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Fate of Rainfall Over the North Indian States in the 1.5 and 2°C Warming Scenarios

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Key Points:

- Study performs a detailed analysis of rainfall behavior of the northern states India during preindustrial, present, 1.5 and 2° scenarios
- Six climate models were selected out of 26 CMIP5 climate models based on the capability of representing the monsoon rainfall over India
- In the 2°C scenario, the recurrence period for intense rainfall events will likely to increase by a factor of 3

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Abstract Rise in mean temperature put a great deal of uncertainty about how weather and climate extremes may play out, particularly in India's varied climatic zones. Consequently, it is important to understand the possible changes in both magnitude and direction of weather and climate extremes like rainfall for different warming levels of 1.5 and 2°C scenarios concerning preindustrial and present levels. Hence in the present study, the precipitation behavior of seven North Indian states that is, Haryana, Himachal Pradesh, J&K, Punjab, Rajasthan, Uttar Pradesh, and Uttarakhand carefully studied using CMIP5 models. Future projections of precipitation has been done for the Paris Agreement global warming level of 1.5 and 2°C scenarios. Along with model validation and future projections of precipitation, the return period of extreme rainfall is also discussed to understand the behavior of the occurrence of extreme precipitation. Statistical analysis shows that the ensemble means have the least error as compared to the other six CMIP5 models. Therefore, future analysis has been done with the ensemble mean. Our findings show that the precipitation is likely to decrease in the 1.5°C scenarios, while it is likely to increase in the 2°C scenarios. The occurrence and intensity of extreme rainfall events are likely to be more frequent in all the models. The return period of the extreme rainfall events is likely to increase in all the states in both the warming scenarios. A three-fold rise is likely to increase extreme rainfall events in the 2°C scenario.

1. Introduction

Due to climate change, the rate of extreme weather events like extreme rainfall events, heat waves, cyclones, typhoons, severe thunderstorms, etc., has increased, in which the frequency and intensity of precipitation play a significant direct and indirect role (Awasthi et al., 2022; Li et al., 2021). Along with other parameters, precipitation is one of the meteorological variables responsible for different types of weather formation (Gavahi et al., 2022). Rainfall is crucial as it is a commonly available source of water for agriculture (Yang et al., 2020). So, variations in rainfall are closely connected to the cultivation calendar, hence playing an important role in the economy of any country. Whereas, extreme rainfall events are accountable for numerous socioeconomic losses, particularly in urban areas, as well as human losses due to natural disasters (Cabré et al., 2016; Corada-Fernández et al., 2017; Dash et al., 2015; Shi et al., 2021). Hence, it is important to understand the spatial and temporal characteristics of rainfall in the warming atmosphere.

Due to change in the normal composition of the atmosphere, pollution level is increasing gradually due to which different natural phenomenon are varied that ultimately poses a serious effect on society in different ways (Awasthi et al., 2017). To understand the behavior/pattern of rainfall, Satellite microwave and infrared (IR) remote-sensing data have been used to calculate monthly and daily precipitation over the oceans, as well as over land. Nowadays, algorithms have been created that generate near real-time hourly or 3-hourly precipitation of resolution of 0.25° or finer resolution. After quantitative assessments, this type of high-resolution and near real-time data can be highly valuable in different types of research related to hydrology, weather, climate, etc.

The 2015 Paris Agreement recommended, "Holding the increase in the global average temperature to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C above pre-industrial levels" (UNFCCC, 2015). The concentrations of greenhouse gases (GHGs) must fall before 2060 to accomplish the 1.5°C warming objective, whereas to achieve the 2°C warming target, GHGs must fall before 2085 (Sanderson et al., 2016). Due to the change in the concentration of GHGs, the ocean warming pattern changes and

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hence show different climate response in term of precipitation in the atmosphere (Chadwick et al., 2013; Long et al., 2014; Pattnayak et al., 2018).

Temperature and rainfall data is used mainly for understanding the various climate trends. Alteration in the rainfall volume, frequency, distribution, and intensity is supposed to be a consequence of climate change (Duan et al., 2015, 2019; Zhang et al., 2012) which requires immediate thought and in-depth investigation. Change and variability in climate due to an increase in GHGs result in change in the rainfall pattern throughout the world (Bhatla et al., 2016; Deng et al., 2019; Gergis & Henley, 2017; Pattnayak, Tindall, et al., 2019; Singh et al., 2019). In the Indian context, several studies demonstrate a decrease in the number of rainy days and total annual precipitation and an increase in the frequency of heavy rainfall events (Dash & Hunt, 2007; Dash et al., 2009; Goswami et al., 2006; Lal, 2003; Maharana et al., 2022). The southwest monsoon season (June–September), brings about 60%–90% of India's yearly rainfall, which is crucial for the nation's economy (Joshi & Rajeevan, 2006; Pattnayak, Panda, et al., 2019). Rainfall's pattern, intensity and frequency play an important role in irrigation and extreme events like drought and flood, etc (Guo et al., 2018; Kulshrestha et al., 2009). Hence, seasonal and annual rainfall and changes in extreme rainfall are important to understand, and proper investigation is required.

Lacombe and McCartney (2014) carried out a rainfall analysis from 1951 to 2007 and showed increasing trends in rainfall in southern peninsular India and decreasing trends in rainfall over central India. Increasing trends in precipitation during autumn and winter, whereas decreasing trends during monsoon and spring were reported by Pal and Al-Tabbaa (2011) based on the analysis for the period of 1954–2003. Many other studies were done by the authors in which rainfall pattern, distribution, frequency, etc. of different North Indian states were studied, that is, Haryana (Chauhan et al., 2022; Nain & Hooda, 2019), Himachal Pradesh (Jaswal et al., 2015), Punjab (Kaur et al., 2021), Rajasthan (Mundetia & Sharma, 2014; Pingale et al., 2013), Uttarakhand (Malik & Kumar, 2020) and Uttar Pradesh (Guhathakurta et al., 2020). Mondal et al. (2022) showed that the extreme precipitation events across South Asia may increase up to 3.5%–6.6% due to increase in warming from 1.5 to 2.0°C. Based on the Community Earth System Model low warming (CESM-LWR) experiment, authors studied a worldwide evaluation of precipitation extreme forecasts under 1.5 and 2°C warming scenarios and revealed that in central Africa, eastern South America, and northern high latitudes, consecutive dry days (CDD) will occur less frequently (Ju et al., 2021). G. Wang et al. (2020) found that the extreme precipitation increased by two times with an addition of 0.5°C warmer climate.

According to one of the reports by the Intergovernmental Panel on Climate Change in 2007 that dry climate zones are anticipated to get drier and wet climate zones to become wetter (IPCC, 2007). Hence, it is important to understand the past behavior of rainfall patterns to forecast their future occurrence, so that proper risks associated with extreme precipitation events will be designed. Moreover, precipitation plays a significant role in the economic growth of a country (Damania et al., 2020), hence it is interesting and important to discuss the precipitation pattern of India, which is emerging as one of the strongest economies across the globe. Earlier researchers reported that the 1.5 and 2°C scenarios might lead to higher warming at the regional scale, particularly over the landmass of the Northern Hemisphere (Karmalkar & Bradley, 2017; Sahu et al., 2008; Sharma & Babel, 2014; Tiwari et al., 2014; Vautard et al., 2014; Xu et al., 2017). Therefore, it is a challenge for the economist and Government to design balanced strategies and plans to fulfill the Paris Agreement's target along with the economic growth of India. In this paper, the authors present the performance of precipitation for four periods that is, preindustrial period (1871–1890), present (1986–2005), 1.5 and 2° scenario to understand and project the future climate scenario. The 1.5 and 2° scenario periods have been considered based on global temperature anomalies reaching respective values in the CMIP5 models (Maharana et al., 2020).

2. Study Region

The northern states of India occupy the largest region of the country comprising seven states Haryana, Himachal Pradesh, Jammu and Kashmir (J&K), Punjab, Rajasthan, Uttar Pradesh, and Uttarakhand. This part of the country has consistently outperformed India's national average in terms of GDP, with the region accounting for approximately 26% of the national GDP. The dominant geographical features of North India are the Indus-Gangetic Plain and the Himalayas, which demarcate the region from the Tibetan Plateau and Central Asia. The northern part of India is endowed with immense topographical diversity, historical monuments, different cultures, wildlife parks and sanctuaries, holy temples and rivers, and diversified climatic conditions. The entire northern part of the country shares its borders with countries like Pakistan, China, Nepal, and Bhutan (Figure 1). Toward its north is

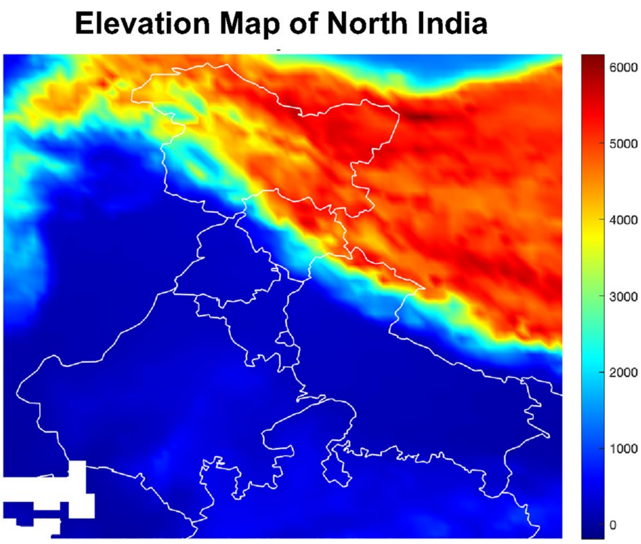

Figure 1. Elevation map of north India from the Global Land Data Assimilation System (Rodell et al., 2004).

the Himalayas which define the boundary between the Indian subcontinent and the Tibetan plateau. To its west is the Thar desert, shared between North India and Pakistan and the Aravalli Range, beyond which lies the state of Gujarat. The Vindhya mountains are, in some interpretations, taken to be the southern boundary of North India. The predominant geographical features of North India are the Indo-Gangetic plain, which spans the states of Punjab, Haryana, and Uttar Pradesh, the Himalayas, which lie in the states of Uttarakhand, Himachal Pradesh, and J&K, and the Thar desert, which lies mainly in the state of Rajasthan. The states of Himachal Pradesh, Uttarakhand, and J&K also have a large forest coverage.

The northern state of India lies mainly in the temperate zone. The general pattern of this region is cold winters, hot summers, and moderate monsoons. It is one of the most climatically diverse regions on Earth. The region receives heavy rain in the plains and light snow in the Himalayas (J&K, Himachal Pradesh, and Uttarakhand) through two primary weather patterns: the Indian Monsoon and the Western Disturbances. The monsoon carries moisture northwards from the Indian Ocean, occurs in late summer, and is important to the autumn harvest (Jain & Chatterjee, 1972; Katiyar, 1990). Western Disturbances is an extratropical weather phenomenon that carries moisture eastwards from the Mediterranean Sea, the Caspian Sea, and the Atlantic Ocean (Datta & Gupta, 1967; Dimri, 2004; Tiwari et al., 2014; B. Wang, 2006). They primarily occur during the winter season and are critically important for the spring harvest, which includes the main staple food of North India, wheat (B. Wang, 2006).

2.1. Data and Methodology

Historical and future climate data have been obtained from the Fifth Coupled Model Inter-comparison Project (Taylor et al., 2012). The models used in this study are listed in Table 1, along with their host institutions, and the abbreviations used in this study. There are 26 climate models from CMIP5 that have been considered for this study. For evaluating the model simulations, fifth generation ECMWF reanalysis ERA5 (Hersbach et al., 2020) have been used in the present work. The recent study by Mahto and Mishra (2019) have demonstrated that ERA5 outperforms other reanalysis products such as ERA-Interim, Japanese 55-year Reanalysis (JRA-55) and Modern Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) over Indian region, including seasonal precipitation, maximum and minimum temperatures, total runoff, evapotranspiration, and soil moisture. Rivoire et al. (2021) compared moderate to extreme daily precipitation from the ERA-5 reanalysis with two observational gridded data sets, EOBS and CMORPH. Their assessment reveals that the observational dataset agrees well with more than 80% of the grid points on average across the globe. Therefore, it has been used as a reference dataset for selecting models out of the 26 CMIP5 models. The models have been validated for the reference period. Further, Climatic Research Unit (CRU) gridded rainfall (Harris et al., 2014) with 0.5° grid resolution at land points have been considered. To compute model bias against CRU observations, the CMIP5 data at coarser resolution has been interpolated to the CRU data at finer resolution onto a 0.5° × 0.5° grid. The multi-model ensemble has been calculated in a similar way. For calculating the interannual variations, the climatic fields have been computed by masks of the corresponding states, then the grid points present within the mask have been averaged. Analysis of the future projections has been carried out at the model resolution (without applying any interpolation).

Sub-selecting a representative subset from available General Circulation Models (GCMs) provides an efficient approach to generating a set of regional climate projections which represent the range of future climates indicated by the full ensemble (McSweeney et al., 2012). The methodology employed to select the CMIP5 GCMs which perform satisfactorily over India is to generate higher-resolution scenarios of future climate for North India under 1.5 and 2° scenarios. The models were first assessed in their simulation of a realistic baseline climate, with unsatisfactory models being eliminated before; second, a subset of models was selected to span the range of projected changes in precipitation. The approach of the evaluation criteria and the method is described in Table 2. The evaluation criteria were set out according to the phenomenon those are highly important for the Indian monsoon viz.

Table 1
Details of Selected CMIP5 GCMs Used in This Study

Modeling group	Group acronym	Model designation	Spatial resolution
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1-0	1.25° × 1.875°
Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	CSIRO-BOM	ACCESS1-3	1.25° × 1.875°
Beijing Climate Center, China Meteorological Administration	BCC	bcc-csm1-1	2.8° × 1.875°
Beijing Climate Center, China Meteorological Administration	BCC	bcc-csm1-1-m	1.125° × 1.125°
College of Global Change and Earth System Science, Beijing Normal University	GCESS	BNU-ESM	2.8° × 1.875°
Canadian Centre for Climate Modeling and Analysis	CCCMA	CanESM2	2.8° × 2.8°
National Center for Atmospheric Research	NCAR	CCSM4	1° × 1°
Centro Euro-Mediterraneo per I Cambiamenti Climatici	CMCC	CMCC-CM	0.75° × 0.75°
Centre National de Recherches Météorologiques	CNRM-CERFACS	CNRM-CM5	1.4° × 1.4°
Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	CSIRO-QCCCE	CSIRO-Mk3-6-0	1.8° × 1.8°
EC-EARTH consortium	ICHEM	EC-EARTH	1.125° × 1.125°
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-CM3	2° × 2°
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-ESM2G	2° × 2°
NOAA Geophysical Fluid Dynamics Laboratory	NOAA GFDL	GFDL-ESM2M	2° × 2°
Met Office Hadley Centre	MOHC	HadGEM2-AO	1.2° × 1.8°
Met Office Hadley Centre	MOHC	HadGEM2-CC	1.2° × 1.8°
Met Office Hadley Centre	MOHC	HadGEM2-ES	1.2° × 1.8°
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-LR	2° × 4°
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5A-MR	2° × 4°
Institut Pierre-Simon Laplace	IPSL	IPSL-CM5B-LR	2° × 4°
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute and National Institute for Environmental Studies	MIROC	MIROC5	1.4° × 1.4°
Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute and National Institute for Environmental Studies	MIROC	MIROC-ESM	3° × 3°
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-LR	1.8° × 1.8°
Max Planck Institute for Meteorology	MPI-M	MPI-ESM-MR	1.8° × 1.8°
Meteorological Research Institute	MRI	MRI-CGCM3	1° × 1°
Norwegian Climate Centre	NCC	Nor-ESM1-M	2° × 2°

all India rainfall, low-level Somali jet, upper-level easterly jet and monsoon trough. The evaluation was carried out based on the model which capture these phenomena. These features were compared with the ERA5 datasets. Here the most important and difficult decision occurs in allocating a model its position on the performance scale (Table 3) between "Include" and "Exclude." The models were included for the study which possesses satisfactory performance in simulating the key monsoon feature outlined in Table 2. We compare the performance summary information in Table 4 with the projections for future change in mean rainfall to assess which models are to be eliminated, according to the decision-making framework set out in Table 2. Based on the decision-making framework, six models have shown satisfactory performance. The performance scores in the final column of Table 4 allocated based on the following criteria: Criteria for overall "Implausible" highlighted in Peach: any one category is scored "implausible," or 4 or more categories scored "Significant biases" shown in Orange color. Overall Significant Biases: Two "Significant Biases" or three "Biases"/"Significant Biases," of which at least one is "Significant biases." Overall, Biases (Yellow): One "Significant Biases," or two or more "Biases." Overall Satisfactory: Fewer than three "Biases." Thus, those six models were chosen to study the future projection in this study shown in Green in Table 4.

Table 2
Summary of Evaluation Methods Employed

Evaluation criteria	Evaluation method
All India Rainfall	Calculate the rainfall over Indian land points in both IMD observation and CMIP5 models. The bias more than one standard deviation is considered as significant bias
Low level Somali jet	Comparison by visual inspection of circulation at 850 hpa in CMIP5 models with ERA5 (Hersbach et al., 2020) for the summer monsoon months that is, June–September, looking for evidence that key features are captured. Misplaced flow or mis-directed flow are considered more serious biases than systematic errors in strength of flow.
Upper-level easterly jet	Comparison by visual inspection of circulation at 200 hpa in the CMIP5 models with ERA5 (Hersbach et al., 2020) for the summer monsoon months that is, June–September, looking for evidence that key features are captured. Misplaced flow or mis-directed flow are considered more serious biases than systematic errors in strength of flow.
Monsoon trough	Comparison by visual inspection of the MSLP in CMIP5 models with ERA5 (Hersbach et al., 2020) for the summer monsoon months that is, June–September, looking for evidence that key features are captured. Misplaced flow or mis-directed flow are considered more serious biases than systematic errors in strength of flow.

The model simulations are available from 1860 to 2100. This historical period of simulation has been divided into two periods, the pre-industrial period (1870–1900) and the present-day climate (1976–2005). The historical simulations have been forced by observed atmospheric composition changes (including Green House Gas (GHG), natural and anthropogenic aerosols, and volcanic forcing), solar variations, and time-evolving land cover in a bid to simulate the observed climate of the recent historical period. The projected climate simulations have been forced by GHGs, solar constant, ozone, and aerosol are kept changing with time.

3. Results and Discussion

The results have been analyzed broadly in two categories, namely model validation for the reference period and future climate projections. First, the model simulations have been validated against the corresponding observations in terms of climatology and interannual time scales. Further, the climate change in the two future scenarios with respect to the preindustrial and present periods has been analyzed in detail.

3.1. Model Validation

Rainfall variability has been represented in terms of a box and whisker plot for the period of 1976–2005 on the basis of 6 CMIP5 models and ensemble with respect to the CRU (Figure 2). The minimum, first quartile (Q1), median, third quartile (Q3), and maximum of the box plots in the figure are used to compare the distribution of rainfall during the period among the different data sets. It is observed on the basis of symmetry of different plots, that variability is minimum in the case of ensemble data with respect to CRU in comparison to other data sets. Box plot in case of ensemble data shows a minimum spread, and is tightly grouped, more symmetrical, and skewed in comparison to other data sets. The confirmation of model validation and selection of the best-mapped data set is

Table 3
Decision Making Matrix for Potential Elimination of Ensemble Members

		Model simulations	
		Outliers	Other models predict similar outcomes too.
Model Performance	Model suffers shortcomings sufficiently serious to significantly reduce our confidence in its projections (“Implausible”)	Exclude	Exclude: These models can be avoided without affecting the range of projected outcomes
	Model suffers significant shortcomings which we cannot clearly link to confidence in its projections. (“Biases/Significant Biases”)	Include: We do not have strong evidence to exclude these outcomes from the projections	Exclude: These models can be avoided without affecting the range of projected outcomes
	Model performance is satisfactory (“Satisfactory”)	Include	Include

Table 4
Summary of Model Performance

	All India Summer Monsoon Rainfall	Somali Jet	Easterly Jet	Monsoon Trough	Overall
ACCESS1-0	Green	Peach	Peach	Orange	Peach
ACCESS1-3	Peach	Peach	Yellow	Peach	Peach
bcc-csm1-1	Peach	Orange	Orange	Peach	Peach
bcc-csm1-1-m	Peach	Peach	Peach	Peach	Peach
BNU-ESM	Yellow	Peach	Peach	Yellow	Peach
CanESM2	Peach	Peach	Orange	Peach	Peach
CCSM4	Green	Peach	Yellow	Peach	Peach
CMCC-CM	Peach	Yellow	Peach	Peach	Peach
CNRM-CM5	Peach	Yellow	Peach	Peach	Peach
CSIRO-Mk3-6-0	Orange	Orange	Peach	Yellow	Peach
EC-EARTH	Green	Peach	Peach	Peach	Peach
GFDL-CM3	Green	Green	Yellow	Green	Green
GFDL-ESM2G	Green	Green	Green	Yellow	Green
GFDL-ESM2M	Green	Yellow	Green	Green	Green
HadGEM2-AO	Green	Green	Yellow	Green	Green
HadGEM2-CC	Yellow	Green	Green	Green	Green
HadGEM2-ES	Green	Green	Green	Green	Green
IPSL-CM5A-LR	Peach	Peach	Green	Yellow	Peach
IPSL-CM5A-MR	Green	Yellow	Yellow	Orange	Yellow
IPSL-CM5B-LR	Peach	Yellow	Yellow	Peach	Peach
MIROC5	Yellow	Yellow	Yellow	Yellow	Yellow
MIROC-ESM	Yellow	Orange	Yellow	Yellow	Yellow
MPI-ESM-LR	Yellow	Peach	Orange	Orange	Peach
MPI-ESM-MR	Yellow	Yellow	Green	Peach	Peach
MRI-CGCM3	Yellow	Orange	Orange	Green	Orange
Nor-ESM1-M	Yellow	Green	Yellow	Peach	Peach

Note. Peach = "Implausible," Orange = "Significant Biases," yellow = "Biases" and green = "Satisfactory." Overall performance scores in the final column are allocated based on the following criteria: Criteria for overall "Implausible" (Peach): Any one category is scored "implausible," or four or more categories scored "Significant biases." Overall Significant Biases (Orange): Two "Significant Biases" or three "Biases"/"Significant Biases," of which at least one is "Significant biases." Overall Biases (Yellow): One "Significant Biases," or two or more "Biases"*. Overall Satisfactory: Fewer than three "Biases"*.

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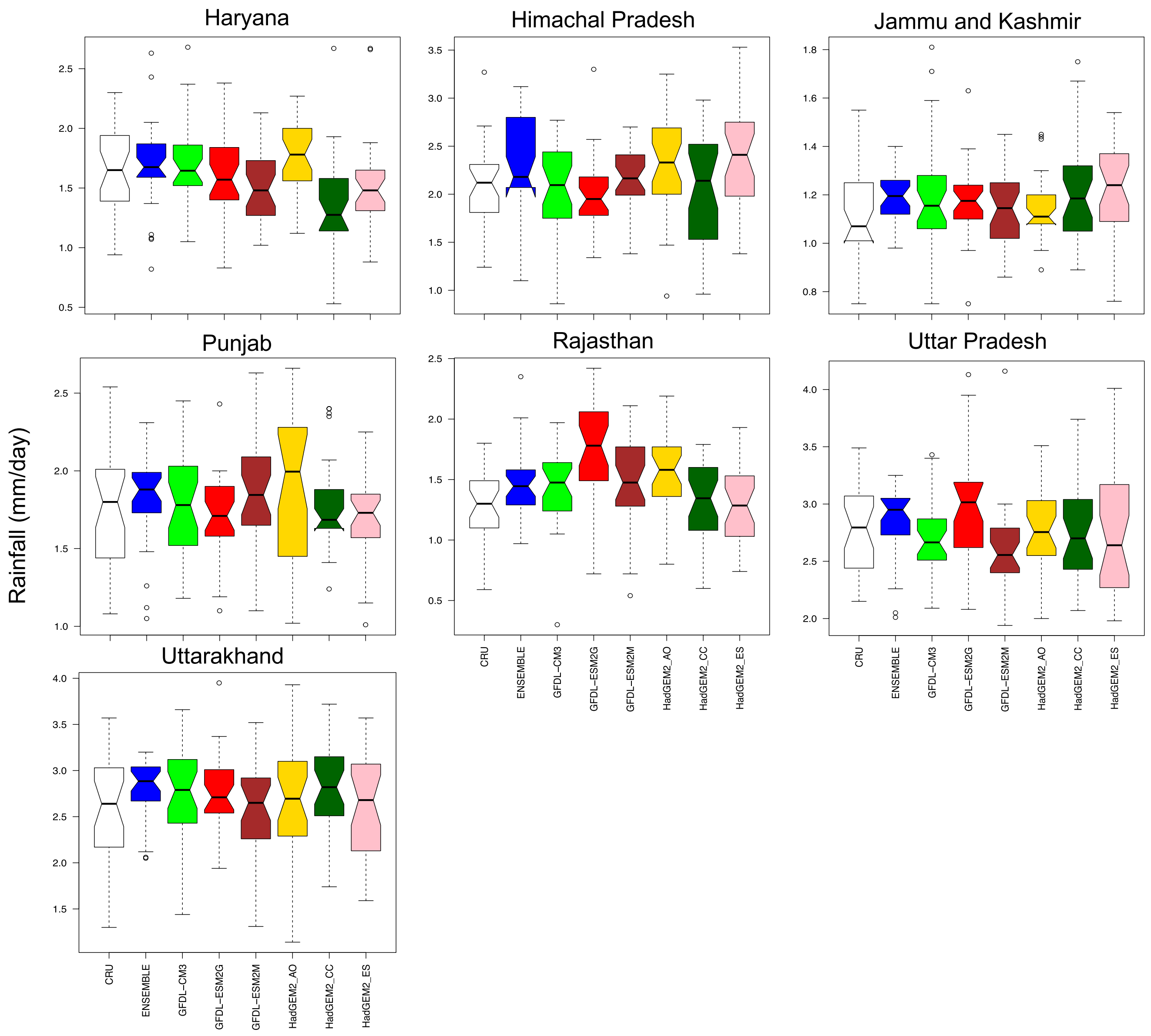

Figure 2. Box and whisker plot of annual rainfall as observed by CRU and simulated by CMIP5 Models over (a) Haryana, (b) Himachal Pradesh, (c) Jammu and Kashmir, (d) Punjab (e) Rajasthan, (f) Uttar Pradesh, and (g) Uttarakhand for 1976–2005.

shown in Figure 3. Taylor diagrams are drawn to understand which model is most realistic for the approximation on the basis of correlation coefficient and standard deviation. In most of the states, except Himachal Pradesh, the correlation coefficient value is maximum (>0.8) for the Ensemble in comparison to other models. It is also observed that the deviation is less than or equal to 20% for the ensemble data set for all the states except Punjab. Based on the median, standard deviation, and correlation values of most of the states, it is observed that error and uncertainty in the ensemble mean plot are minimal in comparison to other models. This is the reason that in the coming section data on the basis of ensemble means are taken into main focus for further analysis and discussion.

The precipitation climatology in the ensemble mean of CMIP5 models has been validated with the CRU observation for the present/reference periods (1976–2005) as shown in Figure 4. The left and middle columns represent mean precipitation based on the CRU and CMIP5 model during the years 1976–2005, while the right column (Figure 4c) shows the difference between the model and observation. The starting year is chosen as 1976 since the precipitation data from the CMIP5 model are available from that year. The ENSEMBLE mean can reproduce the mean rainfall features over the North Indian states as in the CRU observation, such as low rainfall over Rajasthan,

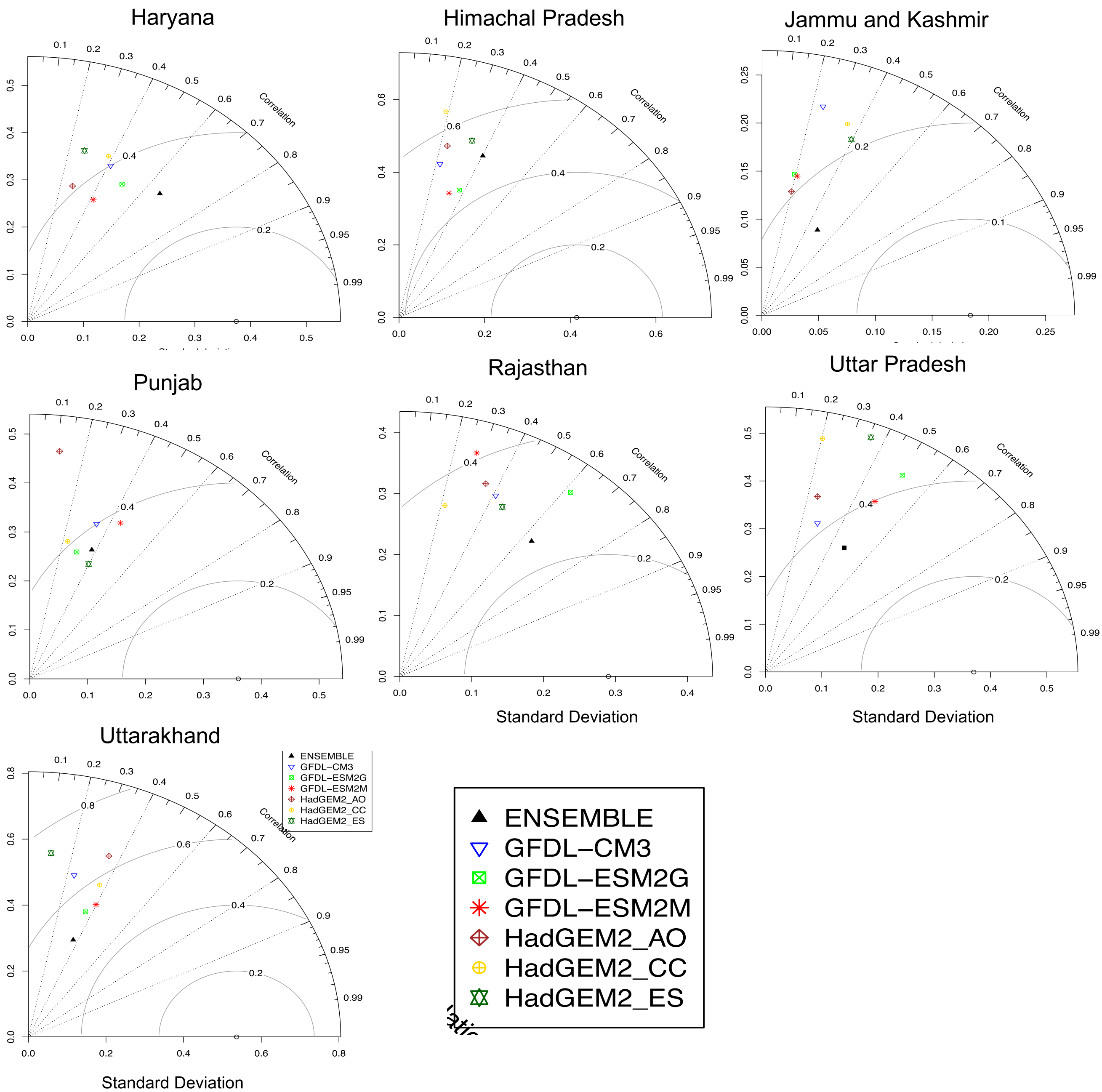

Figure 3. Taylor diagram of annual rainfall as observed by CRU and simulated by CMIP5 Models over (a) Haryana, (b) Himachal Pradesh, (c) Jammu and Kashmir, (d) Punjab (e) Rajasthan, (f) Uttar Pradesh, and (g) Uttarakhand for the period 1976–2005.

and high rainfall along the Gangetic plains and foothills of the Himalayas. The model shows a bipolar bias, that is, wet bias over the Himalayas and dry bias over central India.

The mean precipitation simulated by CMIP5 models during the reference period is compared with the corresponding CRU values in Figure 4c and white patches depict a small difference lying within −1 to 1 mm/day. The model has a significant difference compared to the observation based on CRU. Figure 4c shows that the difference in the precipitation is negative for Rajasthan (up to −2 units), whereas other states have a positive value of the precipitation difference. This indicates that the model underestimated the value of precipitation in Rajasthan, whereas for other states, values are overestimated. It is also observed that overall precipitation during the period (1976–2005) was lower in Rajasthan in comparison to other North Indian states. The precipitation is slightly

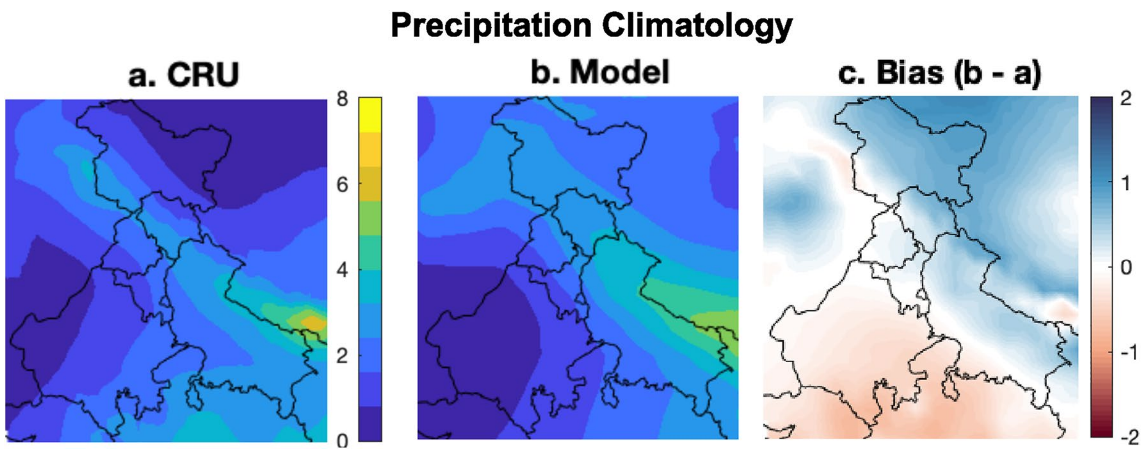

Figure 4. Climatology of precipitation from CRU observation (left panel) and CMIP5 ensemble mean (middle panel) for the base line period (1976–2005). The right-hand panel represents the bias between the model and observation.

overestimated in most of the states except in Rajasthan, J&K, Himachal Pradesh, and Uttarakhand as compared to the other states.

3.2. Future Projection of Precipitation

Four scenarios/periods are investigated in the present study. These periods are categorized as the present/reference period (1975–2005), 1.5, and 2° which are compared with the preindustrial period (1871–1890). Figure 5 shows mean precipitation in the preindustrial, present, 1.5, and 2°C scenarios and changes during the three scenarios with respect to the preindustrial period based on the ENSEMBLE mean of the models. The left column represents the mean precipitation of the preindustrial period, and the middle column presents the mean precipitation for the present, 1.5, and 2.0°C scenarios. The right column represents the projected changes by taking the differences between various scenarios with respect to preindustrial periods. Figures 5c and 5e show almost common behavior, which indicates that precipitation decreased during the reference period and in a 1.5°C scenario with respect to the preindustrial period. Whereas Figure 5g indicates an increase in precipitation up to 0.5 mm/day with respect to the 2°C scenario, and white patches are also observed which depicts a small difference in precipitation during 2°C with respect to the industrial period. The precipitation is likely to increase up to 0.7 mm/day during the 2°C scenario in almost all observed northern states of India. Based on the 1.5°C scenario, all the states show a significant decrease in precipitation, which is interesting to understand.

Figure 6 represents the box plots that display the ensemble spread, medians, interquartile (IQ) ranges, and outliers of the changes in the different rainfall for seven states at the preindustrial, present, and two warming levels of 1.5 and 2°C scenarios. Based on the median and interquartile range of precipitation values of seven states shown by the box plot in Figure 6, it is observed that rainfall values observed during the present period and 1.5°C scenario are almost similar to that of preindustrial values for almost all the studied states. Whereas the value of precipitation in a 2°C scenario shows a large range in comparison to the preindustrial values. Large interquartile range of rainfall during the 2°C scenario in comparison to the preindustrial, present, and 1.5°C scenarios signifies the high rainfall during the 2°C scenario.

It is observed from the Heatmap of annual rainfall (Figure 7) that precipitation is maximum during the 2°C scenario in comparison to the present and 1.5°C scenario. Both Heatmap and box-whisker plots clearly indicate the increase in rain events during the warming scenario of 2°C. Similar remark was given by Lee et al. (2018) in which the conclusion was done that extreme precipitation is projected to increase very strongly in a 2°C scenario.

3.3. Return Period of the Extreme Rainfall Events in the Future Scenarios

The incidence of intense rainfall events is a popular topic across the world since the repercussions of such occurrences are the primary cause of human deaths from natural disasters as well as innumerable socioeconomic losses (Marengo et al., 2009). In addition, some of the studies have predicted a rise in the recurrence of intense rainfall

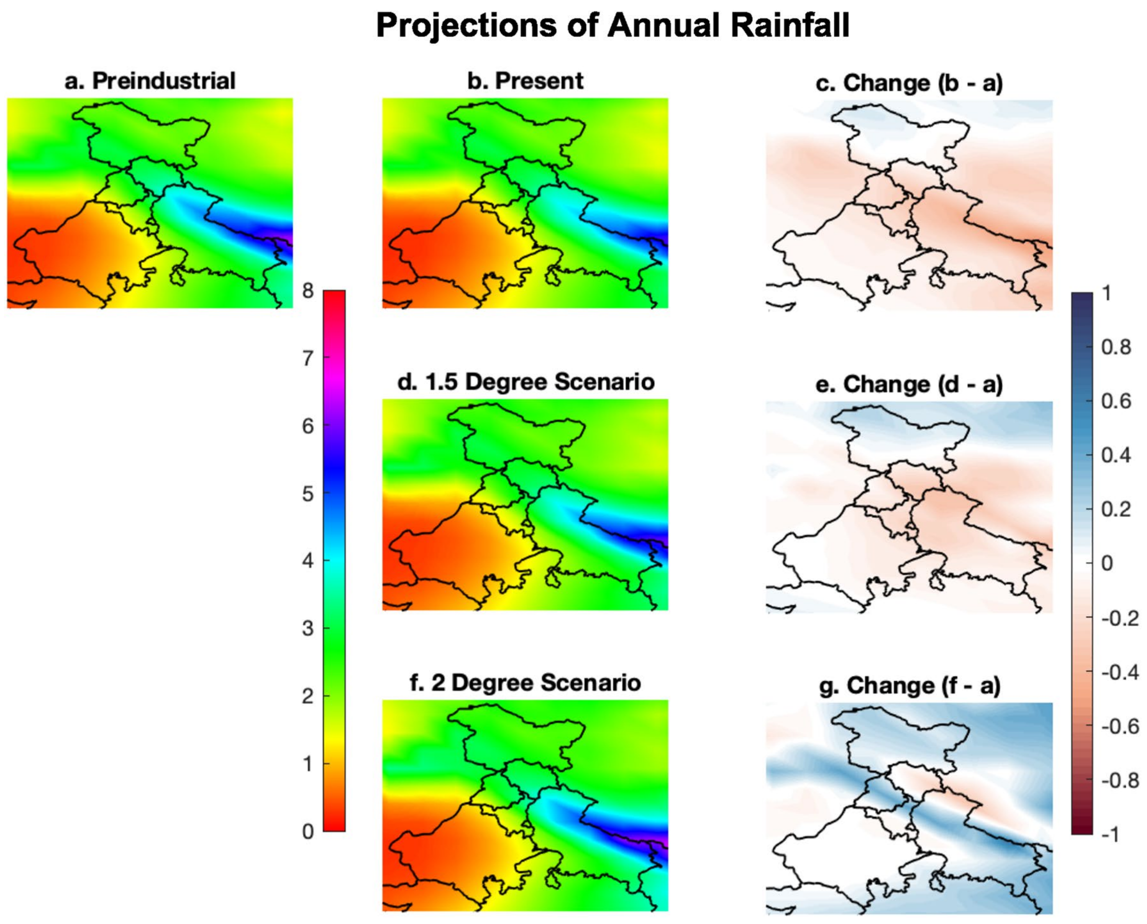

Figure 5. Annual mean rainfall (mm/day) as ensemble mean CMIP5 models during the reference period (1975–2004), preindustrial period and projected in the 1.5 and 2° scenarios. The right-hand side panels show the corresponding projected changes with respect to the reference period.

events (De Oliveira et al., 2014; Niyogi et al., 2017; Zou & Ren, 2015). Keep this thing in mind, Figure 8 represents the return level of extreme events for all the seven states in the Preindustrial period, Present Period, 1.5 and 2.0°C scenarios as simulated by ensemble mean. Our analysis shows that their predominance of rainfall estimates higher than 7 mm in all the return periods. It is observed that northern states which are close to the Himalayas that is, J&K, Uttarakhand, and Himachal Pradesh show a large return level of more than 10 mm that reaches up to 15–20 mm in the return periods of more than 60 years. It is also observed that the recurrence level of rainfall increases in all the states and the rise is maximum as per 2°C scenario.

4. Conclusion

For policy formulation, it is essential to understand the behavior of variation in rainfall in the present, industrial and future global warming levels. This study performs a detailed analysis of rainfall behavior in four periods that is, preindustrial period (1871–1890), present (1986–2005), 1.5° scenario, and 2° scenario are cautiously studied to recognize and project the future climate scenario. There were 26 CMIP5 climate models considered for this study. However, only six models were selected based on the capability of simulating the different aspects of rainfall and its associated mechanism.

An interesting feature is seen in the 1.5°C scenario, the precipitation is likely to decrease in most of the states except J&K. However, in 2°C scenario, the precipitation is likely to increase in all the North Indian states except Himachal Pradesh. There is no significant change is likely to occur in Rajasthan in both scenarios. This result is consistent with Dash et al. (2015) and Pattnayak et al. (2017). The return period of the extreme rainfall events is likely to increase in all the states in both the scenarios. In a 2°C scenario, there is a three-fold rise likely to

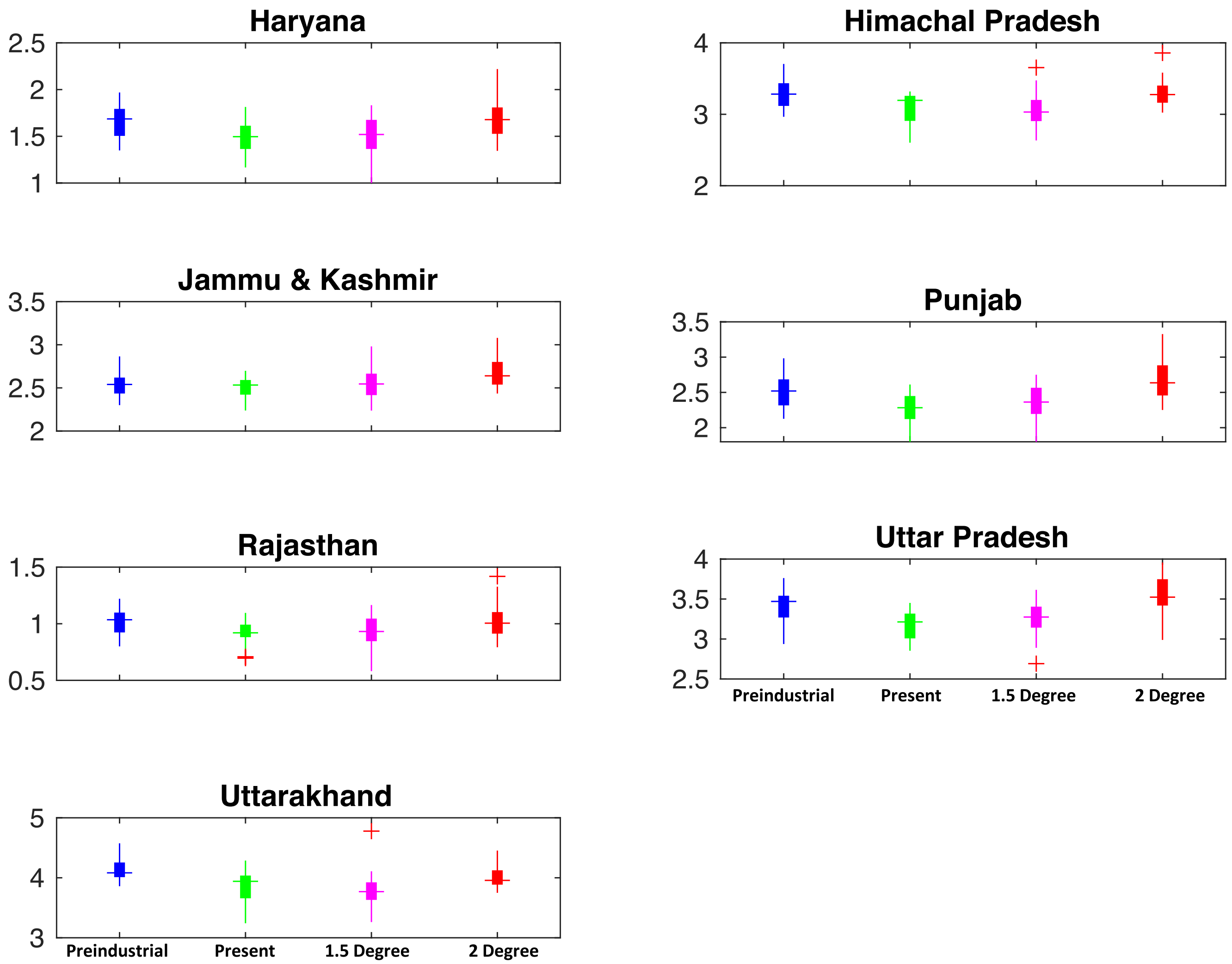

Figure 6. Comparison of annual rainfall in Preindustrial period, Present Period, 1.5 Degree Scenario and 2.0 Degree Scenario as simulated by CMIP5 Models over (a) Haryana, (b) Himachal Pradesh, (c) Jammu and Kashmir, (d) Punjab (e) Rajasthan, (f) Uttar Pradesh, and (g) Uttarakhand through box-whisker plot.

increase in extreme rainfall events. These projections are associated with a range of limitations and uncertainties which are driven mainly by the model and scenario uncertainties (Dash et al., 2015; Pattnayak et al., 2017) and it is generally more reliable at the global scale than at smaller regional scales (Taylor et al., 2012). The uncertainties are more where the region has sharp orography gradient, and the coarse-resolution global models are not able to represent this heterogeneity in the orography. Thus, the uncertainty is more in Himachal Pradesh, Jammu and Kashmir and Uttarakhand which are on the foothills of Himalayas and has sharp topographic gradient. Multi-model ensemble means approaches try to represent the uncertainties in regional climate projections in a reasonable manner which have been addressed in this study. Inter-model comparison shows that there are large uncertainties within the CMIP5 model projections. Overall, this study robustly provides some conclusions with some degree of confidence, but it still has some limitations. The major limitation is the resolution of the models, the selected models are very coarse resolution. This coarser resolution makes it difficult to reduce the uncertainty at the local scale. Further, this type of study is required to help the policymakers to adapt to the 1.5 and 2°C scenarios. Our plan is to extend the present work in the future to study the changing climate extreme under future climate change scenarios using CMIP6 climate model outputs.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

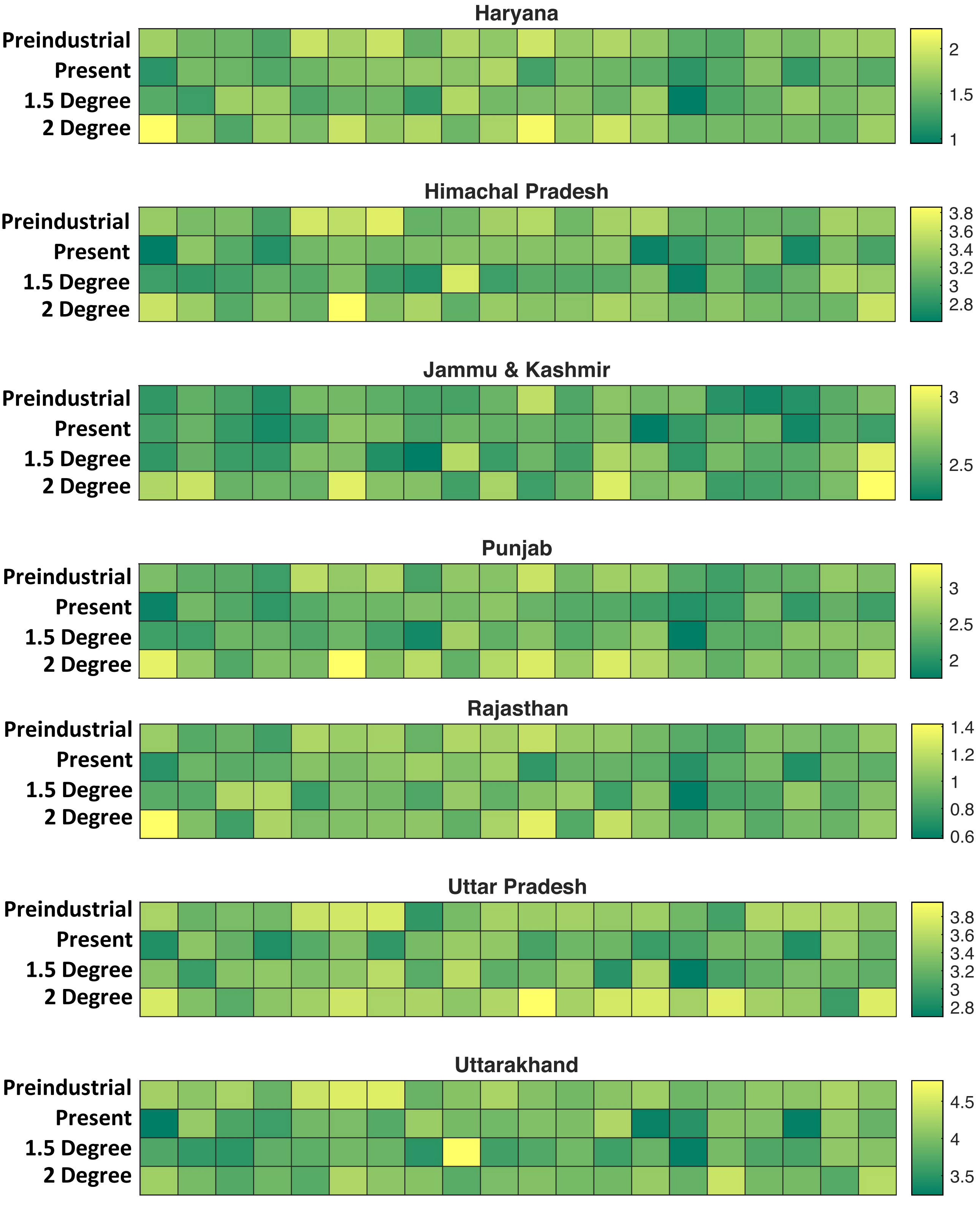

Figure 7. Heatmap of annual rainfall in the Preindustrial period, Present Period, 1.5 Degree Scenario and 2.0 Degree Scenario as simulated by CMIP5 Models over (a) Haryana, (b) Himachal Pradesh, (c) Jammu and Kashmir, (d) Punjab, (e) Rajasthan, (f) Uttar Pradesh, and (g) Uttarakhand.

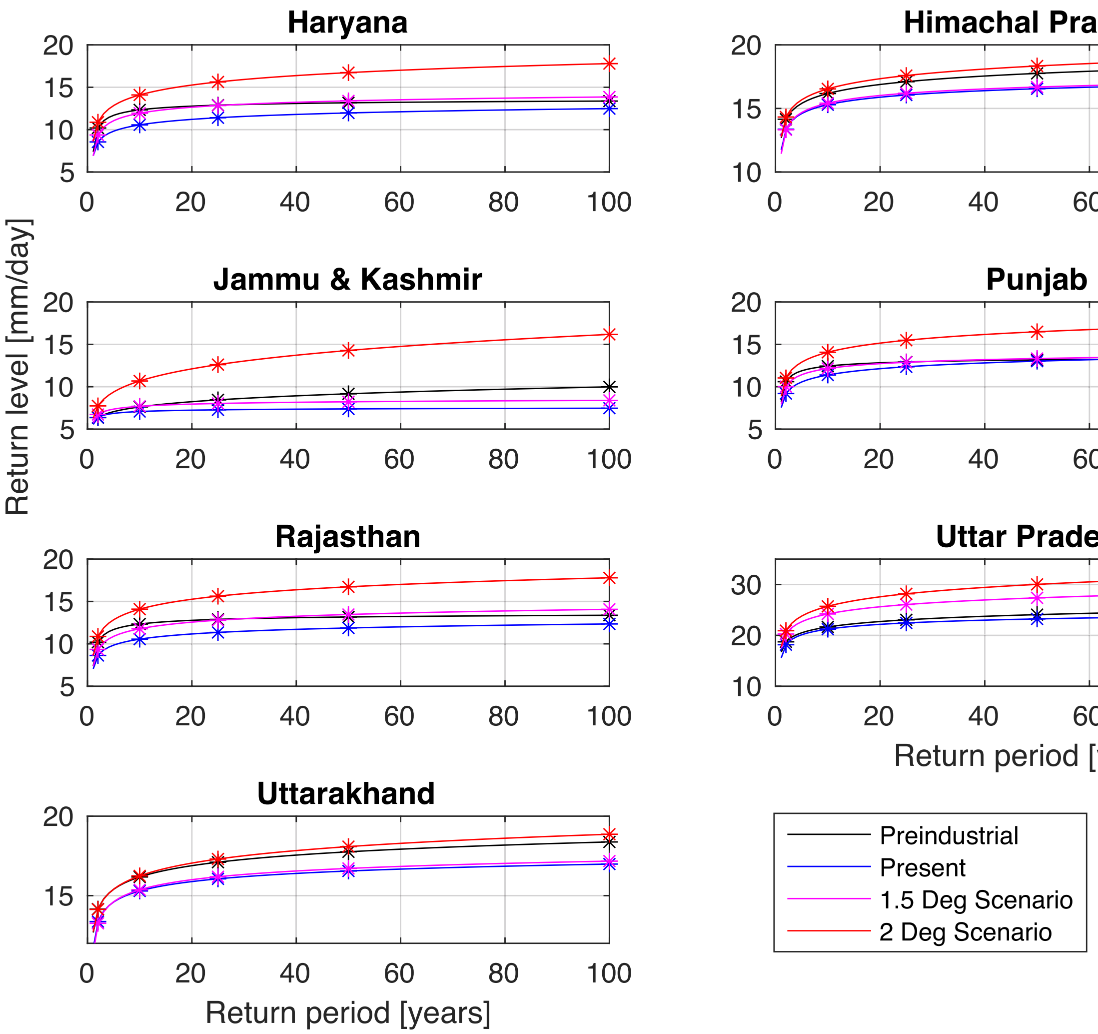

Figure 8. Return period of extreme rainfall events in the preindustrial period, present period, 1.5° scenario and 2.0° scenario as simulated by CMIP5 Models over (a) Haryana, (b) Himachal Pradesh, (c) Jammu and Kashmir, (d) Punjab, (e) Rajasthan, (f) Uttar Pradesh, and (g) Uttarakhand.

Data Availability Statement

All data used in this study are freely available and can be requested from the authors or obtained directly from the source: CRU data (http://www.cru.uea.ac.uk/data), ERA5 data (https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset) and CMIP5 data (https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip5-daily-single-levels?tab=form).

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