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Original Article

Evaluating the Influence of Climate Variation on Water Resources Elements of Bhima Fluvial Catchment Area, Maharashtra Utilizing CMIP6 Frameworks

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Abstract *- The current investigation's focus is to analyse the implications of climate shift on the hydrological elements and parameters of the Bhima watershed through the application of the SWAT model. This investigation utilized three Climate Simulations from GCMs sourced from CMIP6. The three GCMs selected for future prediction and analysis were CNRM-CM6-1, GFDL-ESM-4, and Miroc6. The SWAT model simulated future periods of the basin's hydrological processes under the SSP245 and SSP585 emissions routes. The outcome demonstrated an upward trend in streamflow within the anticipated time frame caused by the basin's increasing precipitation. Within the context of the SSP245 scenario, yearly precipitation is anticipated to rise by about 12%, 21.7%, and 31.5% during 2021, 2051, and 2081, respectively. In contrast, under the SSP585 scenario, the corresponding increases in precipitation are estimated to be around 10.87%, 35.41%, and 78.38%. The Chaskaman sub-basin is projected to undergo a significantly greater increase in average annual streamflow relative to the Pargaon sub-basin in both emission scenarios. The stream flow varies annually in the Chaskaman sub-basin are anticipated to range from -1.38% to 26.43% in 2021, -0.72% to 55.77% in 2051, and 14.74% to 126.42% in 2081, based on various General Circulation Models (GCMs). These findings could be valuable for policymakers in developing future management approaches for the Bhima River basin.*

Keywords *- Bhima river basin, Climate changes, CMIP6, SWAT model, Water availability.*

1. Introduction

The accessibility of water resources and hydrological cycles are drastically changing due to climate change, which has become a major worldwide concern. Particularly in monsoon-dependent areas like Maharashtra, fluvial catchments are extremely vulnerable to changes in temperature and precipitation. It is essential to comprehend these factors in order to manage water resources sustainably and lessen the impact of major hydrological events like droughts and floods.

A crucial tributary of the Krishna River, the Bhima River watershed is crucial to Maharashtra's socioeconomic structure. Climate fluctuation affects the supply of potable water, hydroelectric power generation, and agricultural output in this basin. Although there have been many studies on regional hydrological patterns, a thorough assessment of how climatic fluctuation affects important water

It is still insufficient to use sophisticated climate models to model resource aspects like streamflow, groundwater levels, and surface water storage. Future water resource forecasts are questionable since many earlier studies either used antiquated modeling frameworks or concentrated on historical hydrological trends.

By using the most recent CMIP6 climate forecasts to assess the effect of climate-induced fluctuations on the water resource components of the Bhima fluvial watershed, this research work is to close the current knowledge deficit. Through the integration of hydrological studies and cutting-edge climate models, this study offers a more comprehensive picture of future water resource scenarios. The results will help stakeholders and policymakers create adaptive methods to counteract climate-induced variability in water resources, which will lead to better water management strategies.

The effect of climate shifts on natural systems in recent decades is evident through increased temperatures, altered precipitation patterns, reduced glaciers, and rising sea levels. (van vuuren et al. 2011). Furthermore, it precipitates extreme events like floods and droughts on a global scale, thereby affecting the key elements of the hydrological cycle (Gurung et al., 2022). Consequently, enhanced scrutiny is imperative to analyse how climate shift affects water supplies at the watershed level in order to effectively address the forthcoming water requirements for human populations, agricultural practices, and industrial activities (Haleem et al. 2022; IPCC 2022). Furthermore, due to differences in landscape, land utilisation, soil types, and climate across various river basins, these watersheds are anticipated to see different effects from climate change on their water resources. (Abeysingha et al., 2022). Consequently, assessing the outcome of climate shift on each river basin separately is necessary for formulating efficient administrative techniques and mitigation plans for the future time. General Circulation Models are produced by various international organizations. Evaluating the effect of climate shift on different water resource systems requires modelling future estimates of climate variables such as rainfall, T_{max} and T_{min}, moisture, solar energy, and wind energy velocity. These elements are crucial for understanding how future climate conditions will influence water resources and hydrological dynamics (Iranmanesh et al. 2021).

By using CMIP6 (Coupled Model Intercomparison Project sixth phase) frameworks to assess how climate variation affects the water resources in the Bhima Fluvial Catchment Area of Maharashtra, this study presents a fresh approach. The Bhima River catchment area, a vital water source in Maharashtra, has not been thoroughly examined in the context of current climate shift models, despite the fact that climate shift and its effect on water resources have been investigated in many places throughout the world.

Using the most recent generation of climate forecasts within the CMIP6 framework, this study stands out for offering a thorough examination of the region's potential for extreme hydrological events, streamflow variability, and future water supply. This strategy gives vital insights for managing water resources in a region that is becoming more and more climate-stressed, in addition to adding to the expanding corpus of research on the effects of climate change.

Furthermore, this research incorporates high-resolution models and advanced statistical techniques to produce more localized and precise projections. It could greatly improve the Bhima catchment's adaptive tactics for managing and planning its water resources.

The application of General Circulation Models (GCM) has significantly expanded, thanks to the initiatives of the CMIP6 (Carmin et al. 2012). The most recent IPCC Assessment Report six (Assessment Report 6) integrates the climate models in the CMIP6 framework (Eyring et al. 2016). A significant advancement in CMIP6 models in direct comparison to CMIP5 framework models is the incorporation of social and economic development elements alongside greenhouse gas emissions, mentioned as social and economic pathways (Gidden et al. 2019). In addition to the prior RCPs (Lovino et al. 2021). Future predictions of environmental parameters have been created using the Shared Socioeconomic Pathways structure, which includes scenarios with high, medium and low emissions (Yue et al. 2021). The selected General Circulation Models (GCMs) typically operate at a spatial resolution of hundreds of kilometres, representing Earth’s land, ocean, and atmosphere systems (Li et al. 2010; Ougahi 2022). However, there is a need to improve the resolution for capturing finer local-scale details, which would be advantageous for researchers conducting regional probes (Ougahi, 2022).

Scaling down and normalization correction methods are crucial to mitigate uncertainties. (Mishra et al. 2020) generated a daily data refinement for projected rainfall, as well as T_{max} and T_{min} temperatures, derived using GCMs of CMIP6. This data has a geospatial resolution of 25 km and covers the South Asian region, containing India, Bangladesh, Sri Lanka, Nepal and Bhutan. The data collection provides both past data (1951 to 2014) and future forthcoming projections (2015 to 2100) for the entire Asian region of the south.

A thorough analysis of previous studies that include hydrological modeling and understanding how climatic variance affects water resources requires knowledge of climate change projections and regional case studies. CMIP5 and CMIP6 have been used extensively to investigate the effect of climate shifts on fluvial systems. These frameworks provide enhanced climate forecasts with fine-grained geographical and temporal resolutions (Eyring et al., 2016). Streamflow dynamics are significantly impacted by climate change, according to numerous research, evapotranspiration rates and precipitation patterns, all of which change hydrological regimes (Milly et al., 2005; IPCC, 2014). The semi-arid Bhima River basin in Maharashtra is extremely vulnerable to hydrological changes carried on by climate shifts. To evaluate the availability of water resources under various climate scenarios, hydrological models like HEC-HMS, VIC (Variable Infiltration Capacity), and the Soil and Water Assessment Tool have been widely used. To increase the precision of regional climate variation projections, recent research has combined these models with CMIP6 findings (Gosling & Arnell, 2016). The improvements in CMIP6 allow for higher-resolution simulations that take land-atmosphere interactions and variations in radiative forcing into account.

According to regional studies on Indian River basins, such as the Krishna-Godavari and Bhima sub-basins, rising temperatures and unpredictable precipitation patterns have significantly reduced monsoonal runoff (Ghosh & Mujumdar, 2008). The dependability of climate projections for regional hydrological evaluations has been significantly improved by the use of bias correction techniques, such as quantile mapping and delta change methods. Despite these developments, downscaling constraints and inherent model biases make it challenging to pinpoint the precise magnitude of the impact of environmental change. To improve decision-making for hydrology management in semi-arid settings, recent research has highlighted the necessity of high-resolution, multi-model ensemble techniques.

In conclusion, the literature emphasizes how important it is to combine hydrological frameworks with high-resolution climate models with the intention of properly evaluating the variability of water resources in the Bhima River watershed. By using CMIP6 forecasts to evaluate the region's future water resource dynamics, this work expands on earlier research and advances our knowledge of how climate change affects semi-arid catchments' hydrology. Water resources models simulate different processes within the hydrological cycle and are utilized for real-time forecasting, along with the planning, operation, and planning of water resources (Ghosh & Misra, 2010). A diverse range of models, available both from a free and business point of view (Golmohammadi et al. 2014), are extensively used to meet various requirements and tackle the challenges encountered by users (Daniel et al. 2022). The SWAT is a water resources model that is often applied to large and complicated river basins and networks that feature diverse LULC, types of soil, and topographies over extended periods. The SWAT model is highly efficient in terms of computational performance, grounded on physical principles, and highly effective at running long-running continuous simulations. The SWAT model's reduced calibration requirement, compared to other models, is advantageous. Because of this, the SWAT model is selected for this research work. (Srinivasan and associates, 2012; Gurung 2022) carried out hydrological parameter analysis for the river basins of Myanmar utilizing the SWAT water resources model to assess both present and forthcoming climate situations. The Abeysingha group (2020) The SWAT model, along with the forthcoming climate situation derived from various GCMs, was employed to evaluate the potential effect of climate shift on upcoming water resources management and different flowing patterns in the River watershed.

A number of studies have been used to study the hydrologic model (SWAT) to assess the climate shift effect on stream flowing and water resources science within river basins (Gurung et al., 2022; Aawar & Khare, 2020).

A software tool for calculating calibration and validation, along with sensitivity analysis of the SWAT model, is known as SWAT-CUP. (Arnold et al.2012). The River flows through the states of Maharashtra and Karnataka and is an important branch of the Krishna River. Originating in the Bhimashankar range of the Western Ghats, the Bhima River travels 725 km southeast across Maharashtra. Analysing stream flow and water accessibility within the Bhima River watershed is essential.

2. Methodology and Materials

2.1. Field of Study

The Mountain Range of western India is the rain shadow region where the Bhima River originates. The Upper Bhima basin, which covers an area of around 15,860 km², extends between 73°30'0" to 75°15'0" E and from 18°0'00" to 19°30'00" N (Figure 1). With heights varying between 499 and 1298 meters above sea level, the basin has a diverse landscape. The core region is made up of little hills, while the western edge is noticeably rocky. The eastern region, on the other hand, is distinguished by gently sloping terrain and decreasing hills. The tropical monsoon climate of the basin has maximum and minimum temperatures in April and January, respectively, ranging from about 38°C to 11°C. The southwest monsoon is mostly responsible for the 1233 millimetres (mm) of yearly rainfall that the region receives on average. On the western side of the watershed, the Ghats side mountain spectrum contributes to more than 3000 millimetres of precipitation annually, which progressively drops to 600 millimetres close to the basin's discharge point.

The Bhima waterway, a major limb of the Krishna River, contributes a substantial volume of water flow due to its closeness to the Western Ghats. Wastelands, including open and dense brush, degraded terrain, desolate rocky areas, and stony waste, make up a sizeable portion of the basin. These locations have a high danger of erosion and shallow soil layers, making them unsuitable for farming.

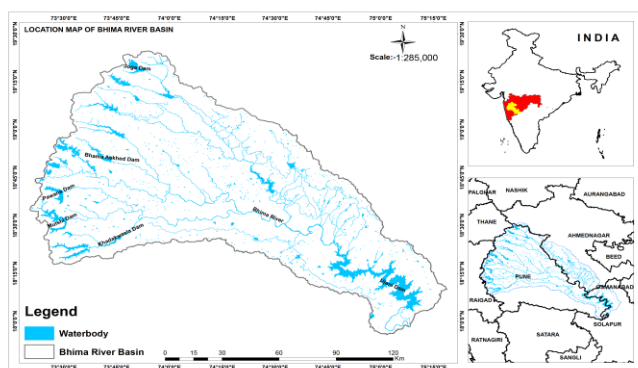


Fig. 1 Location of Bhima river basin

2.2. Data

Hydro-meteorological data, land cover, soil characteristics, and altitude details serve as inputs for the watershed's hydrological simulation. For the years 1984–2014, daily records of precipitation and the highest and lowest temperatures were acquired from the HDUG, Government of Maharashtra. For this study, daily datasets with a grid resolution for precipitation (0.25° x 0.25°) and for max/min temperature (1° x 1°) (Ref Table 1) were employed. Re-gridding the maximum and minimum temperature data to 0.25° x 0.25° resolution allowed it to be consistent with the precipitation data as well as future datasets. The river system and drainage layout were obtained using the 30 meter resolution by Cartosat-1 Digital Terrain Model (CartoDEM), which allowed the watershed to be divided into sub-watersheds. It is available for download from the Bhuvan portal (ISRO) and was created (refer to Table 1). The NRSC website provides a 1:230,000 scale resolution LULC map (Figure 3) that was used for this investigation. The attributes of the soil in the catchment area available from the FAO of the United Nations database (see Figure 4) for each part of the watershed, the Hydrological Response Unit (HRU) was selected based on the LULC, soil, and slope maps that were gathered. The Hydrology Data User Group (HDUG), Nashik, provided the discharge data (1980–1990) needed for the calibration and validation at Chaskaman, Pargaon, Sakhar, and Shirur. The watershed contains five major reservoirs: Pavana, Mulshi, Bhama Asked, Khadakwasla and Pimple Joga. The details of the reservoirs are essential for hydrological modelling. General circulation models (GCMs) are utilized to examine shifts in precipitation patterns, rising temperatures, and sea level increases. The dataset from the CMIP6 model was used for the GCM analysis in this study. The dataset includes four SSPs scenarios representing a low-emissions scenario, which is excluded due to its lack of realism. SSP245 corresponds to low to medium emissions, comparable to the RCP4.5 scenario. SSP585 is comparable to high-emission scenarios. The SSP2 and SSP5 scenarios together encompass the full spectrum of medium and high-emission selected for this research work. Table 2 provides the data sources for the three selected CMIP6 GCM climate models.

Table 1. Information on the data utilized in the SWAT hydrologic model

Source of Data	Agency	Web Reference
Digital elevation Model	Carto DEM (30m)	bhuvan.nrsc.gov.in
LULC	Landsat	bhuvan.nrsc.gov.in
Soil	National Bureau of Soil Survey	nbsslup.icar.gov.in
Precipitation, Tmax and Tmin	HDUG (1984-2014)	www.mahahp.gov.in
Discharge	HDUG (1980-1990)	www.mahahp.gov.in

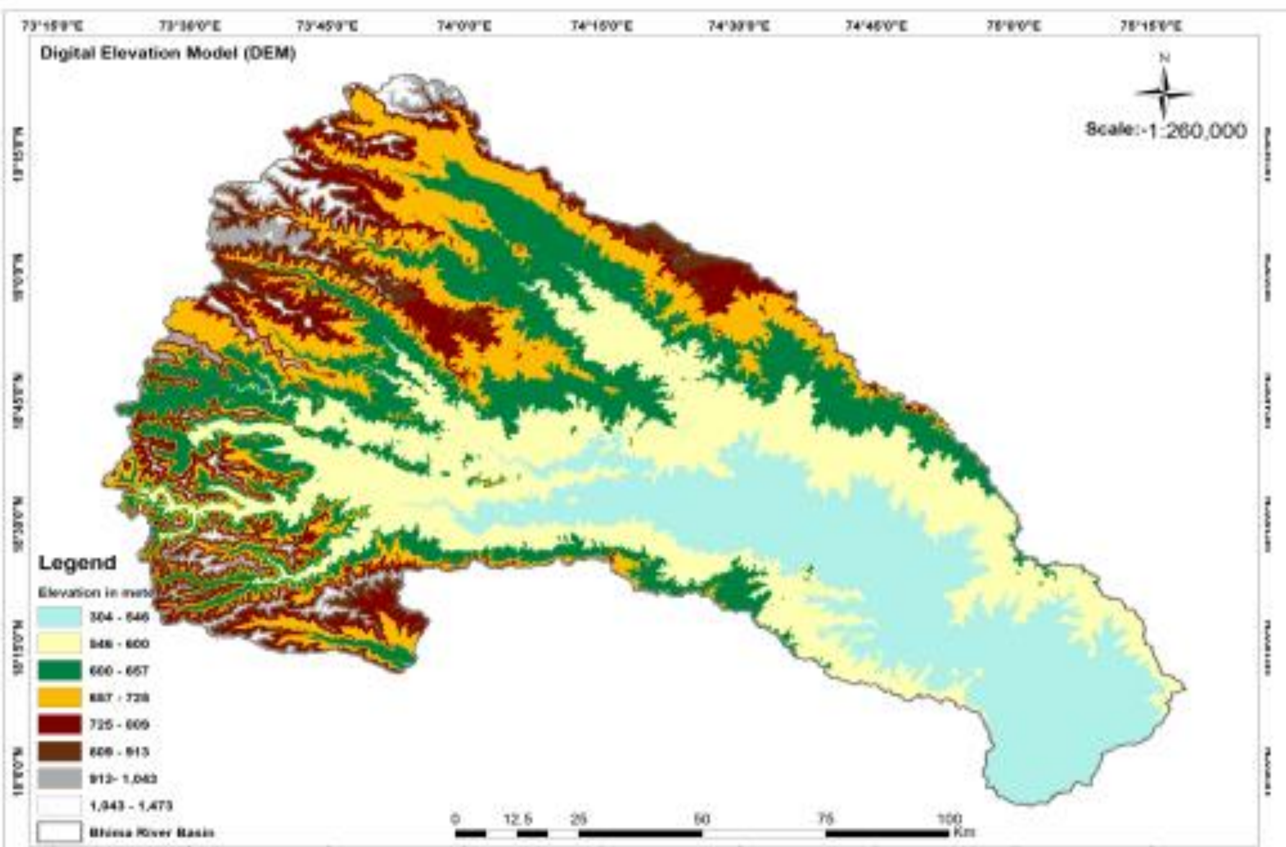


Fig. 2 Digital Elevation Map (DEM) of Bhima river basin

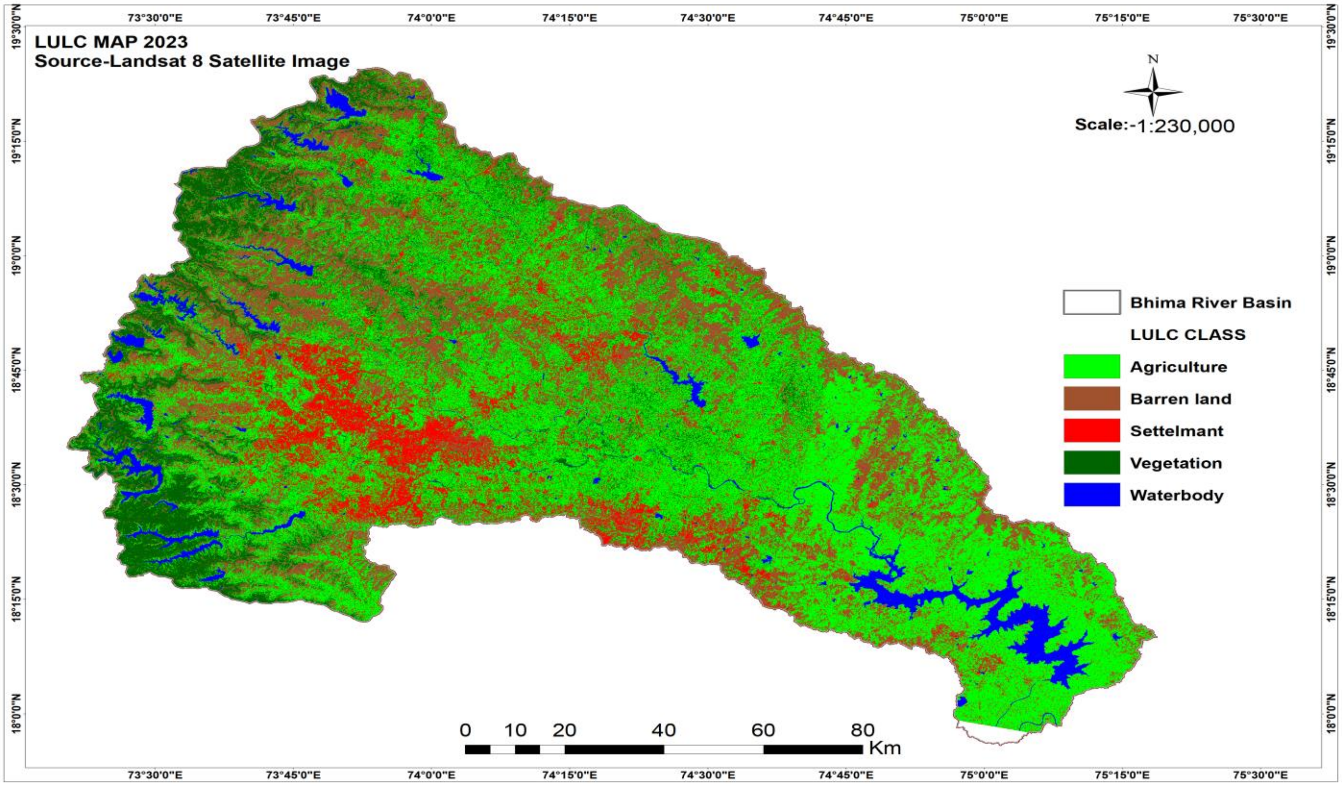


Fig. 3 LULC map of Bhima river basin

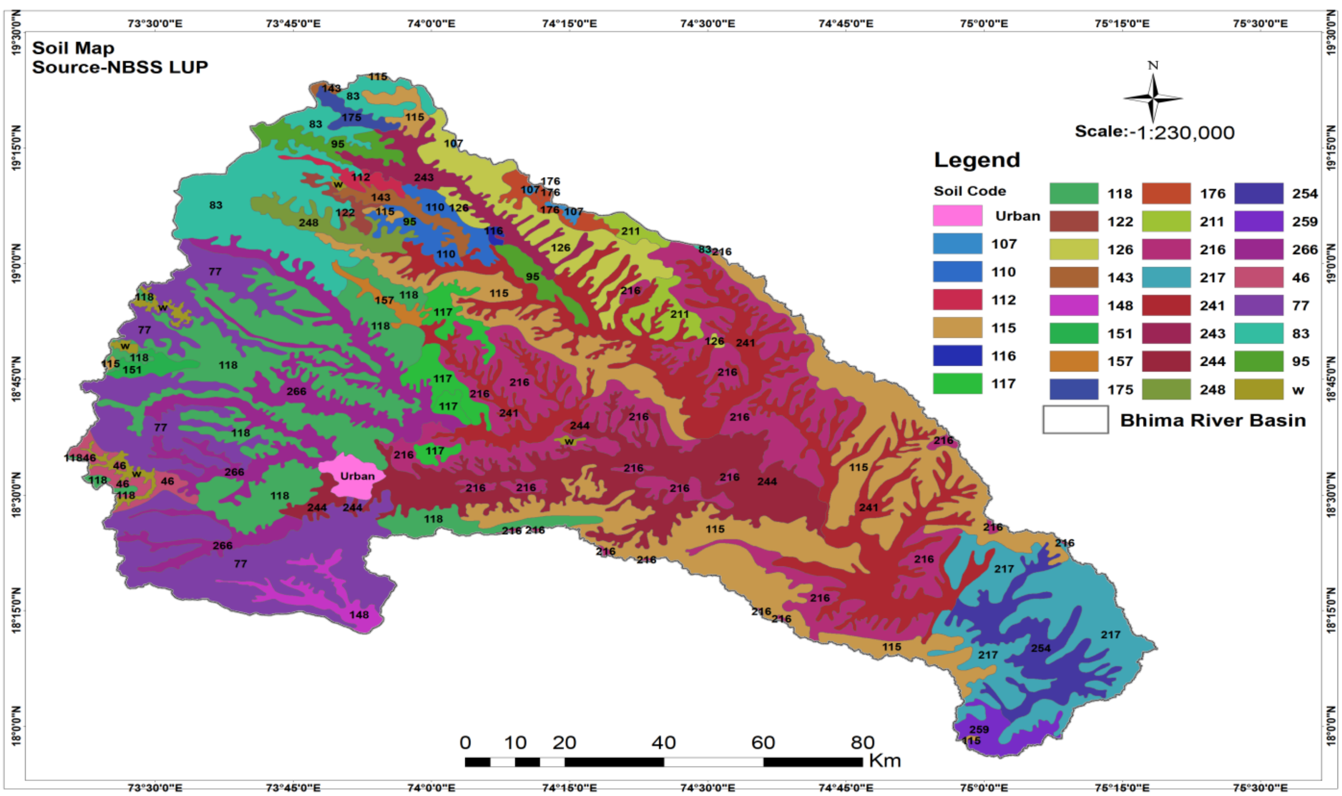


Fig. 4 Soil map of Bhima river basin

2.3. Preference to Select GCM

GCMs are often connected to significant uncertainties when evaluated at geographical and community scales. Selecting appropriate GCMs can help mitigate these uncertainties in future climate forecasts when looked at the smaller, regional, and local levels, Global Climate Models (GCMs) frequently come with a lot of unknowns (Ahmed et al. 2019). Choosing the right GCMs can reduce these unknowns when predicting future climate conditions. Evaluating how well GCMs work is essential by comparing them to real-world data to find the best ones. Selecting the most suitable GCMs increases the trust in the models employed for studies.(Logan than & Mahindrakar 2020). It is essential to evaluate the efficiency of climate models by comparing them against real-world data to find the best options. Selecting the most dependable GCMs increases the trust in the models employed for assessment. Choosing the most dependable GCMs enhances the belief in the models utilized for evaluating impacts on climate. Therefore, the previously reviewed CMIP6 models were examined prior to implementing these measures; it is essential to enhance the accuracy of forthcoming forecasts and policy modifications. This led to the choosing of three models: CNRM-CM6, GFDL-ESM-4, and Miroc6.

The historical models of three Global Climate Models (GCMs) were examined to see how accurately they simulate the real-world rainfall pattern in the Bhima River region. Various indicators, including NRMSE, RMSE, Pearson coefficient, MBE, MAE, and NSE, measured the effectiveness of these GCMs.

2.3.1. Root Mean Square Error (RMSE)

It measures the average variation between the observation and the simulation.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}\left(\mathrm{X_{obs,i}} - \mathrm{X_{model,i}}\right)^2}{\mathrm{n}}}$$

2.3.2. NRMSE

By using a variety of normalizing procedures to match observed and simulated is computed to assess the predicted values

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\mathrm{X_0}}$$

2.3.3. Pearson Correlation Coefficient (PCC)

It measures the linear relationship strength between two parameters on the same scale. It assesses both the direction and magnitude of the association between two continuous variables.

$$\mathrm{r} = \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}\ (\mathrm{O_i} - \overline{\mathrm{O}})\ (\mathrm{P_i} - \overline{\mathrm{P}})}{\sqrt{\sum_{\mathrm{i-1}}^{\mathrm{n}}(\mathrm{O_i} - \overline{\mathrm{O}})^2}\ \sqrt{\sum_{\mathrm{i-1}}^{\mathrm{n}}(\mathrm{P_i} - \overline{\mathrm{P}})^2}}$$

2.3.4. MAE

The MAE and RMSE are 0 to ∞, and they are not affected by the direction of mistakes. These measurements are negatively orientated, meaning lower scores imply better performance. The MAE is determined using the formula.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \times \sum_{\mathrm{i=1}}^{\mathrm{n}} |\mathrm{O_i} - \mathrm{P_i}|$$

2.3.5. MBE

To find the mean deviation between two sets of data, use the mean bias error (MBE) calculation. The unit of the variable being measured is maintained. It is best to have values near zero.

$$\mathrm{MBE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{P_i} - \mathrm{O_i})$$

2.3.6. Index of Agreement (IoA)

It indicates the model's accuracy relative to the possible error range. A number of 0 denotes no agreement, whereas a value of 1 represents the perfect match.

$$d = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(|P_i - \overline{O}| + |O_i - \overline{O}|)^2}, \quad 0 \le d \le 1$$

2.3.7. NSE

It is used to evaluate the forecasting accuracy of hydrological models. It evaluates how well the model predicts outcomes compared to the recorded data and reproduces the observed data. The range of NSE values is -∞ to 1.

$$\mathrm{NSE} = 1 - \frac{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{OBS_i} - \mathrm{SIM_i})^2}{\sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{OBS_i} - \overline{\mathrm{OBS}})^2}$$

Table 2. Specifications of the General Circulation Model (GCM)

No	Model	Model Centre	Country	Source
1	CNRM-CM6-1	CNRM/CERFACS modelling group	France	cmip6
2	GFDL-ESM4	Geophysical F. D. Laboratory.	United States	cmip6
3	Miroc6	MIROC team	Japan	cmip6

2.4. Hydrological Modelling

The SWAT simulation assessed the hydrological water cycle processes were simulated and the impact of the possible future environmental interruption. The Department of Agriculture of the US created this huge-scale water balance model for river basins that is hybrid, process-based, and functional in ongoing time, which is commonly utilized to simulate the watershed's stream flow (Jayakrishnan et al. 2005). Using the topography, the basin was segmented into

89 sub-catchments to simulate the hydrological processes effectively. 2,672 HRUs that shared comparable definitions of Hydrologic Response Units (HRUs) were refined by further classifying land management, soil classification, and environment features depending on land classification, land use, slope, and soil characteristics (Srinivasan & Arnold, 2010). The modelling of the catchment's water balance cycle is composed of two stages: the land use stage and the water use stage. To simulate the land use stage of the water resources cycle, each Hydrologic Response Unit (HRU) was paired with the hydrologic balance equation (Abeysingha et al. 2020).

2.5. SWAT Model Description

The US Agriculture Department developed the hybrid, physically based watershed model known as the SWAT hydrologic model. Physical information, including soil type, DEM model, land use and LULC model, and wind speed, are among the meteorological variables that must be entered into SWAT. The SWAT model serves as an important tool for conducting evaluations and making predictions on how hydrology model alteration in the hydrologic balance segment within a watershed will behave (J.G. Arnold et al. 1995). It incorporates all of the essential parts of the hydrological cycle in a given region and functions on the basis of the hydraulic balance equation (Equation (1)).

$$\mathrm{Wm} = \mathrm{W0} + \sum_{i=1}^{n} \left(\mathrm{I}_{\mathrm{day}\_}\ \mathrm{Q\,r} - \mathrm{ETo} - \mathrm{ws} - \mathrm{Qgw} \right) \qquad (1)$$

Where I_{day} represents the precipitation amount in millimetres (mm) or denotes the surface overflow in cubic meters per second (m^3/s), ET_0 refers to evapotranspiration, and ws represent the water motion through the soil into the unsaturated zone in millimetres (mm). Qgw represents the return flow from groundwater in cubic meters per second (m^3/s) over n days, while Wm is the final moisture content on the i^{th} day. The data obtained from the elevation model (EM) is used to partition the catchment into smaller sub-catchments. After that, these sub-watersheds are separated into homogeneous clusters according to characteristics like slope, soil type, and LULC maps. Hydrologic response units are the result of this clustering process. (Neitsch, S. L. et al. 2011). The SWAT watershed model for groundwater flow assumes a regional groundwater movement format where water is shifted from one aquifer to another and eventually reaches the stream.

2.6. Model Validation and Verification

Because the SWAT model can mimic several water cycle processes, such as surface flow, infiltration, evaporation and transpiration, and groundwater replenishment, it is frequently used for hydrological impact evaluations. To improve reproducibility and guarantee accurate simulations, model calibration and validation are essential processes. Sensitive model parameters must be adjusted during the calibration process to match observed streamflow data. This is usually done automatically or manually using optimization techniques like Particle Swarm Optimization (Abbaspour et al., 2015).

The calibrated model's prediction ability is evaluated by applying it to a separate dataset for validation. Frequently used statistical performance metrics include the Nash-Sutcliffe Efficiency (NSE), Coefficient of Determination (R2), and Percent Bias (PBIAS). Moriasi et al. (2007) state that NSE values between 0.5 and 0.75 imply reasonable performance, whereas values over 0.75 indicate exceptional model performance. Furthermore, PBIAS values for streamflow that fall within ±15% are typically regarded as acceptable.

Daily or monthly discharge data from gauging stations has been used for SWAT model calibration/validation in regional studies. Spatial data inputs for the Bhima watershed hydrological model setup include soil properties, land use/cover maps, precipitation, temperature, humidity, wind speed data, and DEM (Digital Elevation Model). The significance of bias correction in input datasets to lower uncertainty in hydrological estimates is emphasized by studies combining CMIP6 climate data with SWAT (Kumar et al., 2021).

The recorded river flow data from two stream gauge stations, Chaskaman and Paragon, were utilized for calibration/validation of the SWAT hydrologic model. The sufi-2 optimization step-by-step procedure, in conjunction with the program swat-cup, was employed to execute sensitivity analysis and determine which factors had the most impact. Ten of the twenty-five parameters that were assessed were chosen based on t-statistics and p-values, which provide information about the parameters' measurements and sensitivity importance—the selected sensitive parameters together with their corresponding fitted values. The model was validated using ten parameters. According to the results, the key metrics are related to the physical characteristics of the catchment area and hydrological processes. The top-ranked metric is the curve number (CN2), which represents watershed runoff and is mostly impacted by watershed characteristics like soil classification, land cover and use and management techniques. The SWAT model successfully reproduced the stream discharge and produced acceptable results.

Table 3 presents the validation and verification outcome for the Chaskaman and Pargaon stations. During the calibration phase, the NSE values were 0.74 for Chaskaman and 0.77 for Pargaon. The NSE was documented as 0.62 and 0.68 for the validation and verification period, respectively. It demonstrates how well the noticed flow patterns. In the same way, R2 values for the Chaskaman and Pargaon stations were assessed to be 0.75 and 0.78 during the calibration phase, respectively, and 0.81 and 0.73 during the validation phase. At the Chaskaman station, it likewise produces satisfactory percent bias (PBIAS) scores of 19.39% and 20.35%. Alternatively, the model produced an underestimation of the stream flow at Pargaon station. The calculated R2, NSE PBIAS, and RSR values are much higher than the allowable bounds (Khoi et al., 2021). As a result, it verified that the SWAT simulation worked well with the dataset that was seen, and the SWAT simulation model could be applicable to model the hydrology of the Bhima River catchment area. Figure 5 and Figure 6 show the virtual and observed Flow rate for both gauging stations. (Chaskaman and Pargaon).

Table 3. Calibration and validation of the model

	Calibration (1980-1985)				Validation (1986-1990)			
Station	**R2**	**NSE**	**RSR**	**PBIAS**	**R2**	**NSE**	**RSR**	**PBIAS**
Chaskaman	0.75	074	0.47	19.39	0.81	0.62	0.63	20.35
Pargaon	0.78	0.77	0.46	-16.12	0.73	0.68	0.51	-6.88

2.7. Future Climate Change Scenarios

Using the selected GCMs CNRM-CM6-1, GFDL-ESM-4, and MIROC6, the future prediction estimates of yearly precipitation, T_{max}, and T_{min} for the Bhima watershed for the future scenarios are displayed in Figures 7, 8, and 9. The annual rainfall style under the SSP585 scenarios is increasing. In the SSP245 scenario, the total annual rainfall peaks at 1600 mm, whereas in the SSP585 scenario, it goes as high as 1640 mm. The annual rainfall under SSP245 shows significant fluctuation but no discernible pattern. The MIROC6 estimates show more rainfall towards the end of the century than both GFDL-ESM-4 and CNRM-CM6-1. Furthermore, in the SSP245 and SSP585 scenarios, there is an inclined fashion in both maximum and minimum temperatures. The sharp rise or drop in temperature observed in forthcoming years across future scenarios is attributed to some uncertainties inherent in the climate models. The GCM's capacity to predict future climates is not without uncertainty. The GCM may not be as reliable at predicting future climates even if it accurately captures the current climate. Generally, numerous GCMs are used to reduce this uncertainty. However, more research is required to measure the unpredictability related to every model.

2.8. Shift in Temperature

The greatest temperature rises by 0.2 to 0.3, 0.7 to 0.8, and 1.2 to 1.3 for selected GCMs in the years 2020, 2050, and 2080, respectively, for the SSP245 climate scenario. In contrast, it increases by 0 to 0.3, 0.8 to 1.2, and 1.5 to 1.8 for the same periods for the SSP585 climate shift scenario for the years 2020, 2050, and 2080, respectively. The enhancement in low temperature under SSP245 ranges from 0.5 to 0.6, 0.7 to 1.3, and 1.2 to 1.9 and with SSP585, it varies from 0.3 to 0.8, 1.3 to 1.8, and 2 to 3.1. Changes in temperatures are illustrated in Figures 10 and 11.

2.9. Change in Rainfall

According to the SSP245 climate shift scenario, yearly precipitation will increase by about 12%, 21.7%, and 31.5% in the years 2020, 2050, and 2080, respectively. Similarly, at the respective times, the SSP585 climate shift scenario records a rise in rainfall of 10.87%, 35.41% and 78.38%. In the climate shift scenario SSP585, the highest annual precipitation is projected for the year 2080. The average monthly differences in projected rainfall for 2020, 2050, and 2080, subject to the SSP245 climate shift scenario and SSP585 climate shift scenarios, are displayed in Figures 12 and 13. According to all scenarios, all GCMs predict more rainfall throughout the monsoon season (JJAS) and after the monsoon season (Oct, Nov and Dec) seasons for all future periods. Notably, there are anticipated to be major changes in September, October, and November.

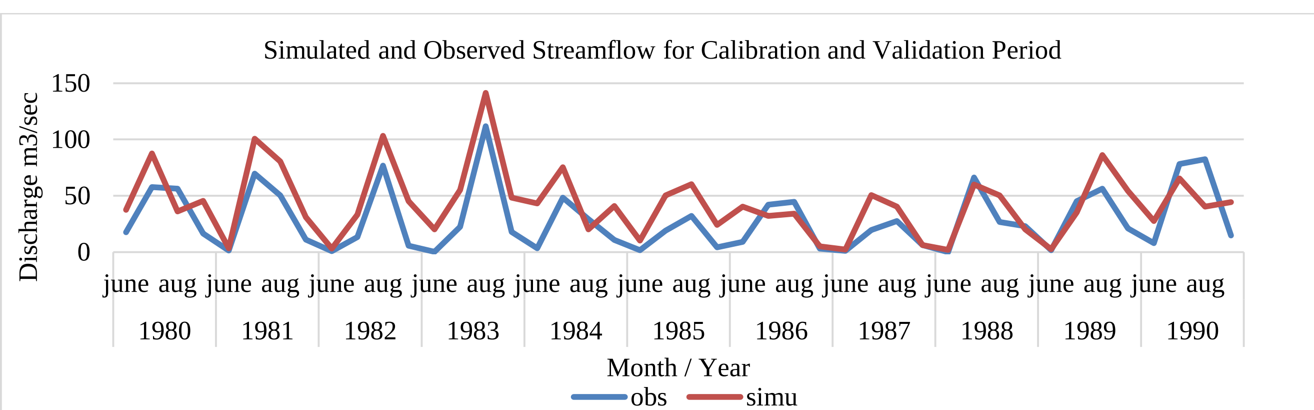


Fig. 5 Observation and simulation of discharge for Chaskaman station

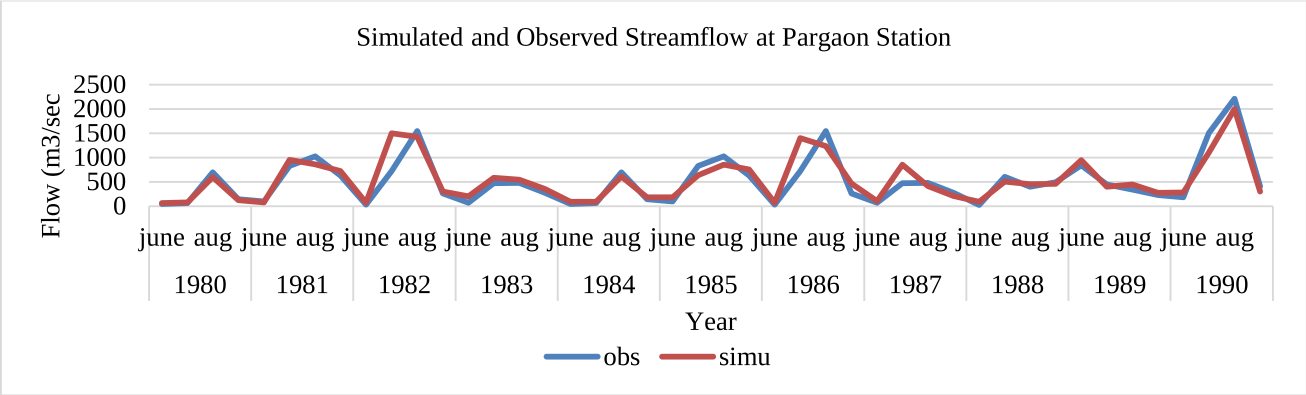
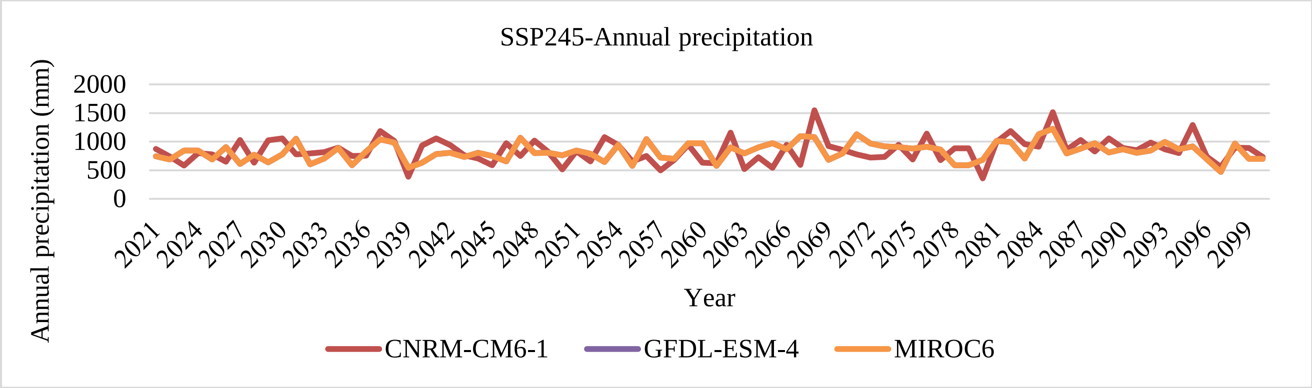


Fig. 6 Observation and simulation discharge for Paragon station



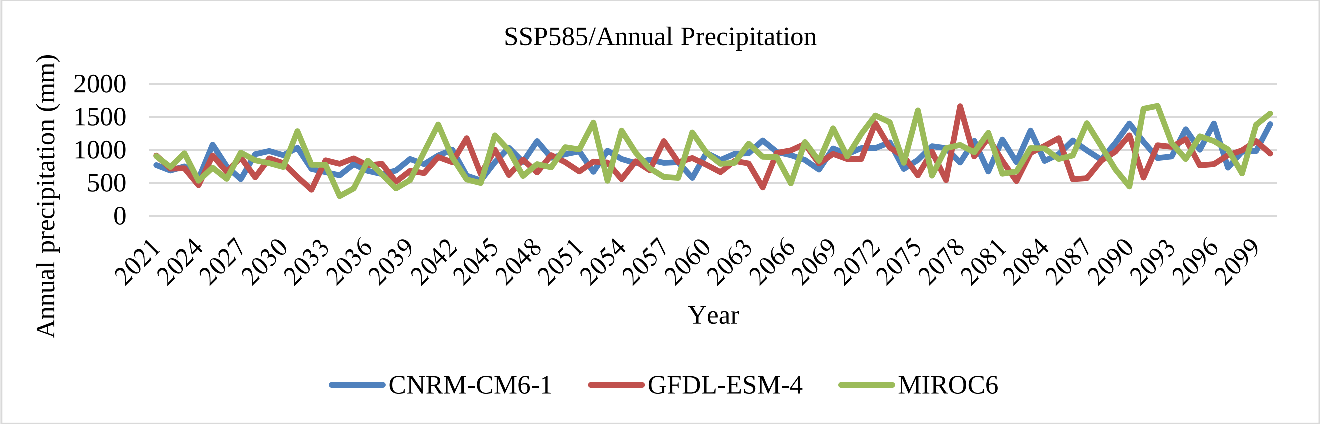
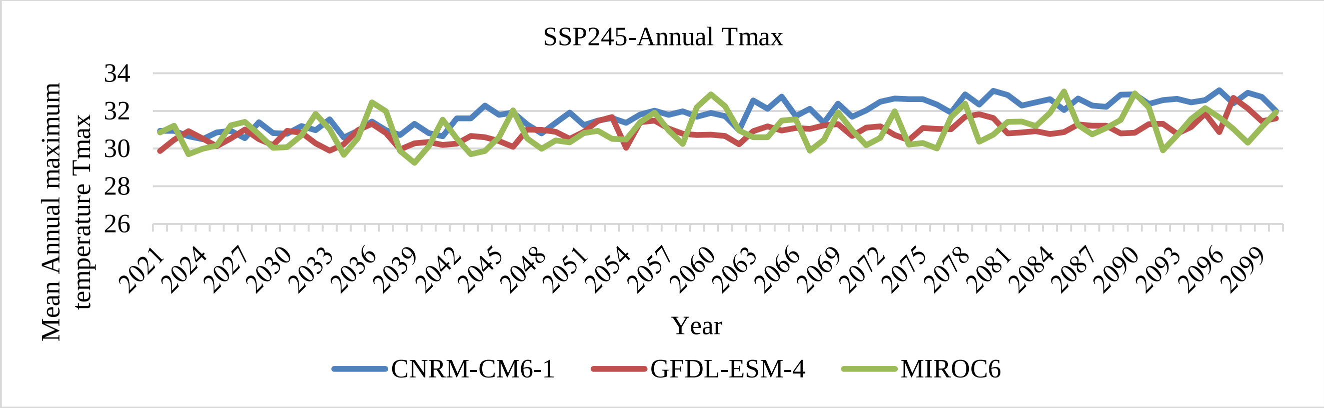


Fig. 7 Forecasting of future precipitation



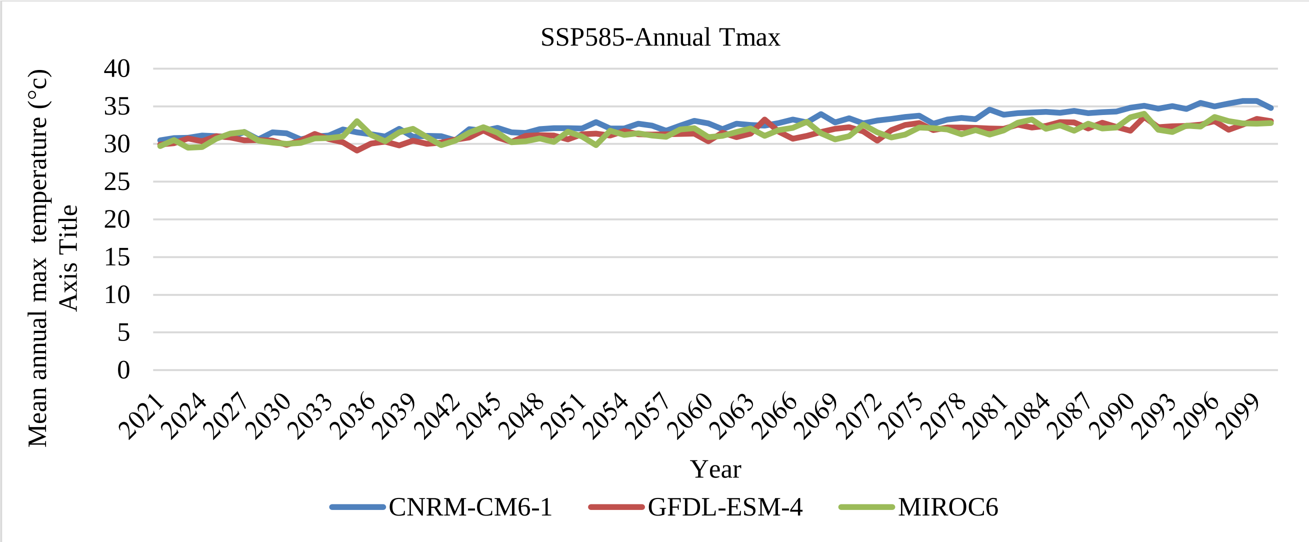


Fig. 8 Forecasting of maximum temperature

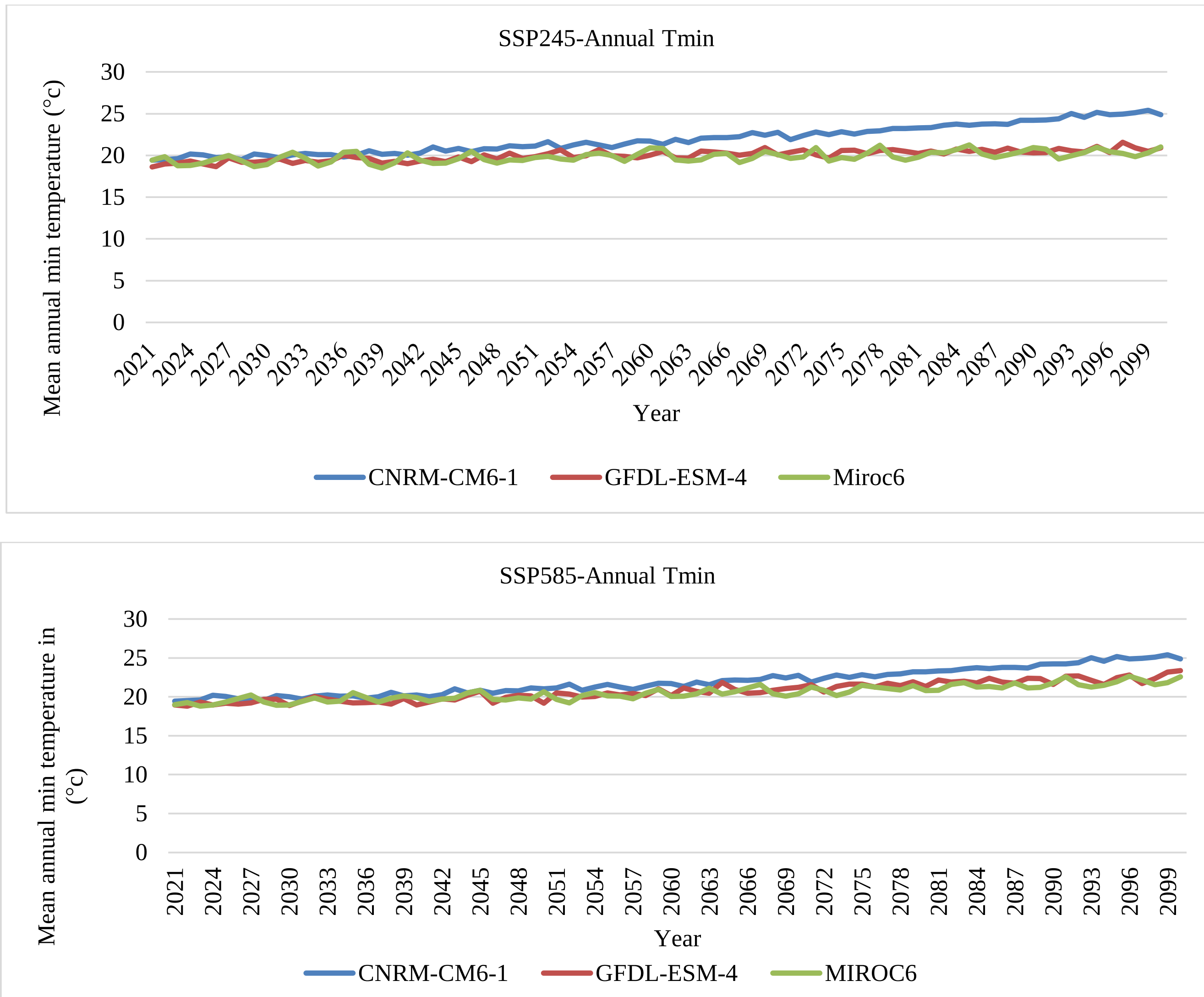
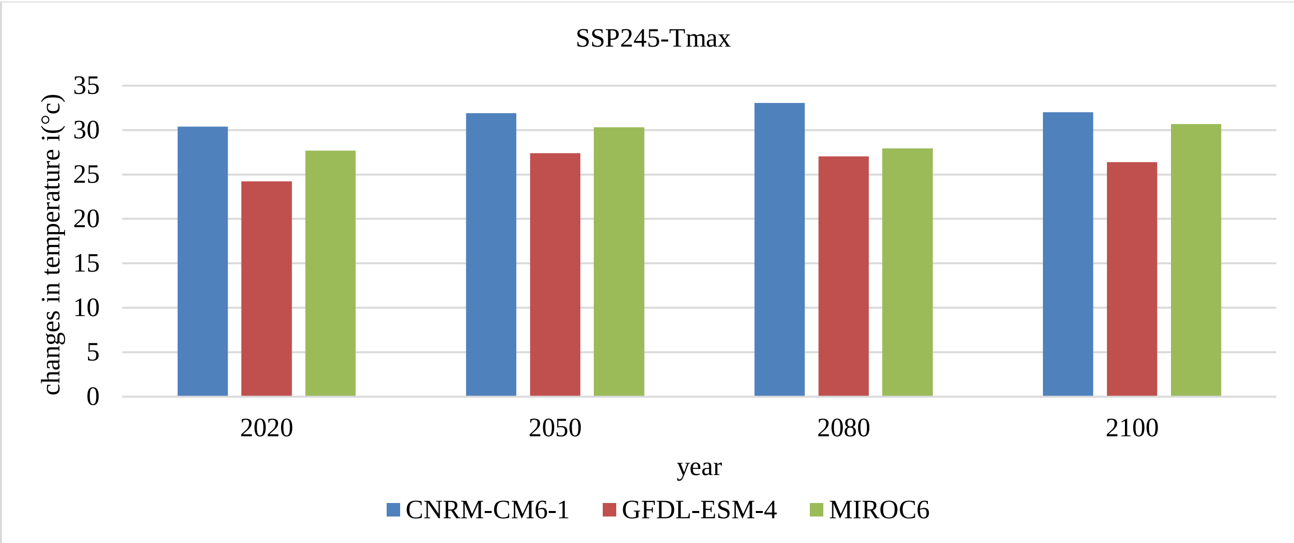


Fig. 9 Forecasting of minimum temperature



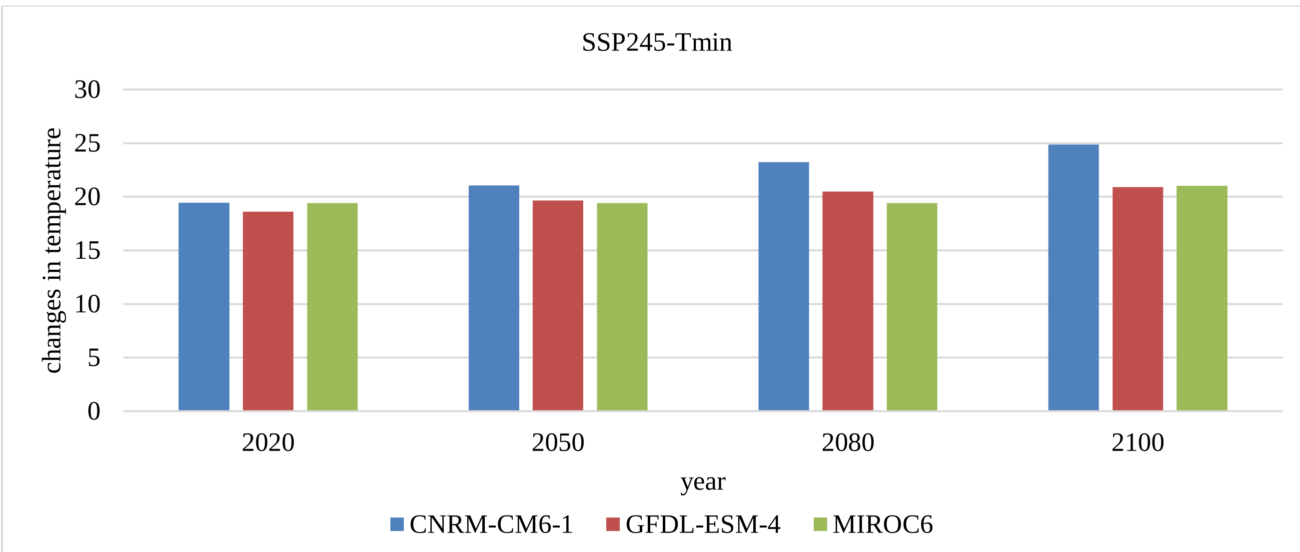
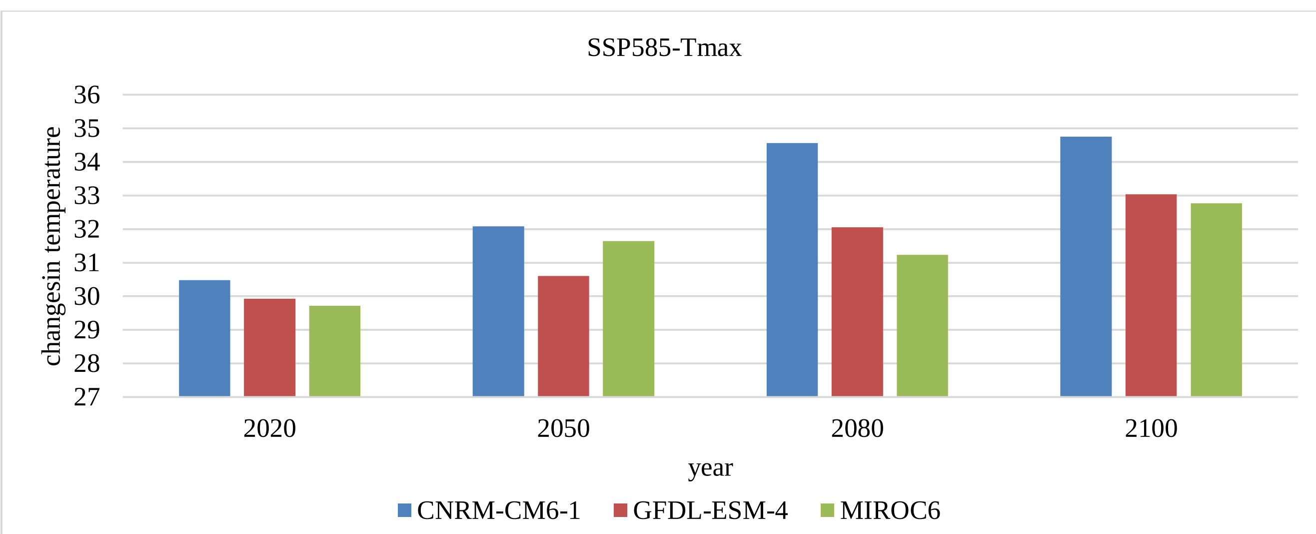


Fig. 10 Variation in Tmax and Tmin for SSP245



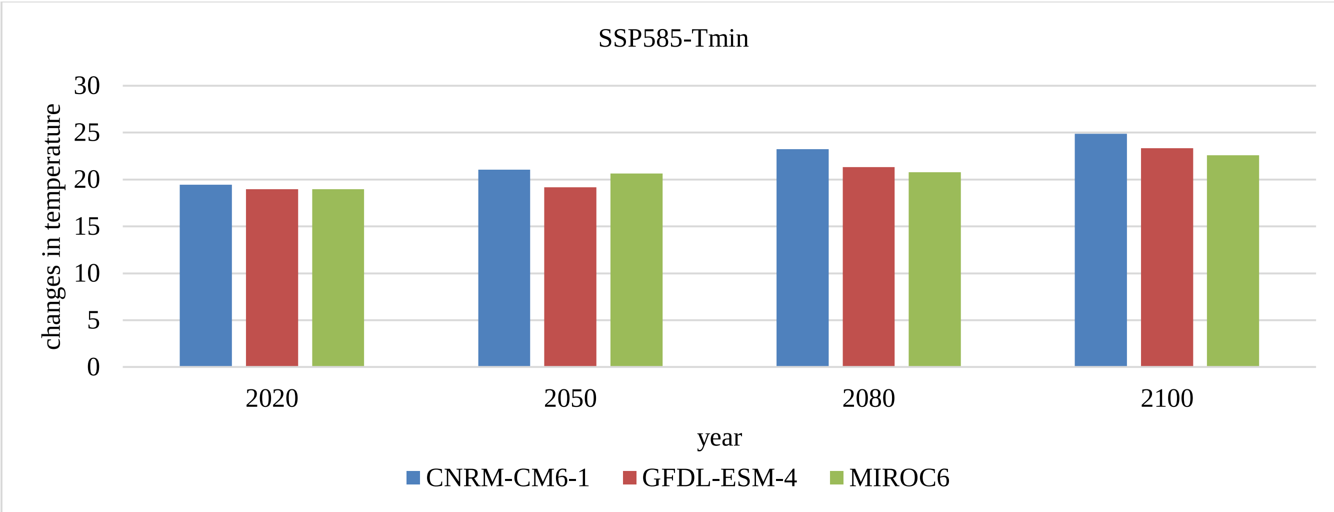
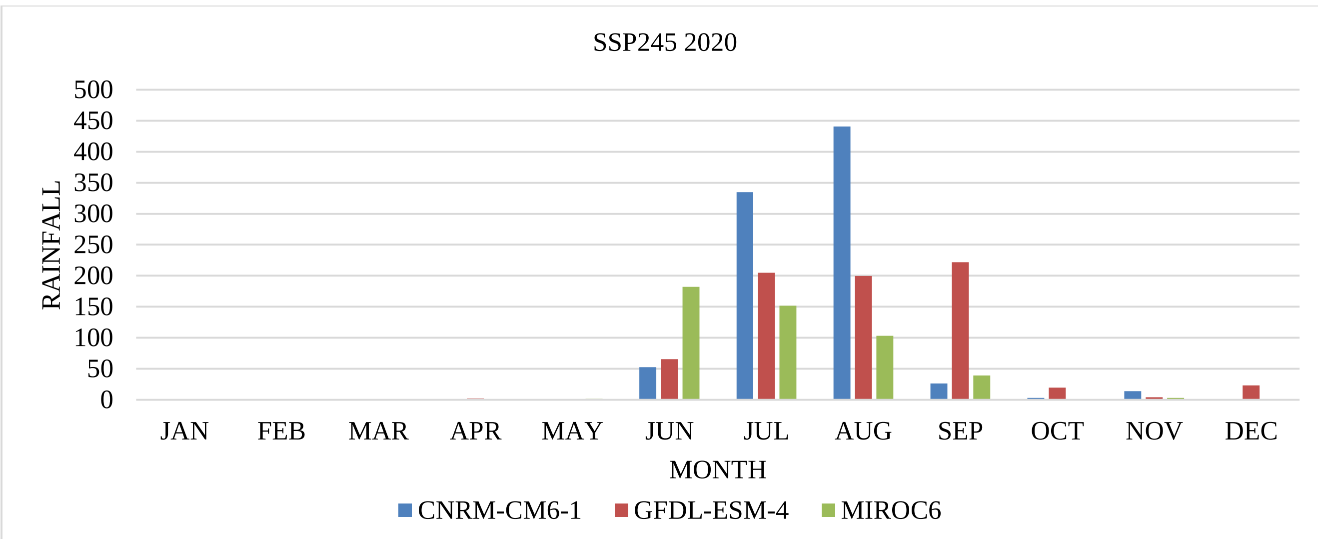
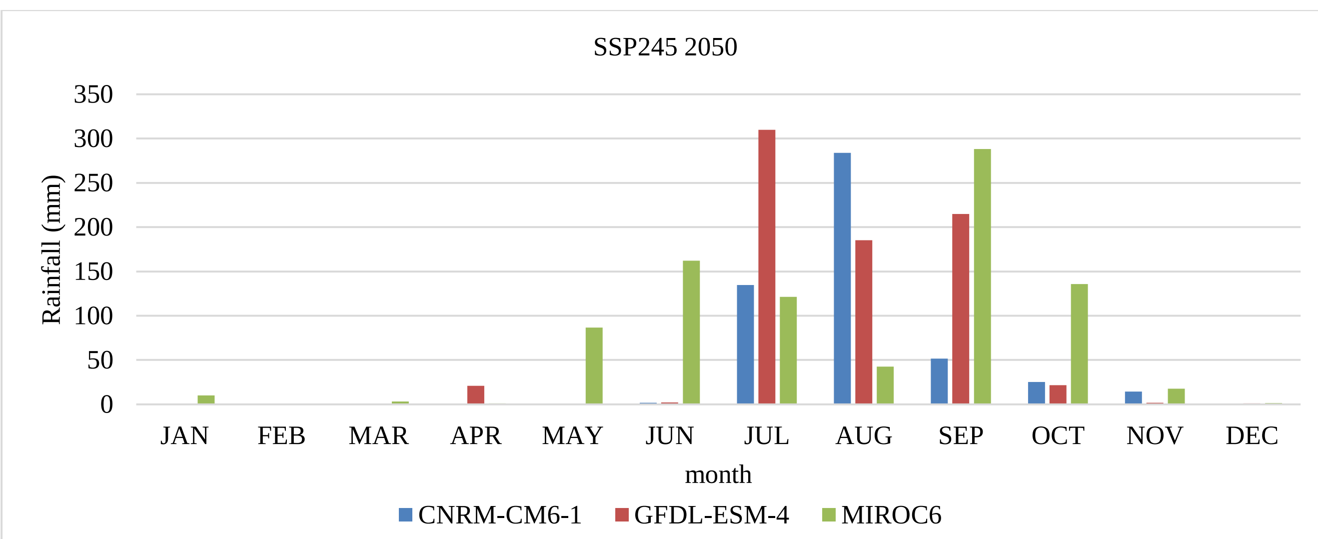


Fig. 11 Variation in Tmax and Tmin for SSP585





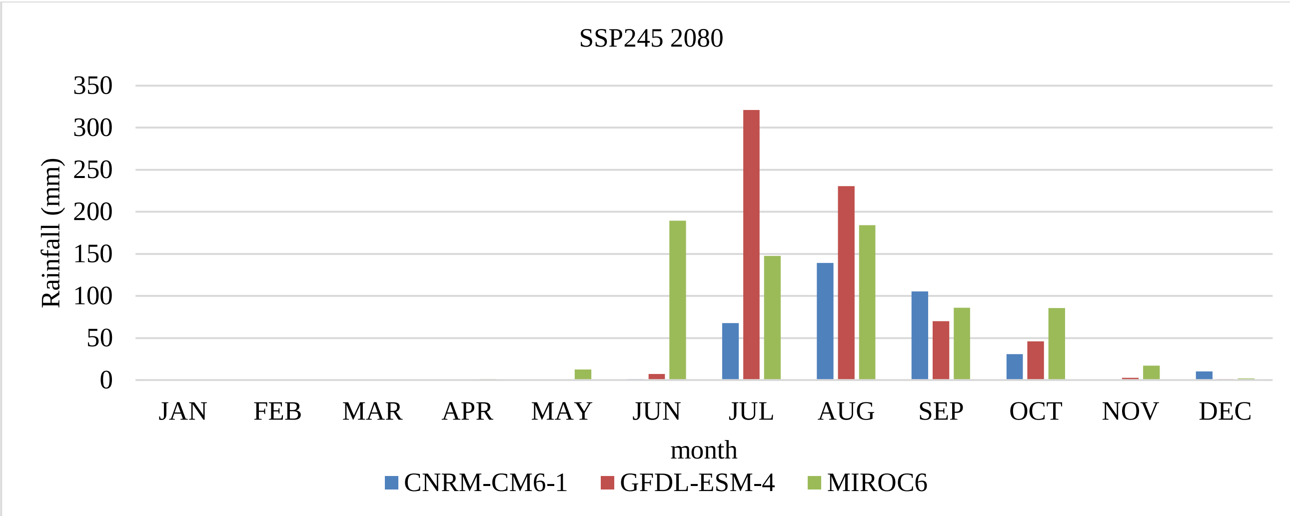
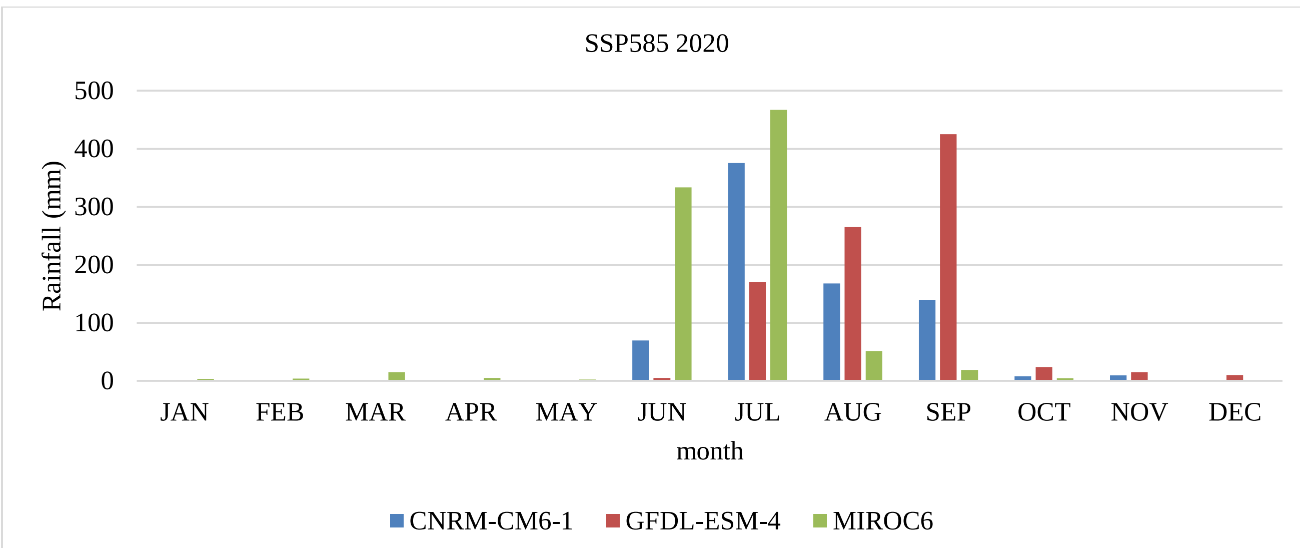
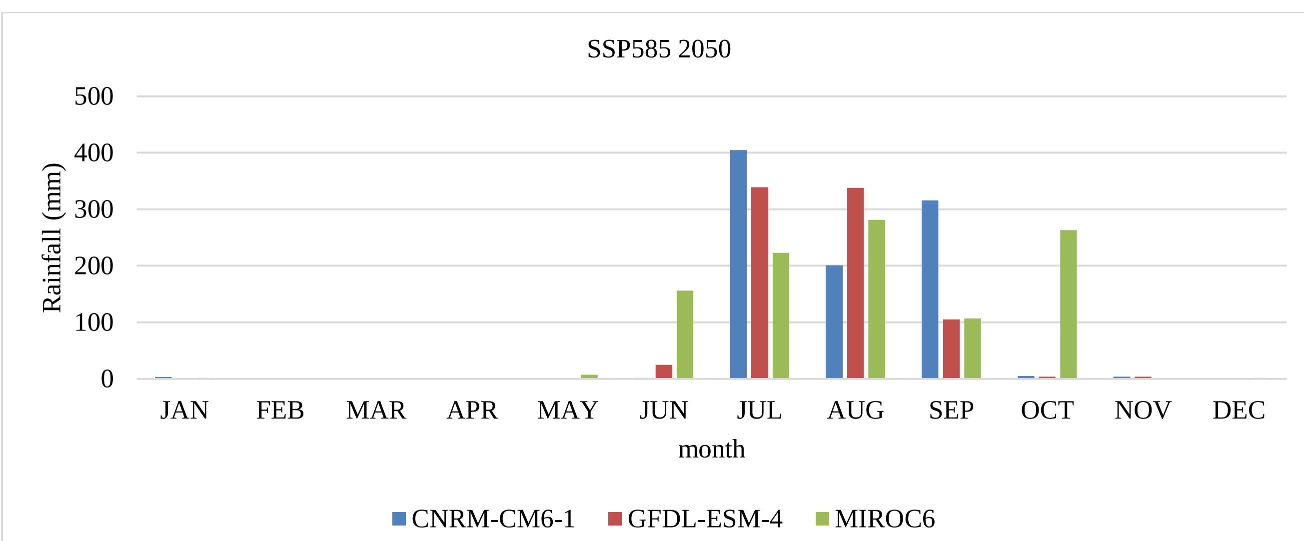


Fig. 12 Prediction of average monthly rainfall under SSP245 for the year 2020, 2050 & 2080





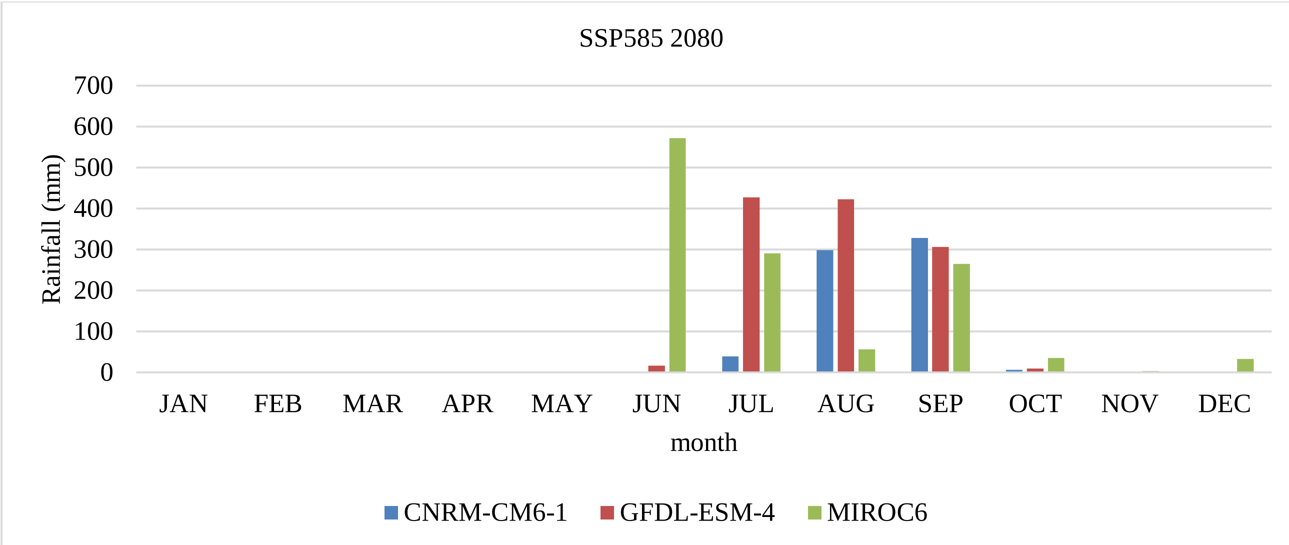


Fig. 13 Prediction of average monthly rainfall under SSP 585 for years 2020, 2050 and 2080

2.10. Climate Shift Effects on Dynamics of Streamflow

Three chosen GCMs, CNRM-CM6-1, GFDL-ESM-4, and MIROC6, were used to run SWAT model simulations for the years 2020, 2050, and 2080 considering SSP245 climate scenario (Pathway no. 2) and SSP585 future scenario (Pathway no. 5) climate emission future scenarios. The result of future simulations was assessed with the 1980–1990 (baseline period) to compute the anticipated modification brought on by climate change. The results show that SSP245 and SSP585 differ significantly from one another. The findings (Table 4) show that all three GCMs show differences in streamflow in the two stations in the basin locations that were chosen. Compared to the stream flow at Paragon, the average yearly increase in stream flow at Chaskaman was predicted to be substantially larger. In the year 2020, 2050, and 2080, the Chaskaman sub-basins annual stream flow variations for both emission scenarios ranged from -1.38 to 26.43%, -0.72 to 55.77%, and 14.74 to 126.42% for all GCMs.

Annual streamflow increased little in the years 2020 and 2050 but increased by 110% in 2080. According to GFDL-ESM-4, stream flow at the Chaskaman station is projected to decline during the 2020s and 2050s. There are other possible explanations for this, including a rise in evapotranspiration and a fall in precipitation in the upper basin.

Similarly, in both emission scenarios, yearly streamflow forecasts increased at the Paragon sub-basin over all future decades. Under SSP245, a rise in yearly flow rate was recorded of roughly 23.30%, 46.56%, and 69.22%; under SSP585, the increase was roughly 21.22%, 71%, and 221.05% in the years 2020, 2050, and 2080 sequentially. Figures 14 and 15 give the mean monthly streamflow for the proposed study region for the upcoming scenario SSP245 (middle situation) and SSP585 (fossil fuel-driven economic growth) for the years 2020, 2050 and 2080.

Table 4. Changes in stream flow subject to SSP245 & SSP585; future scenarios for different GCMs at various future period

Emission scenario (future period)		**Changes in stream flow(%) under SSP245 (Pathway 2)**			**Changes in stream flow(%) under SSP585 (Pathway 5)**		
Weather station	GCMs Model	2020 (near)	2050 (mid)	2080 (far)	2020 (near)	2050 (mid)	2080 (far)
Chaskaman	CNRM-CM6-1	26.43	42.17	55.17	24.68	55.77	126.42
	GFDL-ESM-4	-3.1	-0.72	14.74	-1.38	10.07	88.29
	MIROC6	23.34	38.73	45.74	22.24	24.18	118.22
Pargaon	CNRM-CM6-1	23.30	46.56	61.55	14.12	71.00	221.05
	GFDL-ESM-4	12.35	18.56	61.41	14.17	41.12	211.73
	MIROC6	23.22	47.37	69.22	21.22	33.74	201.73

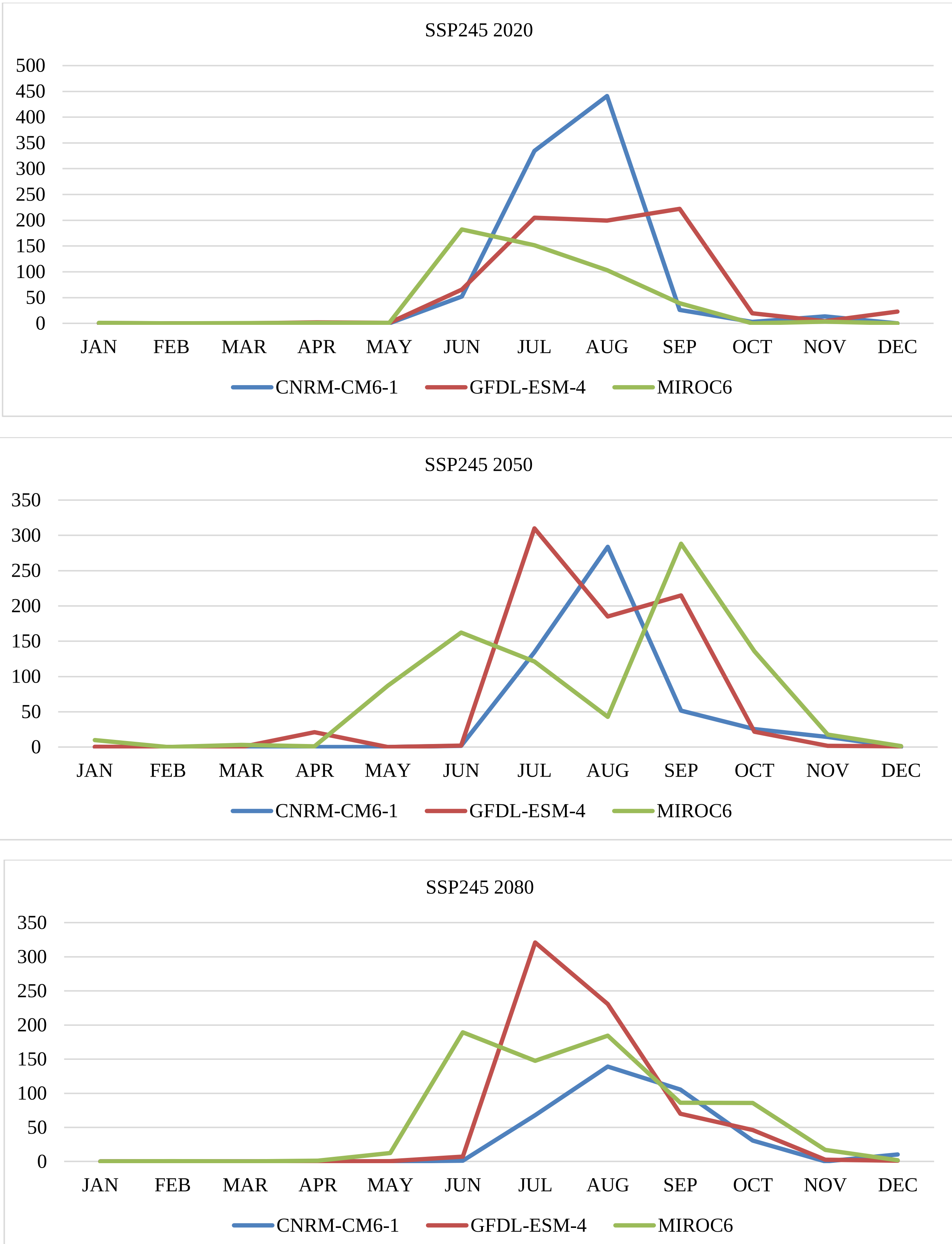


Fig. 14 Prediction of average streamflow under SSP245 for years 2020, 2050, and 2080

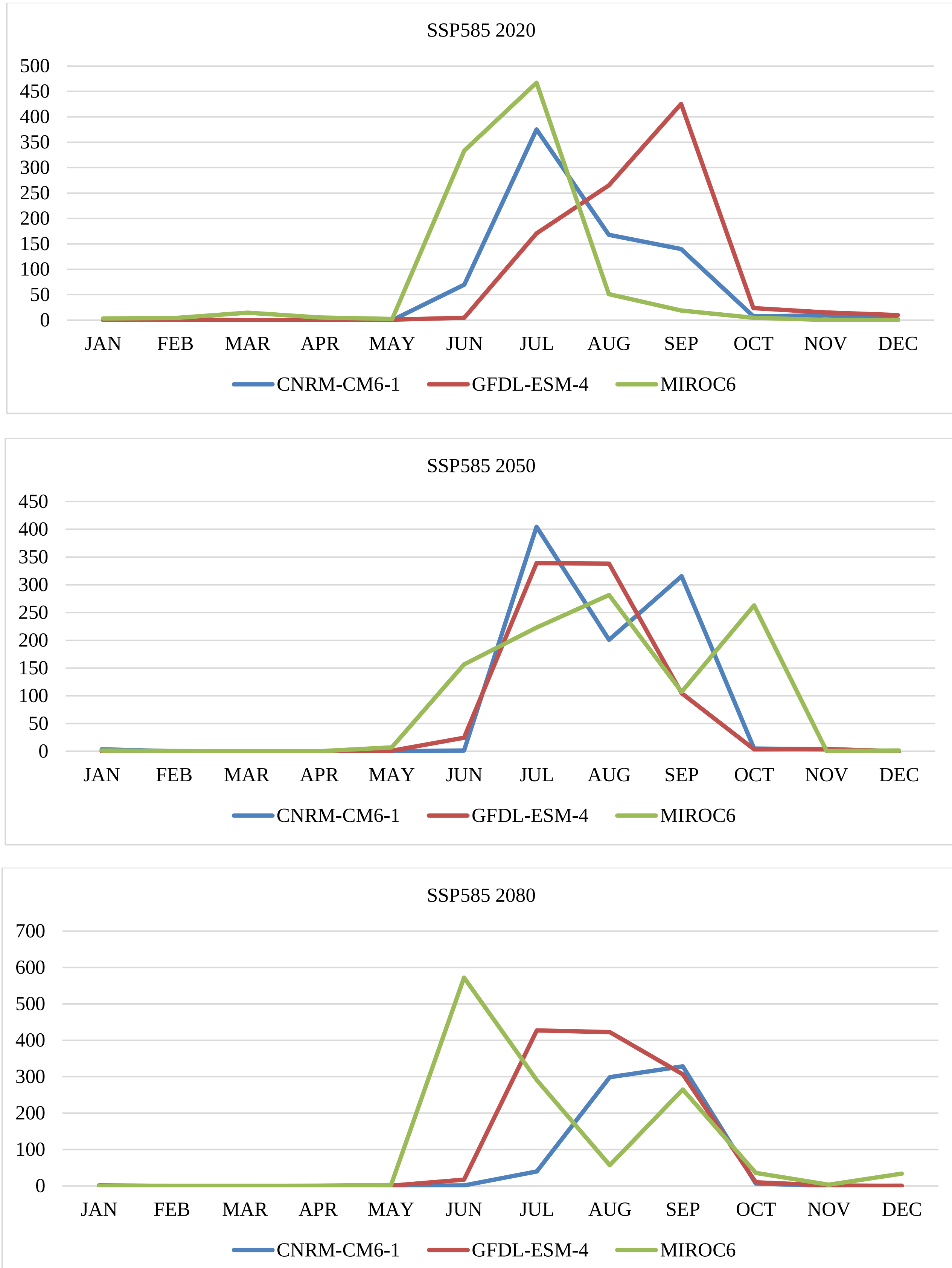


Fig. 15 Prediction of average streamflow under SSP585 for years 2020, 2050, and 2080

3. Conclusion

Using a bias-corrected CMIP6 dataset, this investigation evaluates the impact of environmental shifts on the Bhima basin hydrologic components. This study is one of the first to assess how climate shift is influencing the amount of water available in the Bhima River basin using the recently published CMIP6 estimates. Using the SWAT model, this study examines how streamflow and water availability are affected by climate change. The model matched the observed river discharge effectively and correctly, as shown by the results of the SWAT validation and calibration. The standard of R2, NSE, RSR, and PBIAS fell below permissible bounds. To enhance the findings, we employed multisite single-objective calibration in this investigation. Multi-objective calibration may yield further gains. This is the study's restriction, which can be taken into account for upcoming investigations. Using HDUG observed data, the three accessible GCMs' performances were evaluated. GFDL-ESM-4, MIROC6 and CNRM-CM6-1 were the GCMs chosen for climate shift projections. The SWAT hydrological simulation model was used in the period 2020, 2050, and 2080 using the rainfall, Tmax and Tmin data from the proposed GCMs.

Future climate forecast a rise of 1.7°c and 3.1°c in the Tmax and Tmin temperatures, respectively. According to future rainfall forecasts, the maximum rainfall is predicted to happen in the year 2080s and will increase by up to 87% under SSP585. Annual streamflow is predicted to increase in line with annual rainfall by simulations using the chosen GCMs in both scenarios. The majority of future years are expected to show a rise in annual stream flow at the Chaskaman and Paragon stations despite some periods forecasting a decrease in this amount. At Chaskaman station, the anticipated increases in yearly streamflow under different SSPs range from 3.40% to 26.43%, 0.75% to 57.87%, and 14.24% to 116.42%. Similarly, under future climatic scenarios, the estimated variations in annual stream flow at Paragon station vary from 12.15% to 24.50%, 18.56% to 75%, and 61.23% to 221.03%. The CMIP6 database is applied in this investigation to model and design the Bhima River basin's water availability.

Addressing uncertainties in General Circulation Model (GCM) predictions is essential for accurate climate conclusions. Variability in projections can result from the influence of various factors on GCMs, including model structure, resolution, and assumptions about physical processes. Uncertainty is increased by the complexity of projections caused by emission pathways and socioeconomic assumptions. Ensemble techniques are essential because different initial conditions in model runs can yield different results. By evaluating the range of potential outcomes, sensitivity analysis and uncertainty quantification enhance the communication of model confidence. Accuracy depends on model validation using observable data, and high-resolution models can improve regional forecasts. By recognizing these uncertainties, mitigation plans are strengthened, and a more thorough understanding of the effects of climate change is ensured.

These exposures are helpful for policymakers, stakeholders and investors, government authorities, and agriculturalists, aiding in the creation of preventive measures such as effective planning and adaptation tactics based on the projected climate effect on the river catchment area. However, future changes in land use are not considered into account in this investigation. As an outcome, the combined effects of LULC and climate change in the River basin would be the prime factor of future plan research.

Statement of Data Availability

The database is not openly available; readers can mail the corresponding author for more details.

Acknowledgments

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