CHAPTER 23

Projection of Future Precipitation over Gangotri Glacier at Himalayan Belt Using CMIP5 Climate Model

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ABSTRACT

In the twenty-first century, climate change is considered to be one of the most important environmental threats for the survival of living beings. Climatic variability and its behavior is a complex phenomenon that is directly associated with uncertainties. Changes in climate extremes adversely impact the sustainability in terms of social, environment, and economy consideration. In the climate change study, particularly in hydrological aspects, it is necessary to

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identify the parameters (predictors) that are directly or indirectly associated with predictands. The forecasted results are directly associated with the selection of predictors. In the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), representative concentration pathways (RCPs) are used for climate projections under the Coupled Model Intercomparison Project 5 (CMIP5). This study represents the multiscenario precipitation projections for the Gangotri Glacier region in the Himalayan belt during the long-term period 1961–2100. From the study, it was noticed that CMIP5 ensemble mean climate is closer with observed precipitation dataset. For the purpose of study, CanESM3 model has been utilized to estimate the future projections using three climate scenarios, that is, RCP-2.6, RCP-4.5, and RCP-8.5.

23.1 INTRODUCTION

In 2000, based on different socioeconomic development assumptions, the IPCC developed four families of emission pathways, viz., A1, B1, A2, and B2 in its emission scenario (SRES) special report (Nakicenovic et al., 2000). Because of these emission scenario, future climate is projected using global climate models, also known as IPCC climate models under the Coupled Model Intercomparison Project 3 (CMIP3) (http://www. ipcc-data.org/). In order to characterize the impact of future climate change on society and ecosystem, climate projections based on SRES emission scenario from CMIP3 are used in the Fourth Assessment Report of IPCC (Solomon et al., 2007; Parry et al., 2007). In the past, various future climate change impact studies in India have relied solely on the CIMP3 model climate projections. For instance, Krishnakumar et al. (2010) projected surface temperature and monsoon rainfall using CMIP3 multimodel data outputs for the period 1901–2098 over entire India. The Hadley Centre's Coupled Model (HadCM3) generated climate data are downscaled to fine resolution data and are readily available for Indian regions which have been developed under Providing Regional Climate for Impact Studies (PRECIS) project (Rupakumar et al., 2006); Krishnakumar et al., 2011). Regional climate of India was simulated under SRES scenarios, that is, A2 and B2 for the baseline period as well as long-term projections using PRECIS data sets (Rupakumar et al., 2006). Krishnakumar et al. (2011) also used PRECIS model to simulate SRES scenario A1B-based regional climate of India for the period 1961–2098. Three simulations for three different future projections segments, that is, short (2020s), medium (2050s), and long term (2080s) were employed to drive PRECIS using 17-member perturbed physics-based ensembles from

HadCM3 for quantifying uncertainty in model predictions (QUMP) project. An increase of 4–5% by 2030s and 6–14% toward the end of the century (2080s) in all India precipitation had been projected by under the business-as-usual scenario as compared with the 1961–1990 baseline. Despite the temperature projection being considered, more reliable than precipitation projection, an increase in agreement in precipitation projection had been observed from RCP2.6 to RCP8.5 and from short-to long-term projections. The long-term precipitation projections are presented to be more robust than their short-term counterparts (Chaturvedi et al., 2012).

Several improvements have been made in the new generation climate models used within Coupled Model Intercomparison Project Phase 5 (CMIP5) in terms of physics and resolution (Taylor et al., 2012). However, there exist a lack of accuracy in the simulations made using CMIP5 outputs for regional scale projections, as the outputs are available at relatively coarser resolution. Various statistical downscaling approaches have been developed in the past to obtain regional/local scale projections (Fowler et al., 2007). Ghosh and Mujumdar (2006) applied a modified linear regression model to examine future rainfall scenarios from outputs of Coupled global Climate model (CGCM2) over Odisha state in India. The linear regression model was modified by incorporating principle component analysis (PCA) and fuzzy clustering technique. Ghosh (2010) established a relationship between predictors and predictand using support vector machine (SVM) to predict monsoon rainfall for SRES A2, B2, and 20C3M scenarios in Assam and Meghalaya meteorological subdivision from GCM outputs. The methodology developed is highlighted to be computationally intensive especially for downscaling at daily time steps. Anandhi et al. (2008) used SVM to downscale monthly precipitation to river basin in India using third-generation Canadian general circulation model (CGCM3) for SRES emission scenarios A1B, A2, B1, and COMMIT. The study results projected an increase in the future precipitation for almost all emission scenarios. Ojha et al. (2010) generated the projections of mean monthly precipitation in the Pichila lake catchment in India using a linear multiple regression (LMR) and artificial neural networks (ANNs). CGCM3 simulations were used to project for emission scenario A1B, A2, B1, and COMMIT. An increase in projected precipitation was stated for A2 and A1B scenarios. The present study aims to project precipitation over Gangotri glacier in the Himalayan region by incorporating CMIP5 climate model outputs using multiple linear regression (MLR) technique. It also aims to analyze for any temporal pattern, if exists. The scenarios which are studied in this paper are relevant to IPCC's Fifth Assessment Report (AR5) which was released in 2014 (IPCC, 2014).

23.2 STUDY AREA

This study area is located under Uttarakhand State of India. The areal extension of the glacier lies between 30°43′00″ N and 31°0103″ N latitude and between 79°00′08″ E to 79°17′41″ E longitude and elevation varying from 4000–7000 m (msl). The Gangotri glacier system consists of various small glaciers having dimension of main Gangotri glacier as length: 30.20 km; width: 0.20–2.35 km; and area about 86.32 km². Raktvarn, Chaturangi, Swachand, and Maiandi glaciers contribute to the Gangotri glacier system from the northeast and Meru, Kirti, and Ghanohim glaciers join the trunk glacier from the southwest (Arora et al., 2014). Location map of the study area is shown in Figure 23.1.

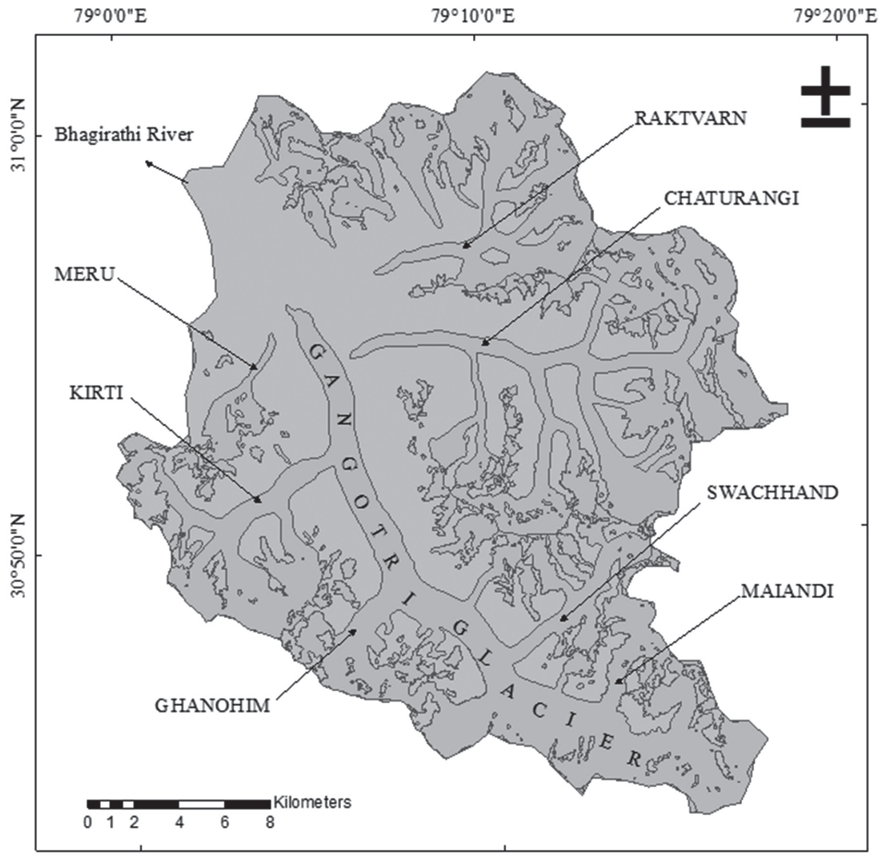

FIGURE 23.1 Map of Gangotri glacier in the Himalayas.

23.3 MATERIAL AND METHODS

The Statistical Downscaling Model (SDSM) is a multiple regression-based tool for generating future scenarios to assess the impact of climate change. It has the ability to capture the interannual variability better than other statistical downscaling approaches (Chandniha and Kansal, 2016). This approach involves three subclasses, such as weather typing, weather generator, and regression/transform function. The model requires two types of daily data, that is, (1) the local data known as "Predictand" (rainfall) and (2) the different atmospheric variables known as "Predictors." Formulating an empirical relationship between predictand and predictor is central to the downscaling technique. This can be derived by various methods such as parametric (Multiple Linear Regression) and nonparametric (artificial neural network; support vector machine). This study uses the multiple linear regression method which falls under parametric methods. The downscaling has been carried out using SDSM tool version 4.2.9. The proposed methodology has been shown in the form of a flow chart as shown in Figure 23.2.

23.3.1 SELECTION OF PREDICTORS

The selection of appropriate predictors is considered to be one of the most important task during downscaling of predictand. The appropriate predictor variables are selected through scatter plots, positive and negative correlation, and partial correlation analysis between predictand (rainfall) and predictors (most appropriate out of 26 possible parameters). The observed daily data set of National Center of Environmental Prediction (NCEP) reanalysis for the period 1961–2001 was used for the selection of predictors. The list of predictors and details of variables used in the present study are given in Tables 23.1 and 23.2.

23.3.2 MODEL CALIBRATION AND VALIDATION

Model calibration is carried out to development of an empirical relationship between the predictand and the predictors using multiple linear regression. NCEP reanalysis data for the period 1961–1990 was used for model calibration, and rest of the data from 1991 to 2001 is used for validation purpose.

Validation process enables to produce synthetic daily data based on inputs of the data considered during the model calibration. The model performance was evaluated based on the coefficient of correlation (R) between the observed values during the validation period and the modeled values, which can be calculated as

$$R = \frac{\sum\left(X_{obs} - \bar{X}_{obs}\right)\left(X_{\text{mod}} = \bar{X}_{\text{mod}}\right)}{\sqrt{\sum\left(X_{obs} - \bar{X}_{obs}\right)^2 \sum\left(X_{obs} - \bar{X}_{obs}\right)^2}}$$

where

X_{obs} = observed value, $\bar{X}_{obs}$ = mean observed value, $\bar{X}_{\text{mod}}$ = Modeled value,

$\bar{X}_{\text{mod}}$ = Mean modeled value.

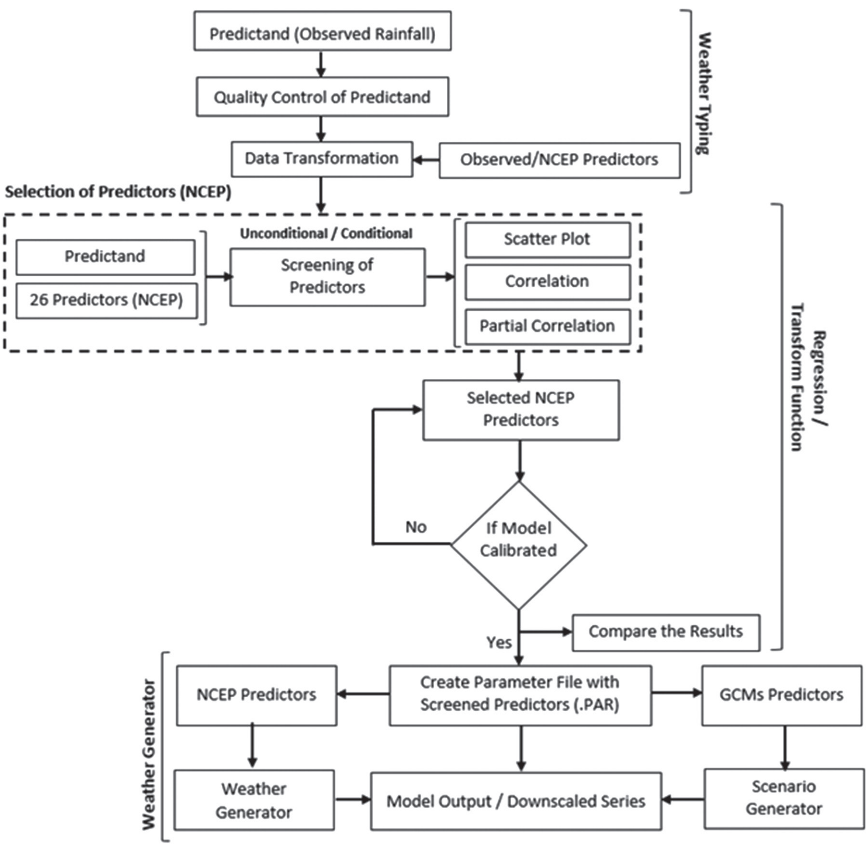

FIGURE 23.2 Methodology of rainfall downscaling.

TABLE 23.1 List of Predictor Variables for Model Calibration, Validation, and Projection.

Predictors	**Origin**	**Duration**
Mean sea level pressure	CanESM2	1961–1990 (baseline climate)
1000 hPa wind speed		2000–2099
1000 hPa zonal velocity		
1000 hPa meridional velocity		
1000 hPa vorticity		
1000 hPa wind direction		
1000 hPa divergence		
500 hPa wind speed	CanESM2	1961–1990 (baseline climate)
500 hPa zonal velocity		2000–2099
500 hPa meridional velocity		
500 hPa vorticity		
500 hPa geopotential		
500 hPa wind direction		
500 hPa divergence		
850 hPa wind speed	CanESM2	1961–1990 (baseline climate)
850 hPa zonal velocity		2000–2099
850 hPa meridional velocity		
850 hPa vorticity		
850 hPa geopotential		
850 hPa wind direction		
850 hPa divergence		
Specific humidity at 500 hPa	CanESM2	1961–1990 (baseline climate)
Specific humidity at 850 hPa		2000–2099
Specific near surface humidity		
Mean temperature at 2 m		

Source: climate-scenarios.canada.ca

23.3.3 SCENARIO GENERATION

The validated regression model is applied to generate future scenario for the watershed utilizing the simulated CanESM2 climate model with RCP2.6, RCP4.5, and RCP4.8 scenarios. The study assumes that the relationship between predictor and predictand remains valid under the future climate conditions.

TABLE 23.2 Description of Predictors (Variables).

Variable	Description	Additional notes
Temp	Mean temperature at 2 m	
Mslp	Mean sea level pressure	
p500	500 hPa Geopotential height	The height of this surface will vary depending on the temperature of the atmospheric column: warmer = higher; cooler = lower
p850	850 hPa Geopotential height	The height of this surface will vary depending on the temperature of the atmospheric column: warmer = higher; cooler = lower
Rhum	Near surface relative humidity	The vapor content of air as a percentage of the vapor content needed to saturate air at the same temperature
r500	Relative humidity at 500 hPa height	
r850	Relative humidity at 850 hPa height	
Shum	Near surface specific humidity	The mass of water vapor as a proportion of the total mass of moist air of which it is a part; can be used for tracking air masses
s500	Specific humidity at 500 hPa height	
s850	Specific humidity at 850 hPa height	
Derived variables	The following variables have been derived using the Geostrophic Approximation	
**_f	Geostrophic air flow velocity	
**_z	Vorticity	A measure of the rotation of the air
**_u	Zonal velocity component	Velocity component along a line of latitude (i.e., east-west)
**_v	Meridional velocity component	Velocity component along a line of longitude (i.e., north–south)
**zh	Divergence1	Relates to the stretching of a fluid, and usually refers to the outflow of air from the base of an anticyclone in meteorology
**th	Wind direction	This is the only variable which is NOT normalized

***Refers to different atmospheric levels*: the surface (p_), 850 hPa height (p8) and 500 hPa height (p5).

Source: climate-scenarios.canada.ca

23.4 DATA USED

23.4.1 METEOROLOGICAL DATA

The daily rainfall data (0.25° × 0.25° grid) were collected from the India Meteorological Department (IMD), Pune, for the period 1961–2005. Statistical downscaling has been performed using the daily rainfall time series as input predictand in SDSM software. Further, daily observed and estimated time series converted into monthly and annual time series.

23.4.2 REANALYSIS DATA (NCEP)

The daily observed predictor data (re-analysis data) of atmospheric variables, derived from the NCEP on 1° latitude × 1° longitude grid-scale for 45 years (1961–2005) are obtained from the Canadian Climate Impacts Scenarios (CCIS) website (http://www.cccsn.ec.gc.ca/index.php?page=gridded-data).

23.4.3 CMIP5 CLIMATIC SCENARIO (CANESM2)

The CMIP-CanESM2 climate scenarios on 1° latitude × 1° longitude grid-scale are also obtained from the CCIS website (http://www.cccsn.ec.gc.ca/index.php?page=gridded-data). Canadian Earth System Model (CanESM2) is a CMIP5 climate model. CanESM2 climate model has been chosen because of its wider acceptance in many climate change impact studies in India. Further, it provides the daily predictor variables, which can be exclusively used for the SDSM model.

23.5 RESULTS AND DISCUSSION

The multiple liner regression-based statistical downscaling technique has been utilized for downscaling the monthly precipitation. However, CanESM2 climate model with three different scenarios, that is, RCP2.6, RCP4.5, and RCP8.5 have been considered for future projections. For the model calibration and validation, observed gridded rainfall data have been considered during the period 1961–2005. However, model has been calibrated with reanalysis NCEP data with the same duration. During the calibration and validation, it was found that the coefficient of determination values are 0.45 and 0.51, respectively. The graphical representation of calibration and validation between observed and estimated precipitation are shown in Figure 23.3.

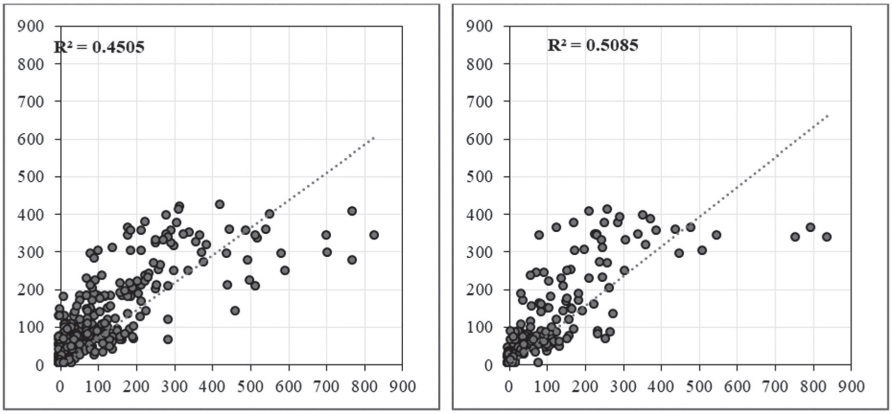

FIGURE 23.3 Scatter plot between observed and estimated precipitation during model calibration (1961–1988) and validation (1989–2005).

Further, the line graph also prepared between observed and the estimated precipitation during 1961–2005. The results present the tendency of model to under-predict the peaks which may be due to climate uncertainty and bias. The graphical representation of observed and estimated precipitation is shown in Figure 23.4. Various statistics of model performance during calibration and validation period are represented in Figure 23.5. It was also noticed that in all climate scenarios, the future precipitation trends are increasing which can be shown by box plot. The decadal future projections of RCP2.6, RCP4.5, and RCP8.5 are shown in Figure 23.6–23.8.

23.6 CONCLUSIONS

The continuous focus of IPCC on the improvement of global circulation model (GCM) which represents the precipitation and strongly relies on rigorous validation efforts for both characterization of precipitation and seasonality. Assessment of the capacity of GCM and its seasonality is very complex phenomenon which is based on historical observations of weather parameters. However, the future changes in hydroclimatic regimes are associated with climatic variability which is more complex and crucial for the realistic projection of predictand. In the recent past, water authorities, scientists, stake-holders, and policy makers were better understanding or

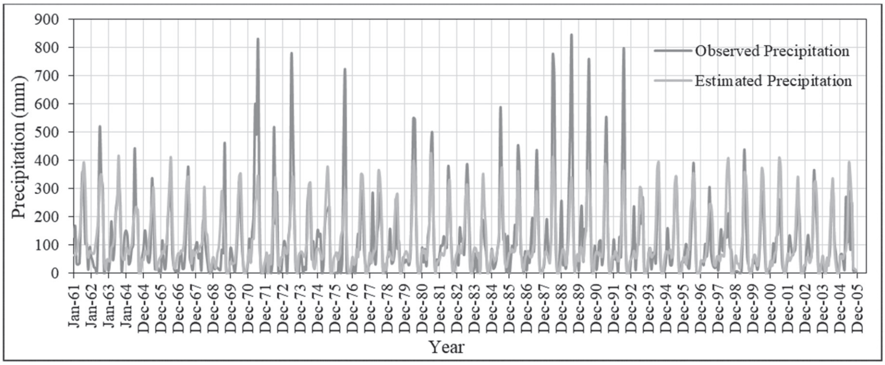

FIGURE 23.4 Observed and estimated precipitation during 1961–2005.

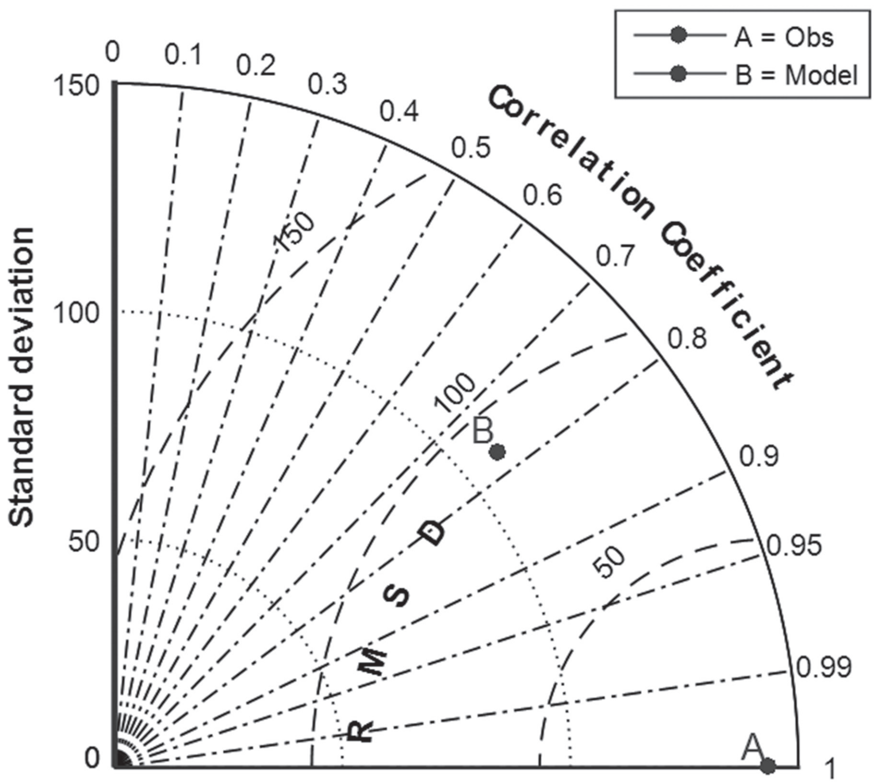

FIGURE 23.5 Taylor diagram representing efficiency statistics of model.

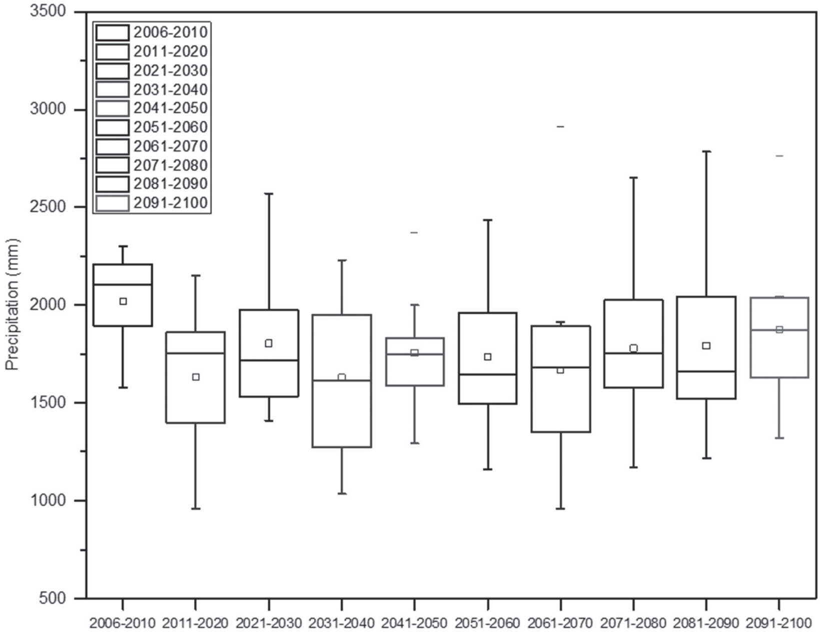

FIGURE 23.6 Projected decadal precipitation of RCP-2.6 scenario.

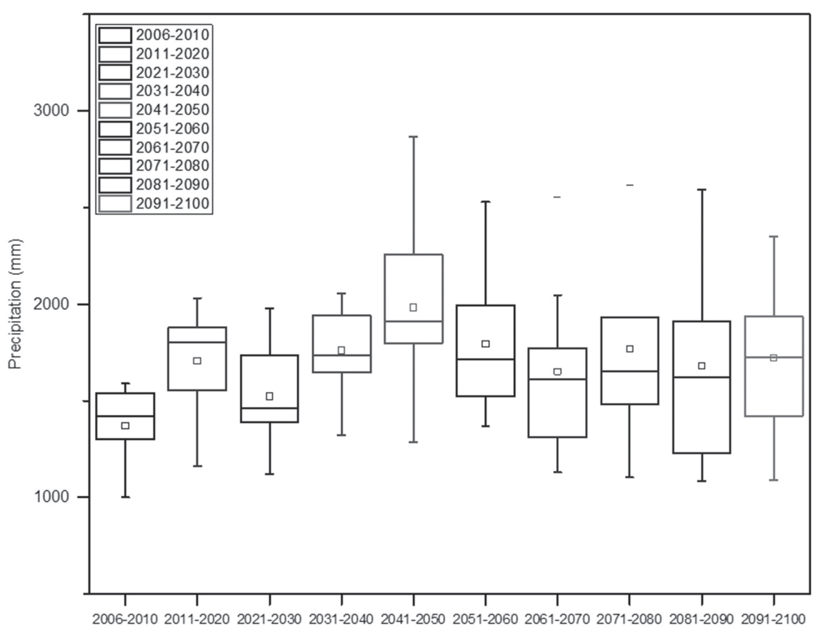

FIGURE 23.7 Projected decadal precipitation of RCP-4.5 scenario.

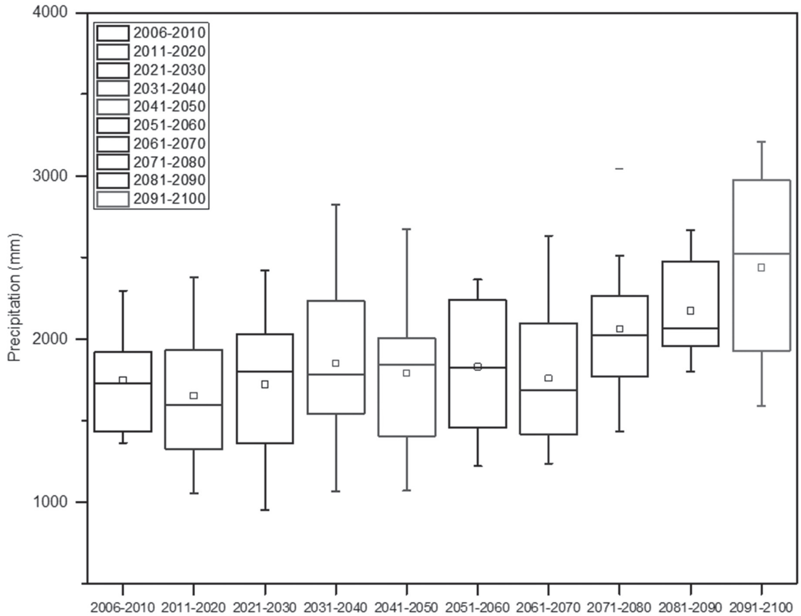

FIGURE 23.8 Projected decadal precipitation of RCP-8.5 scenario.

they anticipated the future drought, flood, and transmission condition of the climate which is directly or indirectly influencing the society. In the current study, the projection of future precipitation over Gangotri glacier at the Himalayan region has been carried out using CMIP5 climate model which can be helpful for scientific groups and society. The study highlights the future possible projections of precipitation which can be utilized for hydrological modeling for future climate in the Gangotri glacier. Additionally, positive trends have been noticed in the future precipitation of the Gangotri glacier.

KEYWORDS

- **climate change**
- **CMIP5**
- **CanESM2**
- **MLR**
- **climate scenarios**

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