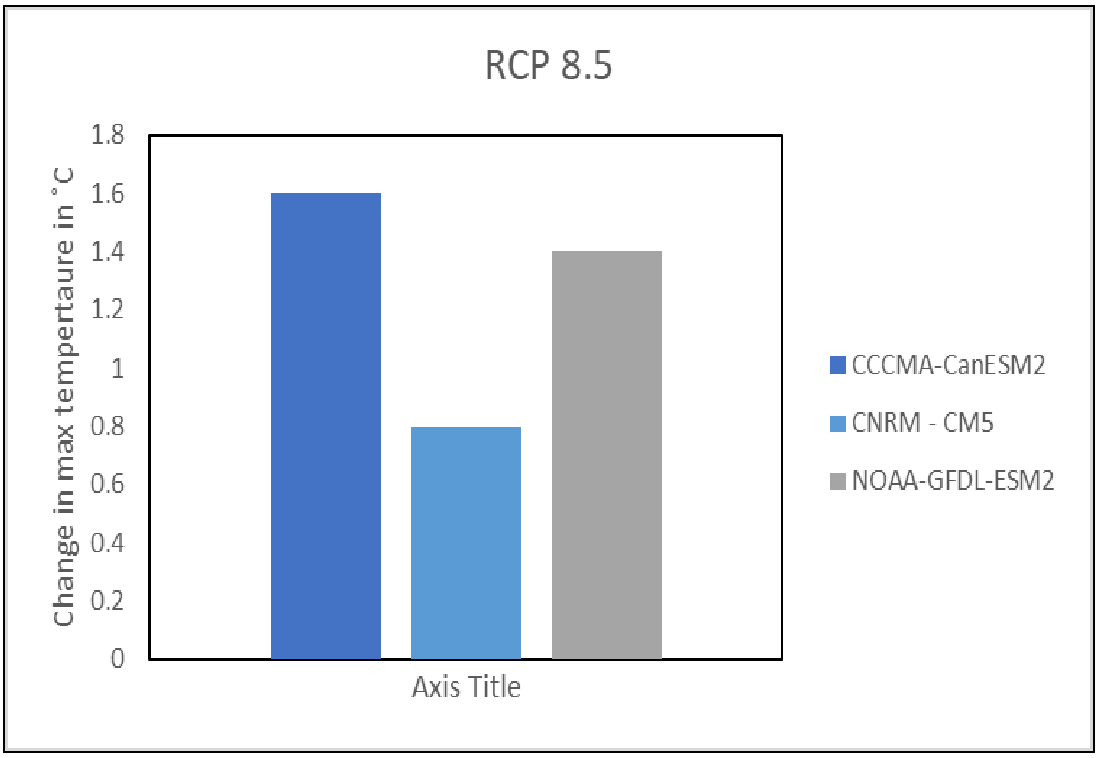


Figure 4.6: Average monthly (a) maximum temperature and (b) minimum temperature variation for RCP 4.5



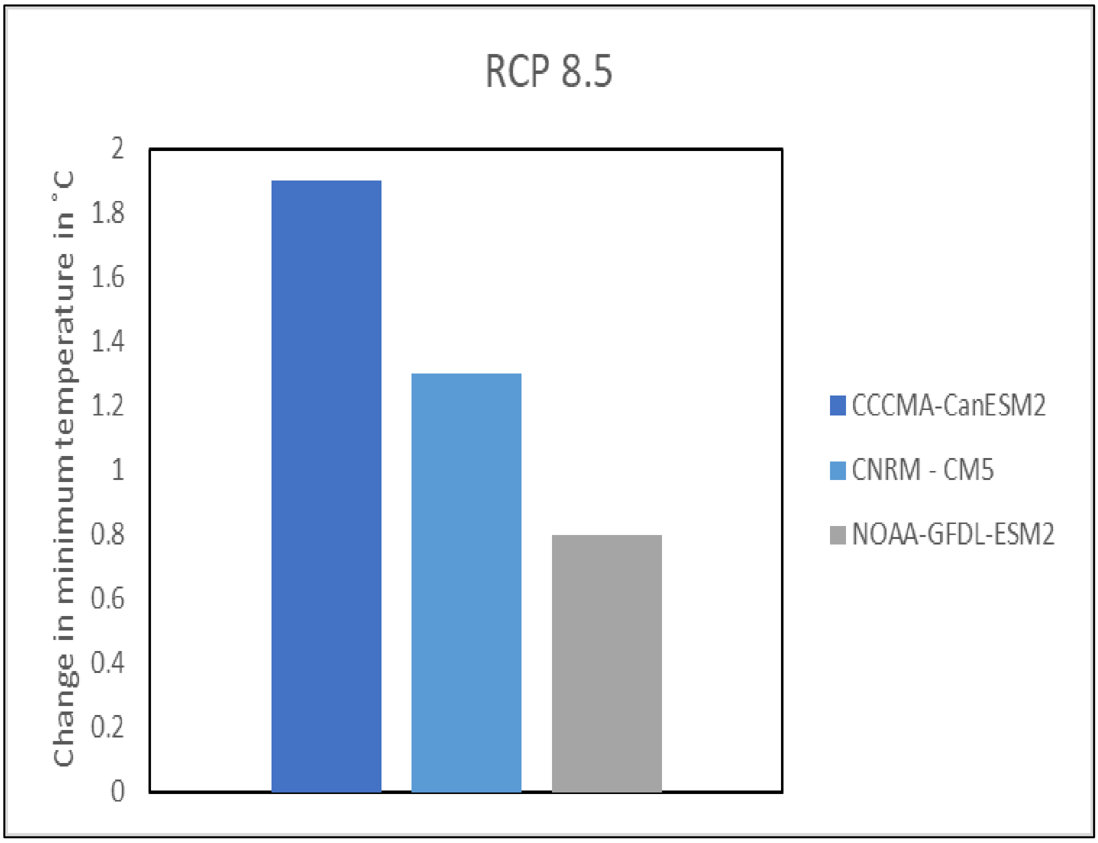
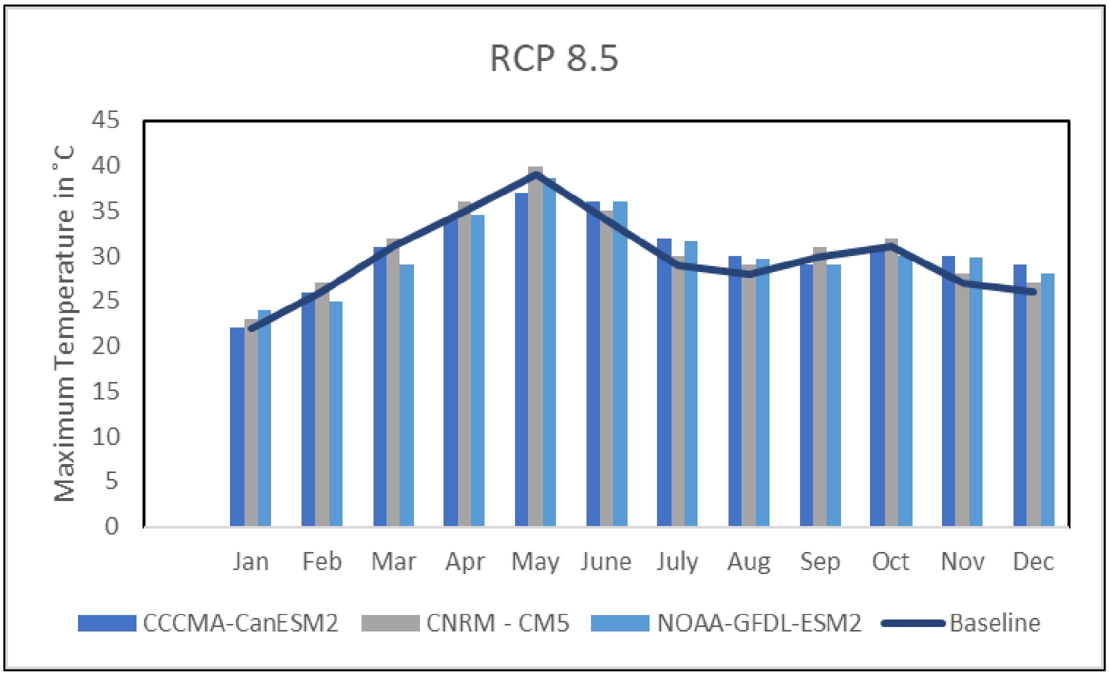


Figure 4.7: Change in Average annual (a)maximum and (b)minimum temperature as compared to baseline period for RCP8.5 scenario



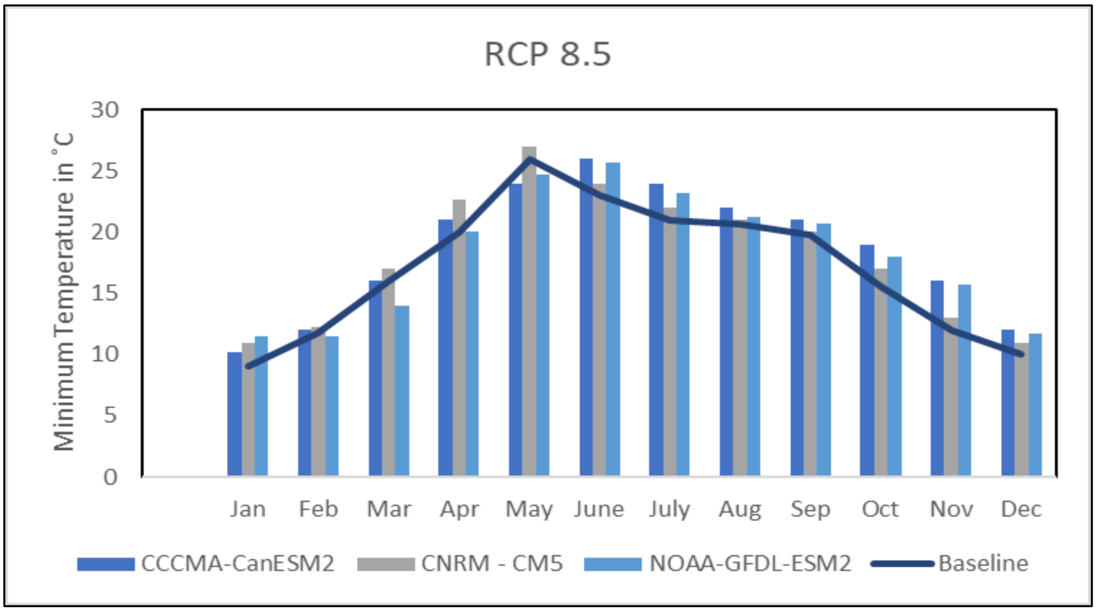


Figure 4.8: Average monthly (a) maximum temperature variation (b) minimum temperature variation for RCP 8.5 scenario

4.3 Impact on water balance component

The calibrated hydrological model was run for baseline period (1988-2015) with IMD observed data and then for future period (2025-52) using climate model data to analyse how streamflow is impacted by climate variables. The average annual values of different water balance components (precipitation, surface runoff, water yield and evapotranspiration) of baseline and future period is shown in table 3.8. A wide range of rainfall is projected by climate models. All the models show a decrease in precipitation (PRECIP) for future period (table 6). It has resulted in a decrease of surface runoff (SURQ) and water yield (WYLD) (table6). WYLD is the net amount of water contributing to streamflow (surface runoff + lateral flow + groundwater contribution to streamflow – transmission loss). It is one of the critical components that must be estimated in order to ensure the long-term management of the investigated area's water resources (Adeogun et al., 2014). For the baseline period, the watershed has annual average precipitation (PRECIP) of 1247.20 mm. The average monthly precipitation is shown in figure.6.4. Evapotranspiration (ET) is a significant cause of loss of water in watershed. SURQ remains the primary source of streamflow during baseline and for future period.

Table 3.8: Average annual water balance component of Upper Narmada River Basin

Model	*Scenario*	*PRECIP (mm/year)*	*SURQ (mm/year)*	*WYLD (mm/year)*	*E.T. (mm/year)*
	Baseline	1480	524.92	769.25	625.2
	RCP 4.5	734.4	294.27	352.45	465.7
CCCMA-CanESM2	RCP8.5	802.9	204.76	403.	549.1
NOAA-GFDL-ESM2	RCP4.5	417	159.2	237.47	338.8
	RCP8.5	862.8	125.4	294.25	693.3
CNRM-CM5	RCP 4.5	894.2	365.22	451.56	602.5
	RCP 8.5	981.9	421.97	552.36	512

Under RCP 4.5, future and baseline period minimum ET was observed in May. In RCP 8.5 also all model except NOAA shows lowest ET in May. The peak of ET was observed in September month for the baseline period. For future scenarios it varies from July to September for different models. ET begins to build up in the basin when the temperature rises in March or April. As peak approaches in May month, the soil becomes too dry to do evaporation, thus all models ET output reach a minimum. Whereas under RCP8.5 NOAA-GFDL-ESM2 shows increase in rainfall in summer (Jan to May) and winter month (oct to dec) as compared to other model simulation. Thus, providing more water for ET. Average monthly rainfall analysis shows it receives the lowest rainfall in the month of Feb (15.32 mm/year), resulting in low water availability causing minimum ET in Feb.

SURQ and WYLD peak for baseline was observed in August month. They both follow similar trend as expected. As monsoon, arrive in June SURQ and WYLD start in June reaching their maximum value in August.

Under RCP 4.5 NOAA-GFDL-ESM2 predicts the lowest precipitation. Thus, having low availability of water to contribute as streamflow. Under RCP 8.5, its precipitation increases significantly but it has an overall maximum ET of 693.3 mm/year resulting in low water for WYLD and SURQ. ET is dominating in this case resulting in almost no significant difference in WYLD between both scenarios. Thus, NOAA-GFDL-ESM2 under both scenario shows the lowest value for Average annual SURQ and WYLD.

4.4 Impact on streamflow

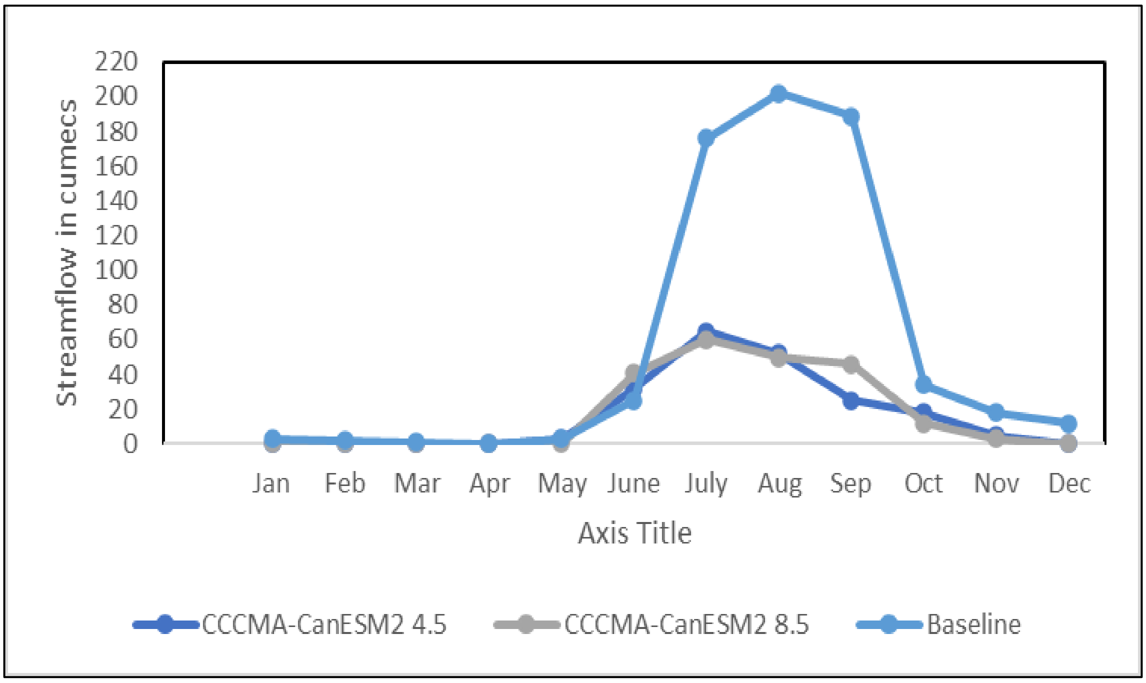
The calibrated SWAT model was further used to estimate streamflow for a future period (2025-2052). Figure 4.9 shows the average monthly streamflow comparison of baseline (1988 – 2015) with the future period under each scenario RCP4.5 and RCP 8.5. As Narmada watershed receives rainfall during the monsoon season (June to Sept), these months are major contributors to streamflow. The simulation of streamflow from all three models shows a reduction as compared to baseline. This decrease was reasonably expected as precipitation is decreasing in the study area for future scenarios.

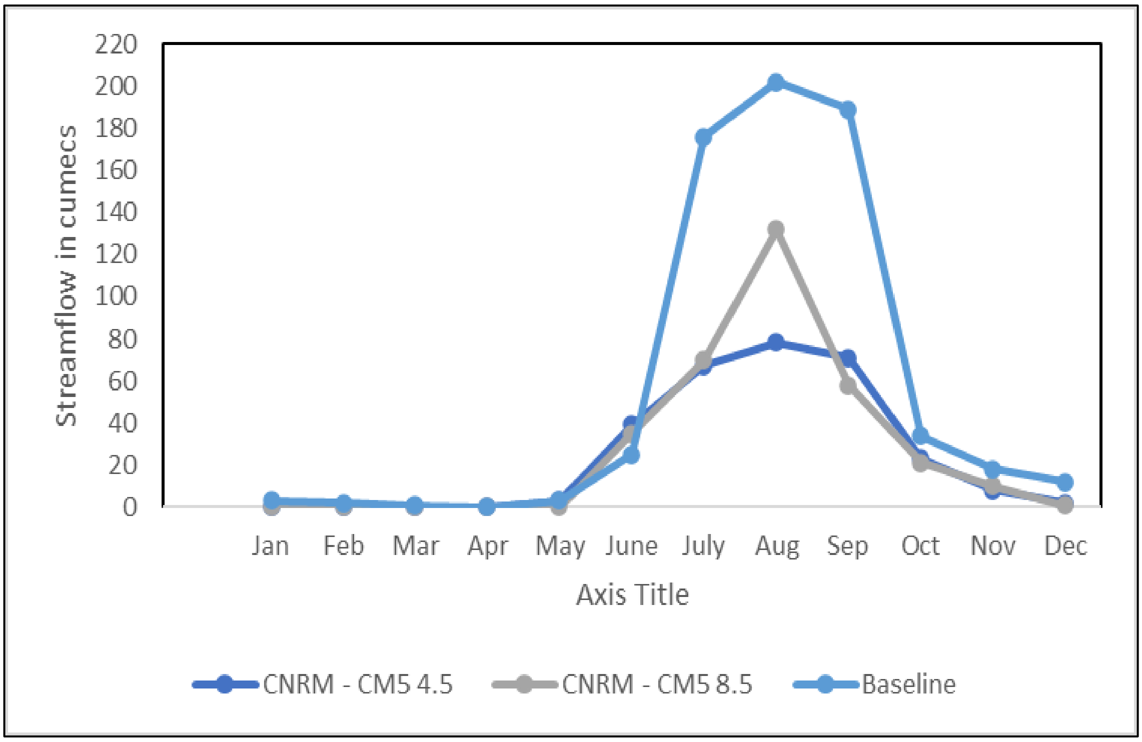
CCCMA-CanESM2 shows a decrease of 48.4% in average annual streamflow for RCP 4.5. In comparison, RCP 8.5 shows a decrease of 43 % (Figure 4.10) as compared to baseline (Figure 4.11). For RCP 4.5 the average monthly streamflow study shows a shift in the peak of streamflow from month of august to July with peak value of 65m3/s (Figure 4.9). For the baseline, peak was observed in August month having a value of 202 m3/s. This shift of peak is due to significant increase in precipitation in July month than August. As ET remains same during these months, for RCP 4.5 scenarios precipitation was dominating factor. In comparison, RCP 8.5 shows approx. peak of 59 m3/s in July and 55 m3/sec in August.

Although under RCP 8.5 scenario, month of August receives more rainfall, ET was also maximum result in lowering august peak. For RCP 8.5, in September, streamflow remains more than the RCP 4.5 as more precipitation occur in month of September for RCP 8.5 scenario as compared to RCP 4.5 (figure6.10).

CNRM-CM5 shows a decrease of 41 % and 32% in average annual streamflow value in RCP4.5 and 8.5 (Figure 4.10 and 4.11). In this case, for both RCP scenarios peak is observed in August same as baseline period. RCP 4.5 shows a peak value of 78.3 m3/sec and for RCP 8.5 peak value is 132 m3/sec (Figure 4.9).

NOAA-GFDL-ESM2 shows a decrease of 56 % in average annual streamflow value under RCP4.5 and a decrease of 58.34 % under 8.5 scenarios (Figure 4.10 and 4.11)). A shift of peak for streamflow was observed from August to July for RCP 4.5. This shift is due to more precipitation in July month (184 mm) than in august (101.6mm). The ET values of 63 mm in July and 59 mm in August show no significant difference, so rainfall remains critical. Under RCP4.5 July peak has value of 51 m3/s whereas for RCP 8.5 peak remains in August month with a value of 39.4m3/sec.





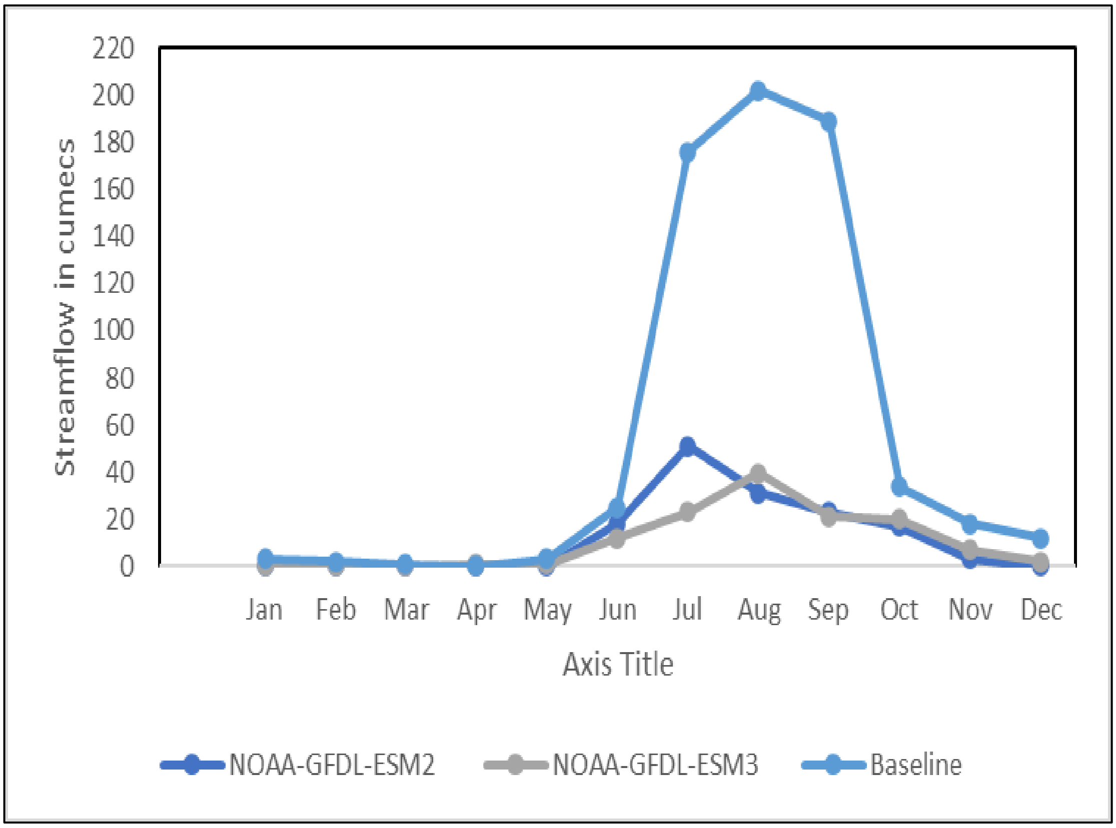


Figure 4.9: Average monthly streamflow at outlet of Upper Narmada Basin for (a) CCCMA-CanESM2 (b) CNRM – CM5 (c) NOAA-GFDL-ESM2

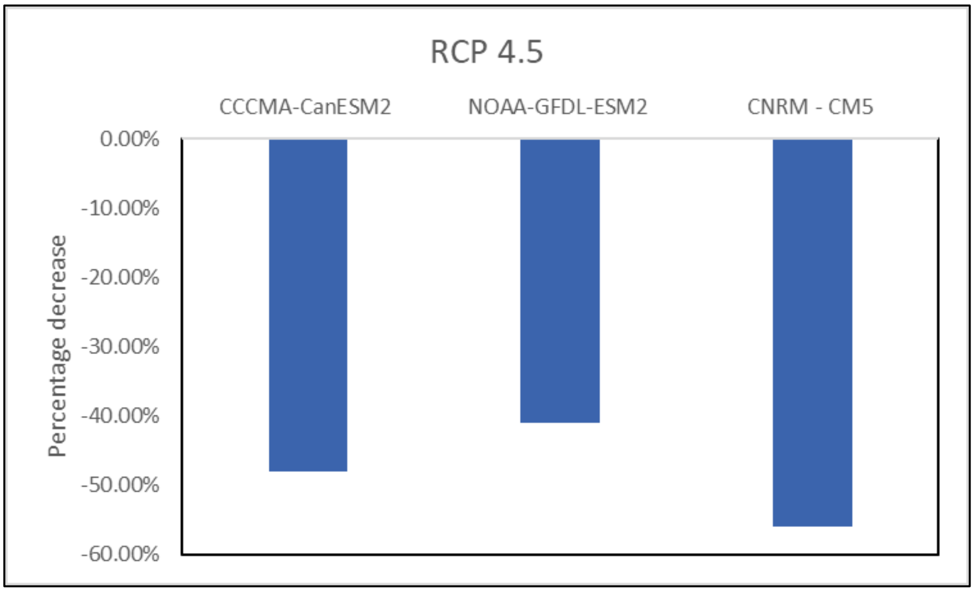


Figure 4.10: Comparison of average annual streamflow with baseline streamflow for RCP 4.5 scenario

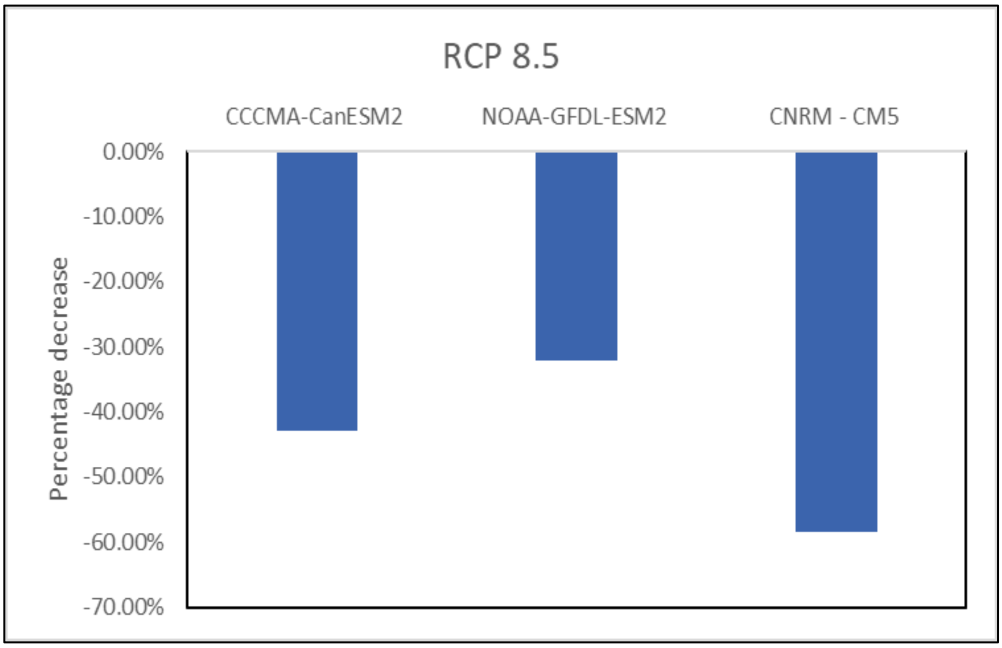


Figure 4.11: Comparison of average annual streamflow with baseline streamflow for RCP 8.5 scenario

4.5 DISCUSSIONS

The results show climate change in future is going to adversely impact SURQ, WYLD and hence streamflow. The baseline results of ET, SURQ and WYLD complement with previous study done for another watershed in Narmada River basin (Goswami & Kar, 2017). The decrease in future SURQ, WYLD and streamflow is due to decrease in rainfall predicted and increase in temperature. The shift in peaks of streamflow in future is due to change in rainfall pattern. The decreasing streamflow and precipitation are documented for other regions of India such as Phakal lake in basin of Krishna River (Jayanthi & Keesara, 2019) and Brahmani River in Odisha (Islam et al., 2012). The identical seasonality of precipitation and streamflow indicates a water-limited system in which flow conditions are tightly connected to the precipitation regime, as is common in most water-limited systems (Pumo et al., 2016).

Although this study tries to compensate various uncertainty in climate models and hydrological model, there are certain limitations. Future assessment of different water balance component and streamflow is done using constant LULC map. The result will be impacted by future irrigation schemes and other land use pattern changes in the study area.

4.2.1 Streamflow is observed to be sensitive to changes in rainfall patterns

The results from the reviewed literature revealed that for most of the study areas, it was observed that streamflow changes were more influenced rainfall variations than the changes determined by the expected increase in temperatures. For example, in Yellow River Basin, China, for example, the projected precipitation observed a general increase under all three applied climate change scenarios and the results of the study showed an increasing streamflow for the future periods under. Hence, it was analysed from the reviewed literature that the combination of climatic scenarios of variations in both temperature and rainfall leads to slight or no prominent variations of surface runoff or streamflow as compared to independent forecasted rainfall scenario. Thus, the results from the reviewed literature highlighted those changes in rainfall regime produces more significant changes in streamflow patterns as compared to the modification of temperature regime.

4.2.2 Evaluation of alternative climate products and various approaches

Evaluation of future streamflow under changing climate scenarios requires certain tools such as hydrological models, outputs from climate models, methods for downscaling and bias correction. Different combinations of RCP scenarios and Global climate Models can be used to obtain results of the studies. This variation in different tools and approaches has led to significant variations in projected streamflow results irrespective of the catchment size and characteristics, topographic features, changes in land use pattern, and human activities as noticed in the reviewed studies. In order to reduce uncertainty and obtain accurate results, many studies in the reviewed literature multiple climate models and bias correction method. The GCM model outputs are able to simulate complex climate aspects and are tested against historical observations and hence are commonly used by researchers.

Different versions of hydrological models, climatic parameters, structural differences in applied models, different baseline conditions and downscaling methodologies are all sources of uncertainty in climate change studies. The uncertainties linked with climate model predictions also leads to variation in streamflow projections. The socioeconomic and technological factors are uncertain variables which further impacts the GHGs emission rates, leading to ambiguous results in hydrological predictions. These uncertainties led to the application of an uncountable number of methodological frameworks. The most efficient methodology is difficult to recognise due to insufficient evidence because the same rivers showed different trend projections depending on the methodology used.

Various international efforts, such as the International Precipitation Working Group (IPWG) (Maggioni et al., 2016) and the Climate Data Guide (Schneider et al., 2013), have been launched to continuously improve open-source climate data for operational and scientific use in order to establish certain standards for intercomparison and validation of results data used.Although the assessment and evaluation of alternative climate products applied in SWAT modelling has increased dramatically in recent times, yet a framework of validation of commonly accepted data sources and statistical approaches is still missing. Presence of uniform statistical metrics is still lacking across studies. Therefore, identification of the most prevailing subset climate products on global and regional scale is critical among researchers and scientific communities. This in turn would lead to suitable application and use of climate datasets as well as ensure consistent comparisons between studies, allowing for continued improvement of data sources and more consistent results. This method could also be beneficial in improving and standardising data sets of downscaled and bias corrected general circulation models (GCMs) or regional climate models (RCMs).

CHAPTER 5

Conclusion and Recommendations

5.1 Conclusion

Variations in hydrological regimes due to changing climate is one of the key issues that integrated water resource management faces. Accurate forecasting of future streamflow under climate change is critical given the world's dynamic and changing weather conditions, as well as the importance of rivers. As evident from the published literature, the application of SWAT has grown rapidly in the recent years. Because of its application in a wide range of processes linked to water quality, hydrological balance and erosion factors, the SWAT model is one of the most extensively used models for environmental studies.

This study analyses the impact of climate change on streamflow in the Upper Narmada River Basin using the hydrological model SWAT. The study incorporated various analysis that dealt with trends of weather data and simulation of existing data to assess the possible outcomes in the near future. The scenarios of IPCC (CMIP5) have been incorporated for the simulation and each of the simulation result witnesses the existence of a considerable decrease in the streamflow of the river basin.

Following are the conclusions drawn from the study:

[a] The SWAT model worked well for the Upper Narmada River Basin. The calibration and validation of the model resulted in R2 values of 0.82, 0.78, and NSE values of 0.79 and 0.76, emphasising a very good SWAT model performance.

[b] The study revealed that NOAA-GFDL-ESM2, CNRM-CM5 and CCMA-CanESM2 climate model selected for the study performed better than other downscaled GCM under IITM-Regcm4 for Upper Narmada region. Also,

[c] Minimum and maximum temperature is projected to increase across all scenario in future. Increase in minimum temperature is more than maximum temperature. RCP 8.5 increase in minimum temperature is more significant. The maximum temperature ranges from +0.53 ˚C to +1.31 ˚C. for RCP 4.5. Under RCP 8.5 it varies from +0.8 ˚C to +1.1 ˚C. For minimum temperature increment varies from +0.82 ˚C to +1.62 ˚C under RCP 4.5 whereas under RCP 8.5 it varies from +1 to +1.55˚C.

[d] The hydrology of the Upper Narmada River basin is mostly determined by rainfall. The results from the models projected a decrease in precipitation for future scenarios (2025-2052)

in the study area. As a result of which the basin is going to be stressed for water availability in future.

[e] NOAA-GFDL-ESM2 resulted in the highest decrement in streamflow by 58.34% as under RCP 8.5 scenarios. Under RCP 8.5 for NOAA-GFDL-ESM2, evapotranspiration become key factor resulting in large decrease of total water yield and hence streamflow.

The results of analysis clearly show the evidence of climate change impact on hydrological regime of the river basin making it more vulnerable towards global warming. The results of the current study could potentially provide useful information to take decision on the trends of streamflow changes in the concerned area and hence mitigate and manage the impacts of changing climate in the near future.

5.2 Recommendations

(a) Future studies could focus on accurate calibration and verification of spatial parameters in SWAT modelling thereby reducing uncertainty in the calibration of model parameters.

(b) In the future, more applications should include the following aspects: (1) hydro-meteorological analysis—including extreme events analysis, useful for flood and drought management practices; (2) uncertainty analysis for input data—for assessment of sensitivity of several input data, such as remote sensing data, on SWAT outputs in order to select the most appropriate datasets.

(c) For regions lacking in availability of ground-based climate observations mainly precipitation data, satellite data such as gridded precipitation data can offer as a useful source of input for SWAT model. In addition, to obtain more accurate precipitation inputs for SWAT modelling, combining global, satellite, and observed precipitation data may provide desirable results.

(d) Future research in impact assessment of climate change using SWAT model in the mountainous areas should focus on identifying reliable alternate data sources for SWAT modelling in these data scarce regions.

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