

A Shifting Baseline: Projecting Hydrological Paradoxes and Temperature Extremes in Bangladesh via CMIP6 Ensemble

Maesha Mushsharat Aadrita

Center for Environmental and Geographic Information Services

Siam Alam

siam94015@gmail.com

Center for Environmental and Geographic Information Services

Research Article

Keywords: CMIP6, ETCCDI indices, Multi-Model Ensemble (MME), Climate extremes, Shared Socioeconomic Pathways (SSPs), Spatiotemporal projections

Posted Date: October 13th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11340292/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

A Shifting Baseline: Projecting Hydrological Paradoxes and Temperature Extremes in Bangladesh via CMIP6 Ensemble

Abstract

Bangladesh is exceptionally vulnerable to climate change. To investigate evolving precipitation and temperature extremes, this study utilized 13 CMIP6 models under four Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5). Temporal and spatial shifts in core ETCCDI indices were analyzed across three future periods: near (2020s), mid (2050s), and far future (2080s). Probability density functions indicate a definitive shift toward wetter conditions, with extreme anomalies peaking near the century's end. Spatially, distinct hazard hotspots emerge. The historically dry northwestern region will experience the highest increases in total precipitation (PRCPTOT), heavy and extreme rainfall days (R10mm, R95p, R99p), and Consecutive Wet Days (CWD). Conversely, increases in Consecutive Dry Days (CDD) are concentrated in the southern regions. The northeastern region faces the greatest intensifications in absolute extreme events (RX1Day, RX5Day) and overall precipitation intensity (SDII). Thermally, a severe warming trajectory is projected nationwide, characterized by a collapsing frequency of cold days (TX10p) and a massive increase in warm days (TX90p). These high-resolution projections identify critical climate hotspots, equipping local decision-makers with the scientific basis necessary for proactive disaster management and adaptive infrastructure planning.

Keywords: CMIP6; ETCCDI indices; Multi-Model Ensemble (MME); Climate extremes; Shared Socioeconomic Pathways (SSPs); Spatiotemporal projections.

1. Introduction

One of the most crucial topics of current climate research is the impact of global climate change on water supplies, agricultural production, ecosystems, and other areas of human social life. (Piao et al. 2010; Seddon et al. 2016; IPCC 2018; Gou et al. 2020). Due to global climate change and anthropogenic emissions, rainfall and temperature patterns are changing at varying rates in various parts of the world. (Khan et al. 2020). From 1880 to 2012, mean temperature has increased by about 0.85 °C (0.65-1.06 °C) globally (Compo et al. 2013). Surface temperature is expected to continue to increase globally, and major changes are likely to occur in the global hydrological and energy cycles under the changing climate (McCarthy et al., 2001). Global warming has exerted strong influences all over the globe on various aspects of human society and the environment, mainly through changes in climate extremes (Field et al., 2012). Increased intensity of precipitation extremes, a sharp decline in the number of wet spell lengths, and an increase in dry spell lengths are also being observed (Giorgi et al., 2019). In more than 80% of regions in the world, the probability of extreme events has increased due to global warming, and in nearly half of the world, the probability of extreme rain and drought has increased due to the impact of human activities (Diffenbaugh et al., 2017). According to the Intergovernmental Panel on Climate Change (IPCC), climate change is “a change in the state of the climate that can be identified (e.g. using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer”. According to the IPCC's Fourth Assessment Report (2007), the 100-year linear trend of global average surface temperature (1906-2005) is 0.74 (0.56 to 0.92) °C, which is higher than the corresponding trend of 0.6 (0.4 to 0.8) °C. (1901-2000). According to the report, precipitation has either increased or decreased in different parts of the world from 1900 to 2005, and the area impacted by drought may have increased globally since the 1970s (IPCC, 2007).

Global climate models (GCMs) generally use mathematical equations derived from physical principles to simulate atmospheric circulation and global climate (Wright et al. 2015). GCMs are continuously updated and improved. These updates are organized through Coupled Model Intercomparison Projects (CMIP) by the Intergovernmental Panel on Climate Change (IPCC) (Kamal et al. 2021). All the new phases of the Coupled Model Intercomparison Project (CMIP) aim at the newer generations of GCMs to demonstrate improvements over the previous ones, as models increasingly improve in terms of their computational efficiency, resolution, and representation of physical processes (Almazroui et al. 2021). The latest Coupled Model Intercomparison Project Phase 6 (CMIP6) offers improved ways of simulating extreme temperatures globally, compared to its predecessor CMIP5 (Zhu et al. 2021). In CMIP6 (CMIP6, O'Neill, 2016; Petrie et al. 2021), GCMs are forced with a new set of scenarios, which are a combination of Shared Socioeconomic Pathways (SSPs; Riahi et al. 2017) and Representative Concentration Pathways (RCPs; van Vuuren et al. 2011), to understand the Earth system response to increased anthropogenic forcing (Almazroui et al. 2021). Improved resolution, dynamic framework, and parameterization schemes are also observed in CMIP6 (Eyring et al. 2019). CMIP5 used older emission scenarios called Representative Concentration Pathways (RCPs) (Zhang et al. 2019). In recent years, CMIP GCMs have become a major and vital tool for projecting future climatic changes (Fan et al. 2021) and have been commonly used for climate change hazard and risk assessments (Almazroui et al. 2021). A number of studies recently conducted by Fan et al. 2020; Grose et al. 2020; Li et al. 2021; Lovino et al. 2021; and Srivastava et al. 2020 have already investigated the performance of CMIP6 in simulating regional historical climate and achieved positive results. Unfortunately, there are only a few climate projection studies over Bangladesh using CMIP6.

Bangladesh is one of the most sensitive countries to the effects of global climate change in terms of rainfall variability; hence, the impact of climate change on rainfall variability in Bangladesh could be disastrous. Deforestation, declining water bodies, air pollution, El Niño and La Niña effects, and other natural and human-induced variables can all contribute to rainfall variability in Bangladesh (Upal 2019). Agriculture and food

security, water resources, ecosystems and biodiversity, human health, socioeconomic conditions, and so on are all affected by rainfall variability. A number of climate change studies have so far been conducted in Bangladesh. For example, Syed et al. (2016), Basak et al. (2013), and Upal (2019) analyzed changing rainfall trends over Bangladesh; Warrick et al. (1994), Karmakar & Shrestha (2000), and Debsarma (2003) assessed the changes in temperature and precipitation over Bangladesh, while Chowdhury and Debsarma (1992) and Mia (2003) reported temperature changes based on analysis of historical data from some selected weather stations in Bangladesh. The consequences of climate change on natural disasters were assessed by Karmakar and Nessa (1997) and Karmakar (2003). Syed et al. (2016) examined the changing trend of rainfall in Bangladesh from 1978 to 2007 and discovered that the average rainfall trend in the pre-monsoon and winter seasons is negative. This study reported an incoherent pattern in the monsoon advancement (southeast to northwest), with the northeast region showing an uncommon early onset compared to the conventional monsoon progression from southeast to northwest. Basak et al. (2013) examined precipitation data from 34 meteorological stations from 1976 to 2008. Some weather stations showed an increasing tendency in rainfall data throughout the monsoon and post-monsoon seasons over the same study period, while some weather stations showed a dropping trend in total rainfall during the winter. A considerable shift in total rainfall during the pre-monsoon season was also reported. Upal (2019) analyzed the rainfall trends of Bangladesh for 1975-2013 and found that in most parts of the country, annual, monsoon, pre-monsoon, and winter rainfall has declined. Only in the post-monsoon season has a rising tendency been observed. The greatest drop was seen in the northeastern area of the country, which is notorious for having the highest rainfall. Only the southeast region, on the other hand, showed an increasing tendency. Throughout the country rainfall increases in the post-monsoon season whereas it decreases in the other three seasons, implying a shift in the rainy season. Kamal et al. (2021) used a 25 km x 25 km dataset from CMIP6 GCMs for two shared socioeconomic pathway (SSP) scenarios, SSP1-1.9 and SSP1-2.6, and 1.5 and 2 °C temperature rise scenarios to evaluate possible changes in rainfall and droughts in Bangladesh. An increase in annual rainfall over Bangladesh for both scenarios was found in the study.

In the past, various studies have also been conducted on climate extremes, which conclude that this region is experiencing notable changes in the pattern of climate extremes (Shahid 2009, SMRC 2009, Nowreen et al. 2010, Basher et al. 2017, Khan et al. 2020). These studies used the climate extremes indices defined by the Expert Team on Climate Change Detection and Indices (ETCCDI). The ETCCDI indices are easy to understand as they represent relatively frequent extreme meteorological events in a given year or month (Kharin et al., 2013). Most of the studies conducted on extreme events in Bangladesh were focused on the change in mean value (Shahid 2009, SMRC 2009, Nowreen et al. 2012) or observed the future trend (Shahid 2011, Khan et al. 2020). Khan et al. (2020) investigated the changes in the extreme rainfall and temperature indices all over Bangladesh at specific warming levels (SWLs) of 1.5 °C, 2 °C, and 4 °C and compared them with a baseline period of 1986-2005 using high-resolution regional climate projections from the Coordinated Regional Climate Downscaling Experiment (CORDEX), forcing the corresponding GCM with Representative Concentration Pathway (RCP) 8.5. They found overall upward changes in warm indices and downward changes in cold indices, and a higher increase in temperature during the winter and post-monsoon seasons. A general increase in the 1-day (Rx1day) and 5-day (Rx5day) rainfall, an increase in consecutive dry days (CDD) over the northeast region, and an increase in extreme rainfall over the southeast region were also predicted. Nowreen et al. (2010) used a 25 km × 25km dataset from the Hadley Centre's high-resolution regional climate model known as PRECIS and reported an increased variability of rainfall during the pre-monsoon season. A significant increase in both Rx1day and Rx5day (5-day maximum rainfall) was projected. A rightward shift in the probability distribution functions indicated an increase in the amount of total rainfall. The decrease in consecutive wet days (CWD) is found to be more noticeable than that of consecutive dry days (CDD). On the other hand, Basher et al. (2017) observed a decrease in the rainfall indices over the same area using the ERA-Interim and WFDEI dataset from 1984 to 2016. They reported a decreasing trend in the seasonal total rainfall and CWD but an increasing trend in CDD, and a

decreasing trend in Rx1day and Rx5day. However, no comprehensive studies on climate extremes, using the projection of recently available CMIP6 GCMs, have been conducted yet.

The objective of this study is to project a number of rainfall and temperature indices all over Bangladesh using thirteen CMIP6 GCMs for SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5 scenarios (Table 1). The projections are used to evaluate the change in frequency and intensity of rainfall and temperature and to assess the spatiotemporal change in their pattern for near (2015-2040, i.e., 2020s), mid (2041-2070, i.e., 2050s), and far (2071-2100, i.e., 2080s) future.

Table 1: Shared Socio-economic Pathways

SSP	Description	Scenario
SSP1-2.6	Sustainability (Taking the Green Road)	Low GHG emissions: CO ₂ emissions cut to net zero around 2075
SSP2-4.5	Middle of the road	Intermediate GHG emissions: CO ₂ emissions around current levels until 2050, then falling but not reaching net zero by 21
SSP3-7.0	Regional rivalry (A Rocky Road)	High GHG emissions: CO ₂ emissions double by 2100
SSP5-8.5	Fossil-Fueled Development (Taking the Highway)	Very high GHG emissions: CO ₂ emissions triple by 2075

2. Study Area

Bangladesh is a small deltaic country bordered by India to the west, north, and east, Myanmar to the southeast, and the Bay of Bengal to the south. It is located between 20°34 and 26°38 north latitude and 88°01 to 92°41 east longitude (Figure 1) (Alam et al., 2023; Rahman & Alam, 2024; Sakib et al., 2023). The country is a low-lying floodplain of the three major rivers Ganges, Brahmaputra, and Meghna (GBM) (Khan et al. 2020). The topography of the country is rather flat, with elevations ranging from 1 to 5 meters in major portions and a few elevated hilly regions in the northeast and southeast (Kamal et al. 2021).

A subtropical climate in the center-north and a tropical climate in the south prevail. Seasonal variation in rainfall and temperature is observed here (Rashid 1991). Bangladesh experiences four distinct seasons: winter (Dec-Feb), pre-monsoon (Mar-May), monsoon (Jun-Sept), and post-monsoon (Oct-Nov). Key characteristics of these seasons are listed in Table 2.

Table 2: Seasonal rainfall and temperature characteristics of Bangladesh

Season	Duration	Characteristics
Pre-monsoon	Mar - May	High temperatures, low amount of rainfall, thunderstorms, northwester and hailstorms
Monsoon	Jun-Sept	Heavy rainfall, about 70% of the annual rainfall
Post-monsoon	Oct-Nov	Moderate rainfall
Winter	Dec-Feb	Lowest temperature, Occasional rainfall

The Southwest monsoon, which originates over the Indian Ocean, is primarily responsible for precipitation. The monsoon passes through the country in October, but rainfall might linger until November, especially in the southeast, or when a cyclone strikes. Pre-monsoon weather is characterized by high temperatures and the

occurrence of thunderstorms. It is the hottest season of the year, and rainfall is common, along with northwesterly winds and hailstorms, as well as the return of tornadoes (Upal 2019). About 70% of the total annual rainfall is received during the monsoon, whereas the pre-monsoon and post-monsoon seasons receive relatively low amounts of rainfall, with rare and occasional rainfall events during winter (Khan et al. 2020). Weak tropical depressions brought by rainy monsoon winds from the Bay of Bengal result in substantial rainfall during the monsoon season (Ahmed and Kim, 2003). The winter season is very arid and contributes less than 4% of the total annual rainfall (Upal 2019). The wind from the Mediterranean region blows into the country from the northwestern section of India along the Ganges basin, bringing rain in the winter (Upal 2019). The humid, warm climate prevailing here is influenced by pre-monsoon, monsoon, and post-monsoon circulations, with significant rainfall and tropical cyclones occurring often.

Bangladesh was identified as the thirteenth most affected country to extreme climate events between 1995 and 2024, according to the Germanwatch long-term Climate Risk Index (CRI) (Adil et al., 2025). Bangladesh's historical climate has had average temperatures of roughly 26°C, with temperatures ranging from 15°C to 34°C throughout the year. The rainy season (April-September) coincides with the warmest months, whereas the winter season (December-February) is cooler and drier. The country's average temperature ranges from 18.5°C to 21.0°C in the winter and 27.8°C to 29.0°C in the summer. The average annual relative humidity ranges from 70.5 percent to 78.1 percent, with a high in September and a low in March (Rashid 1991).

A noticeable regional difference in rainfall and temperature can be observed in Bangladesh, despite this being a monsoon-dominated country (Khan et al. 2019). The average annual rainfall here is 2,200 millimeters (mm). Most places receive at least 1,500 mm of rain each year, with some receiving as much as 5,000 mm, such as the north-eastern border regions. Humidity is high throughout the year, with the monsoon season being the most humid (June to October). About 20% of the land gets flooded annually owing to heavy rainfall and flat topography (Khan et al. 2020). Along with floods and riverbank erosion, the country experiences natural disasters like cyclonic and storm surges in the southeast coastal region, drought in the northwest region, and pre-monsoon flash floods in the northeast region (Islam et al. 2012, Khan et al. 2020).

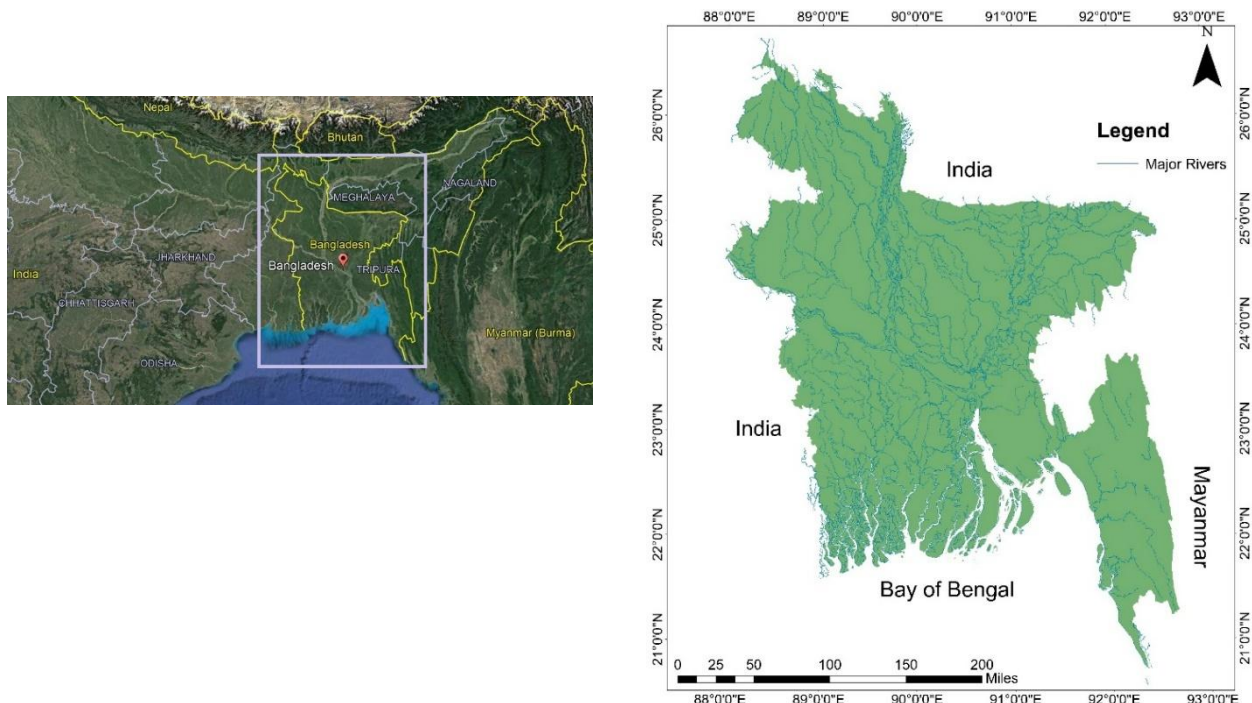


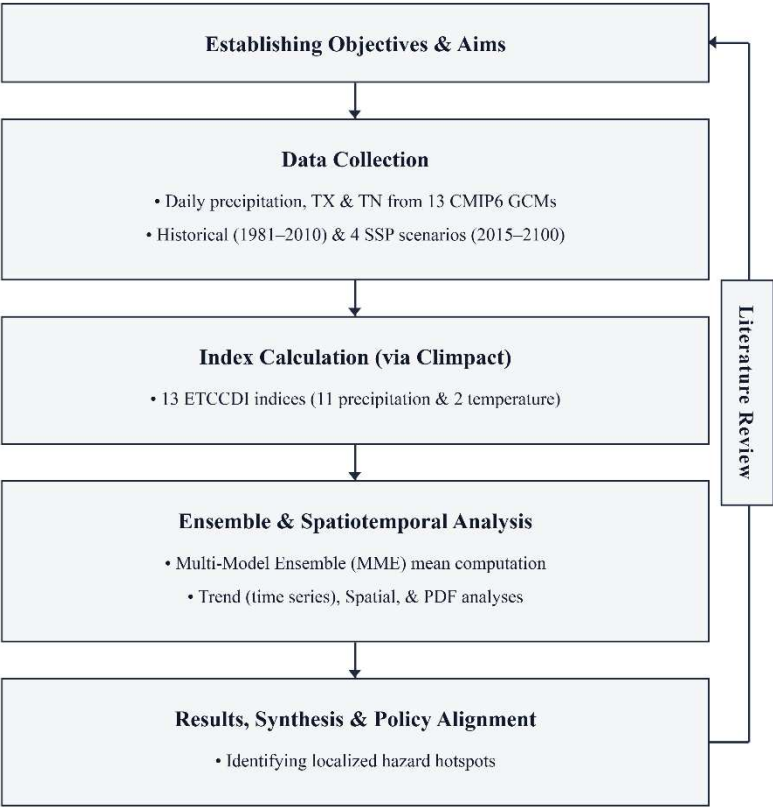
Figure 1: Study Area (Bangladesh)

176

177 **3. Methodology**

178
179
180
181
182
183
184
185
186
187
188
189

The methodology (Figure 2) begins with the extraction of daily precipitation, maximum temperature (TX), and minimum temperature (TN) datasets from 13 General Circulation Models (GCMs) participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) covering a historical baseline (1981–2010) and four future Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) through 2100. Bias corrected and downscaled datasets developed by Mishra et al. (2020) through the Empirical Quantile Mapping (EQM) technique have been employed in this study. Subsequently, 13 standardized climate extremes indices established by the Expert Team on Climate Change Detection and Indices (ETCCDI) are computed using the Climpack software package. Finally, to mitigate individual model uncertainties and isolate the forced anthropogenic climate signal, a Multi-Model Ensemble (MME) mean is generated. This ensemble output serves as the foundation for a comprehensive tri-fold evaluation comprising temporal time-series trend analysis, spatial variation mapping across three future time slices, and Probability Distribution Function (PDF) curve assessments.



190

191

Figure 2: Overall methodology of the study.

192

193 **3.1 Climate Model Data and Bias Correction Strategy**

194
195
196

To project the future evolution of hydro-meteorological extremes over Bangladesh, this study utilized daily precipitation, maximum temperature (TX), and minimum temperature (TN) outputs from 13 General Circulation Models (GCMs) participating in the Coupled Model Intercomparison Project Phase 6 (CMIP6) (Table 3). The

selected models represent a diverse array of global climate modeling centers, providing a robust foundation for capturing large-scale atmospheric and oceanic circulation changes under varying radiative forcing scenarios.

Because raw GCM outputs often exhibit systematic spatial and temporal biases, particularly in complex, monsoon-dominated deltaic regions like Bangladesh, this study employed a bias-corrected dataset developed by Mishra et al. (2020). The dataset provides a high-resolution grid ($0.25^\circ \times 0.25^\circ$) structured at a daily temporal resolution. The bias correction was executed using the Empirical Quantile Mapping (EQM) technique. EQM is a rigorous statistical method that calibrates the simulated cumulative distribution functions (CDFs) of the climate variables against high-resolution observational data, ensuring accurate historical representation of both the mean climatology and the extreme distributional tails. The transformation is mathematically expressed as,

$$x_m^o = f(x_m) \quad (1)$$

Where, x_m^o is the bias-corrected model output. If the statistical distribution of x_m and x_o are known, the transformation can be written as:

$$x_m^o = F_o^{-1}(F_m(x_m)) \quad (2)$$

where F_m and F_o are the Cumulative Distribution Functions (CDFs) of x_m and x_o respectively.

Table 3.1: List of GCMs Used in This Study

No	Model Name	Institution	Resolution
1	ACCESS-CM2	Australian Community Climate and Earth System Simulator, Australia	$0.25^\circ \times 0.25^\circ$
2	ACCESS-ESM1-5	Australian Community Climate and Earth System Simulator, Australia	$0.25^\circ \times 0.25^\circ$
3	BCC-CSM2-MR	Beijing Climate Center and China Meteorological Administration, China	$0.25^\circ \times 0.25^\circ$
4	CanESM5	Canadian Center for Climate Modelling and Analysis, Canada	$0.25^\circ \times 0.25^\circ$
5	EC-Earth3	EC-EARTH consortium, Sweden	$0.25^\circ \times 0.25^\circ$
6	EC-Earth3-Veg	EC-EARTH consortium, Sweden	$0.25^\circ \times 0.25^\circ$
7	INM-CM4-8	Institute for Numerical Mathematics, Russian Academy of Sciences, Moscow, Russia	$0.25^\circ \times 0.25^\circ$
8	INM-CM5-0	Institute for Numerical Mathematics, Russian Academy of Sciences, Moscow, Russia	$0.25^\circ \times 0.25^\circ$
9	MPI-ESM1-2-HR	Max Planck Institute, Germany	$0.25^\circ \times 0.25^\circ$
10	MPI-ESM1-2-LR	Max Planck Institute, Germany	$0.25^\circ \times 0.25^\circ$
11	MRI-ESM2-0	Meteorological Research Institute, Japan	$0.25^\circ \times 0.25^\circ$
12	NorESM2-LM	Climate Modeling Consortium, Norway	$0.25^\circ \times 0.25^\circ$
13	NorESM2-MM	Climate Modeling Consortium, Norway	$0.25^\circ \times 0.25^\circ$

3.2 Standardized Extreme Climate Indices (ETCCDI)

To systematically quantify changes in the intensity, frequency, and duration of extreme weather events, this study analyzed 13 core climate indices (Table 3.2) established by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Kharin et al., 2013). The use of ETCCDI indices ensures globally standardized, statistically comparable metrics that capture the upper and lower extremes of the meteorological spectrum.

Index computation was executed via *Climpack*, an R-based software package that automates the calculation of threshold, percentile, and absolute indices while enforcing rigorous data quality control. The selected indices encompass:

- **Threshold & Duration Indices (CDD, CWD, R10mm):** Evaluate the changing lengths of continuous dry/wet spells and the frequency of heavy rainfall events.
- **Percentile/Extreme Indices (R95p, R99p, Tx10p, Tx90p, R95pTOT, R99pTOT):** Measure anomalies relative to historical 90th, 95th, and 99th percentiles, isolating the most severe hydrological and thermal extremes.
- **Absolute & Intensity Indices (SDII, Rx1day, Rx5day, PRCPTOT):** Provide critical engineering design parameters by evaluating total annual water yields, daily intensity ratios, and maximum multi-day cumulative precipitation.

Table 3.2: List of Indices Used in the Study

Index Type	Index	Long Name	Definition	Unit
Threshold Indices	CDD	Consecutive Dry Days	Maximum Number of Consecutive days with Rainfall < 1mm	days
	CWD	Consecutive Wet Days	Maximum Number of Consecutive days with Rainfall $\geq$ 1mm	days
	R10mm	Number of Heavy Precipitation Days	Annual count of days when Rainfall $\geq$ 10 mm	days
Percentile Indices	R95p	Very Wet Days	Annual total Rainfall when Daily Precipitation > 95th percentile	mm
	R99p	Extremely Wet Days	Annual total Rainfall when Daily Precipitation > 99th percentile	mm
	Tx10p	Cold Days	Percentage of Days when Daily Maximum Temperature < 10th percentile	% days
	Tx90p	Warm Days	Percentage of Days when Daily Maximum Temperature > 90th percentile	% days
	R95pTOT	Total Precipitation from Very Wet Days	Annual total precipitation when daily precipitation > 95th percentile	%
	R99pTOT	Total Precipitation from Extremely Wet Days	Annual total precipitation when daily precipitation > 99th percentile	%
Absolute & Intensity Indices	SDII	Simple Precipitation Intensity Index	Annual total rainfall divided by the number of wet days	mm/day
	Rx1day	Maximum 1-day precipitation	Monthly maximum 1-day precipitation	mm
	Rx5day	Maximum 5-day Precipitation	Monthly maximum consecutive 5-day precipitation	mm
	PRCPTOT	Total Annual Rainfall	Total annual rainfall	mm

3.3 Multi-Model Ensemble, Spatial Mapping, and Probability Distributions

A Multi-Model Ensemble (MME) mean framework was adopted to mitigate individual model structural uncertainties and isolate the forced anthropogenic climate signal. As noted by Knutti et al. (2010) and Brunner et al. (2020), utilizing an MME approach effectively dampens unforced internal variability, providing a more reliable consensus projection than any single GCM. The indices were evaluated over a historical baseline (1981-2010) and projected under four Shared Socioeconomic Pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) across three distinct future time slices: near future (2020s: 2015-2040), mid-future (2050s: 2041-2070), and far future (2080s: 2071-2100).

The analytical phase was divided into three core geospatial and statistical assessments:

1. **Temporal Evolution:** Grid-averaged MME time series (1981-2100) were plotted to evaluate the trajectory of index magnitudes alongside inter-model variance (shaded range), identifying the mid-century divergence of the SSP scenarios.
2. **Spatial Variation:** To identify localized hazard hotspots, percentage change maps were generated for all three future time slices relative to the historical baseline. Geospatial variations were mapped at the 0.25° grid level across the country.
3. **Probability Distribution Functions (PDFs):** To quantify shifts in risk probability, the MME values were fitted to density curves. Comparing the shape and position of the historical PDFs against the future scenarios reveals critical changes in distribution means (rightward/ leftward shifts) and extreme variances (flattening or widening of the distribution tails). The probability density function $f(x)$ for the extremes is defined mathematically as:

$$f(x, \mu, \sigma, \varepsilon) = \frac{1}{\sigma} \left[1 + \varepsilon \left(\frac{x - \mu}{\sigma} \right) \right]^{-\frac{1}{\varepsilon} - 1} e^{\left\{ - \left[1 + \varepsilon \left(\frac{x - \mu}{\sigma} \right) \right]^{\frac{1}{\varepsilon}} \right\}} \quad (3)$$

Where μ , σ , and ε represent the location, scale, and shape parameters, respectively. Comparing the shape and position of the historical PDFs against the future scenarios reveals critical changes in distribution means (rightward/leftward shifts) and extreme variances.

4. Results

For analyzing the spatiotemporal change in future climate index projections, the indices have been presented through time series, spatial plots, and probability distribution functions. Time series represent the temporal evolution of the indices throughout the century. Spatial patterns presented in three future time slices help us understand which index has the minimum or maximum effect over which part of the country, i.e., to find out the hotspots over the country. Probability distribution plots of near, mid, and future time slices will indicate how the probability of extreme events is going to change over the country.

4.1 Temporal Evolution

The multi-model ensemble (MME) mean time series for the period 1981-2100 project significant shifts in climate extremes across the SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios (Figure 3-5). The temporal evolution is evaluated by analyzing both the ensemble mean trajectory and the inter-model variance (shaded regions) to identify the emergence of distinct climate change signals against historical baseline variability.

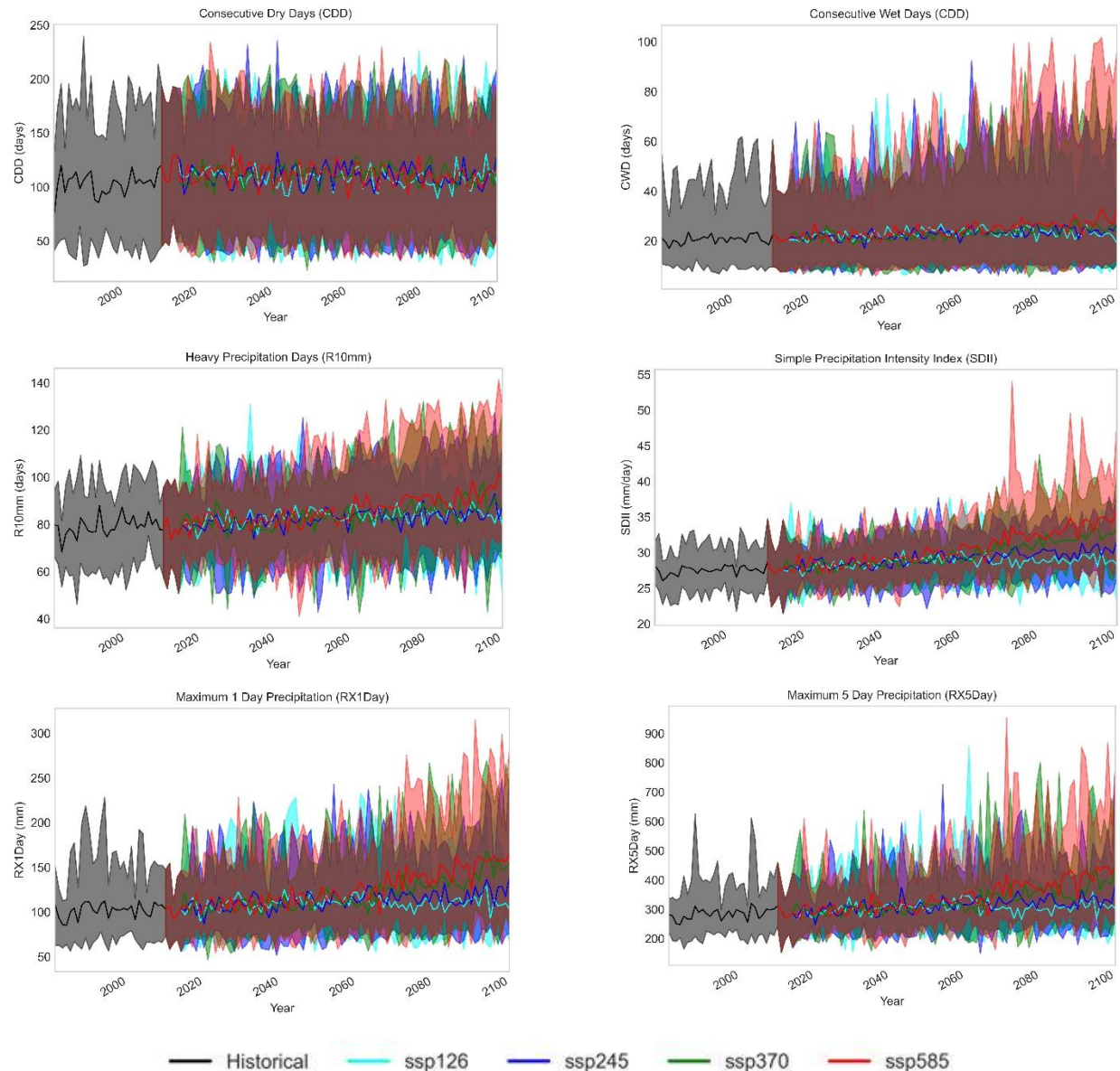


Figure 3: Time series of CDD, CWD, R10mm, SDII, RX1day and RX5day using multi-model ensemble mean for the time period 1981-2100 (horizontal axis represents year and vertical axis represents values of the individual indices). Solid lines represent the multi-GCM ensemble mean, and shading represents the minimum to maximum range of the individual GCMs.

The temporal evolution of precipitation duration and intensity indices indicates a progressive shift toward wetter, more intense hydrological conditions. Consecutive Dry Days (CDD) exhibits a relatively flat trajectory, with the MME mean fluctuating near the historical baseline of 100-110 days across all scenarios through 2100. In contrast, Consecutive Wet Days (CWD) demonstrates an upward trend, rising from a historical mean of 20 days to approximately 30-35 days under SSP5-8.5 by the century's end, with individual model upper bounds reaching nearly 100 days. Up to approximately 2060, the future trajectories for intensity metrics (R10mm, SDII, RX1day, and RX5day) largely overlap, operating within the bounds of historical variance. Post-2060, a clear scenario divergence emerges. SSP1-2.6 and SSP2-4.5 stabilize, whereas SSP5-8.5 dictates the strongest wetting signal. For instance, the MME mean for maximum 5-day precipitation (RX5day) increases from a historical baseline of 300 mm to over 400 mm by 2100 under SSP5-8.5, with maximum model upper bounds exceeding 800 mm.

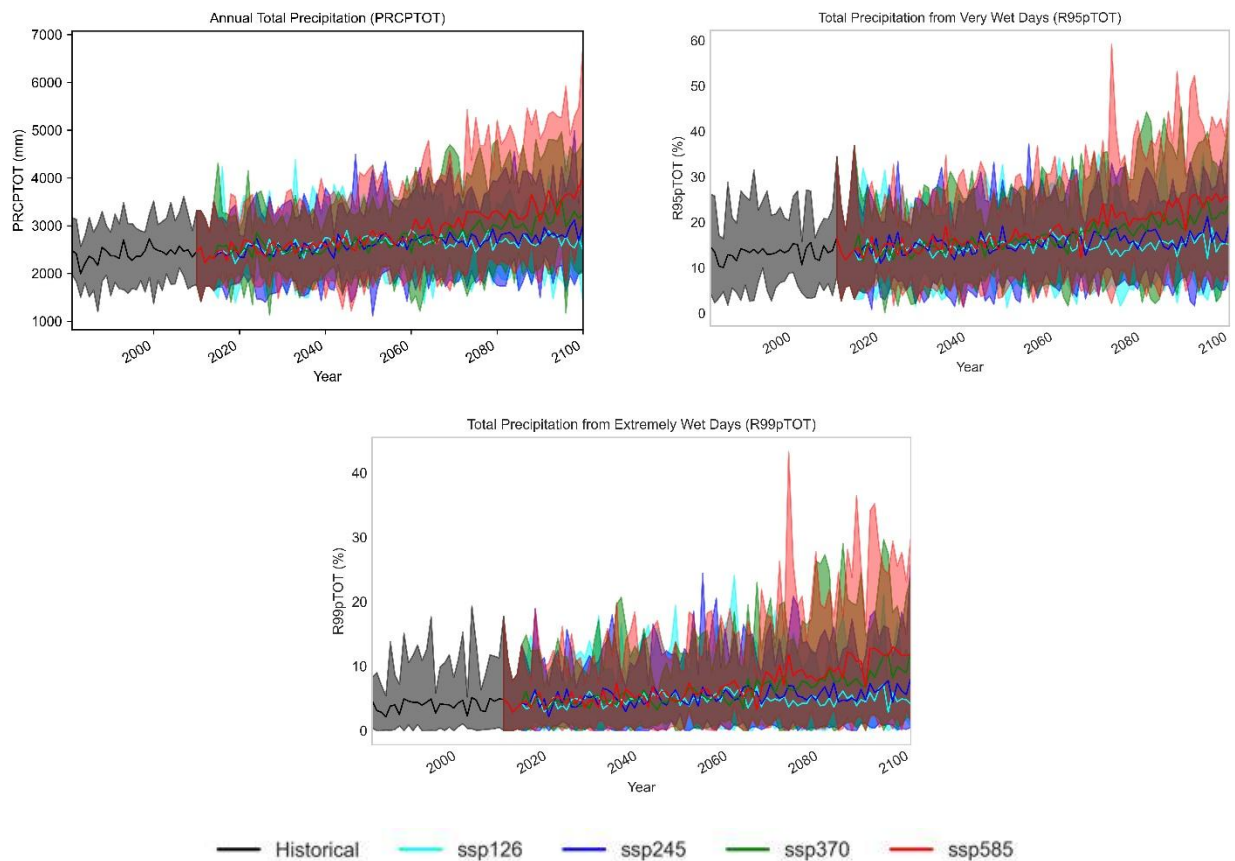


Figure 4: Time series of PRCPTOT, R95pTOT and R99pTOT using the multi-model ensemble mean for the time period 1981-2100 (horizontal axis represents year and the vertical axis represents the values of the individual indices). Solid lines represent the multi-GCM ensemble mean, and shading represents the minimum-to-maximum range of the individual GCMs.

Total annual precipitation (PRCPTOT) and the fractional contribution of extreme events to total rainfall (R95pTOT and R99pTOT) exhibit a similar mid-century divergence point. Prior to 2060, the MME trends progress almost horizontally with a pronounced ensemble spread, suggesting significant internal model variability. In the far future (2080-2100), the trajectories diverge according to radiative forcing. The SSP5-8.5

PRCPTOT MME mean escalates from a historical average of 2,400 mm to nearly 4,000 mm. Furthermore, the contribution of very wet days (R95pTOT) to these annual totals doubles from a baseline of 12-14% to over 25% under SSP5-8.5. Similarly, the contribution of extremely wet days (R99pTOT) to annual totals also increased from 3-4% to over 10% under SSP5-8.5. This indicates that by the end of the century, a substantially larger fraction of the country's annual rainfall will be driven strictly by extreme events.

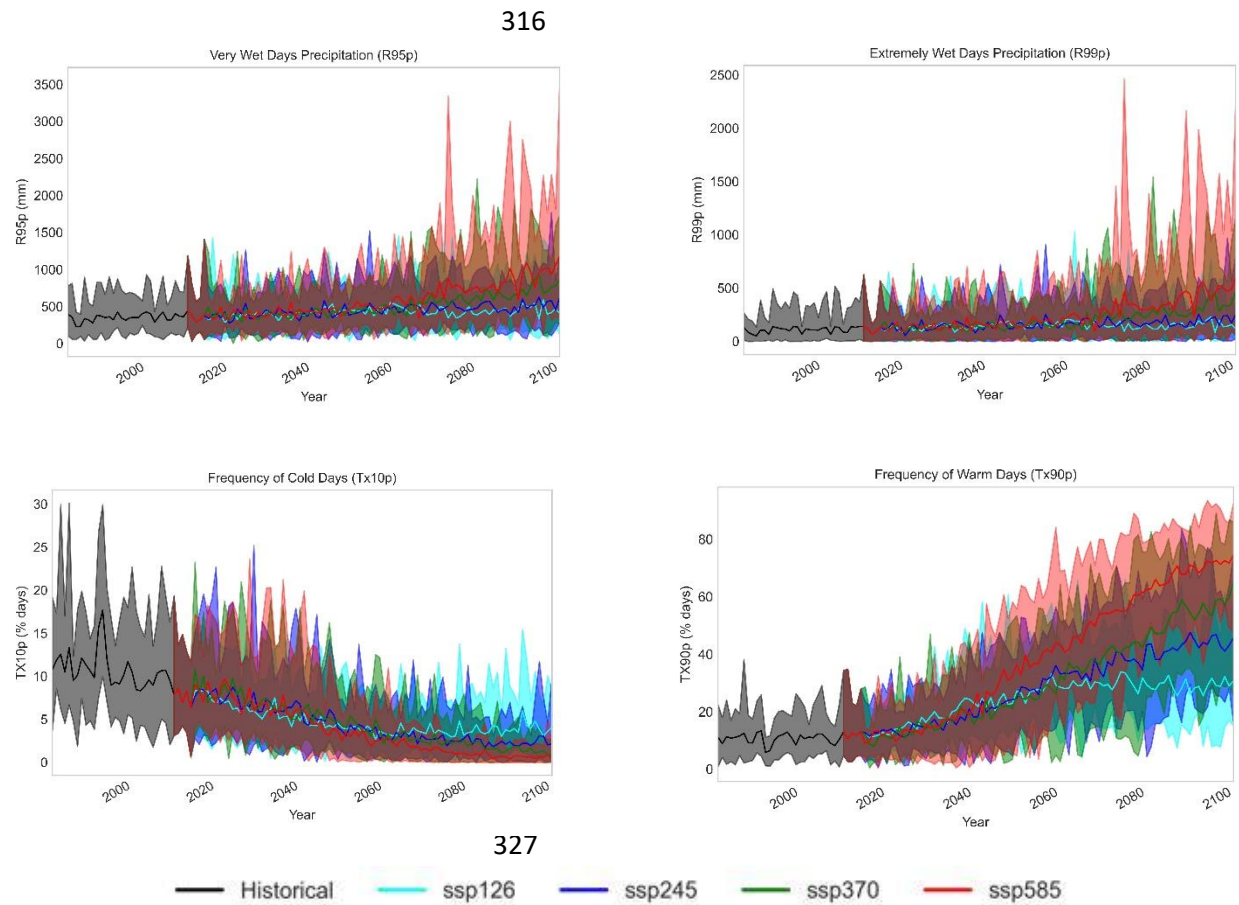


Figure 5: Time series of R95p, R99p, TX10p and TX90p using multi-model ensemble mean for the time period 1981-2100 (horizontal axis represents year and vertical axis represents values of the individual indices). Solid lines represent the multi-GCM ensemble mean, and shading represents the minimum to maximum range of the individual GCMs.

Analysis of the absolute precipitation percentiles (R95p, R99p) and temperature extremes (TX10p, TX90p) reveals the most distinct climate change signals in the dataset. Both R95p and R99p show aggressive upward trends post-2070 under SSP5-8.5; the R95p MME mean nearly triples from a historical 400 mm to roughly 1,100 mm. Conversely, the temperature indices show immediate and stark divergence as early as 2040. The frequency of cold days (TX10p) follows a sharp downward trajectory across all scenarios, declining from the historical 10% baseline to near-zero occurrences under SSP5-8.5 by 2100. Simultaneously, the frequency of warm days (TX90p) escalates from 10% rapidly to approximately 70-75% under SSP5-8.5. While SSP1-2.6 reaches near 30% after 2070, mitigating further extreme warming, SSP5-8.5 projects a continuous, steep climb. This definitively characterizes the far-future climate as both significantly warmer and subject to highly intensified hydrological extremes.

4.2 Spatial Variation

To capture the geographic distribution of evolving climate hazards, the multi-model ensemble (MME) mean was calculated across three future time slices: the near future (2020s, i.e., 2015-2040), mid-future (2050s, i.e., 2041-2070), and far future (2080s, i.e., 2071-2100). The spatial plots (Figure 6-8) illustrate the percentage deviation of these MME means relative to the historical baseline (1981-2010), demonstrating how climatic shifts will manifest regionally across Bangladesh.

4.2.1 Spell Durations, Intensities, and Temperature Shifts

The spatial evolution of spell durations (CDD, CWD) and daily intensities (SDII) reveals a distinct geographic polarization.

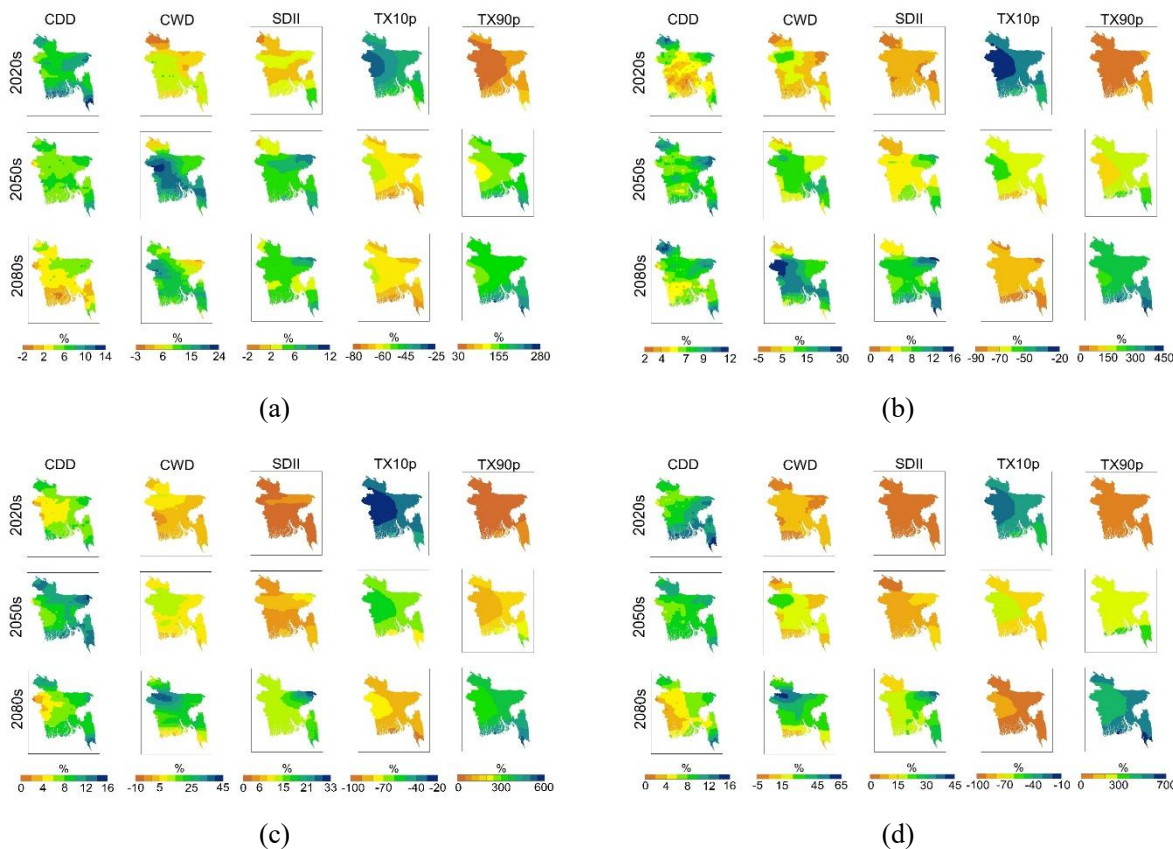


Figure 6: Spatial plot showing percentage change of Multi-Model Ensemble Mean under (a) SSP1-2.6 scenario, (b) SSP2-4.5 scenario, (c) SSP3-7.0 scenario, and (d) SSP5-8.5 scenario of CDD, CWD, SDII, TX10p and TX90p for Near Future (2020s), Mid Future (2050s) and Far Future (2080s).

Consecutive Dry Days (CDD) show a marginal to moderate increase spanning from up to 10% under SSP1-2.6 to a peak of 16% under SSP5-8.5. The highest localized intensifications of dry spells are concentrated in the southern and western coastal regions. Conversely, Consecutive Wet Days (CWD) exhibit a much more pronounced positive shift. This lengthening of wet spells is heavily concentrated in the historically drier northwestern region, reaching up to a 65% increase by the 2080s under the extreme SSP5-8.5 scenario. The Simple Precipitation Intensity Index (SDII) scales congruently with CWD, amplifying by up to 45% under SSP5-8.5, again dominated by the north and northwest regions. Temperature extremes portray a drastic, nationwide shift. The frequency of cold days (TX10p) steadily vanishes over time; under SSP3-7.0 and SSP5-8.5, the occurrence of cold days drops by 40% to 100% across the entire landmass by the far future. Concurrently, the

frequency of warm days (TX90p) experiences an explosive increase, surging by 600% under SSP3-7.0 and up to 700% under SSP5-8.5 by the 2080s, indicating a severe transition to a persistently hotter climate.

4.2.2 Absolute and Percentile Precipitation Extremes

Absolute metrics measuring event-specific precipitation, Maximum 1-day (RX1day) and 5-day (RX5day) rainfall, indicate escalating regional flood potentials.

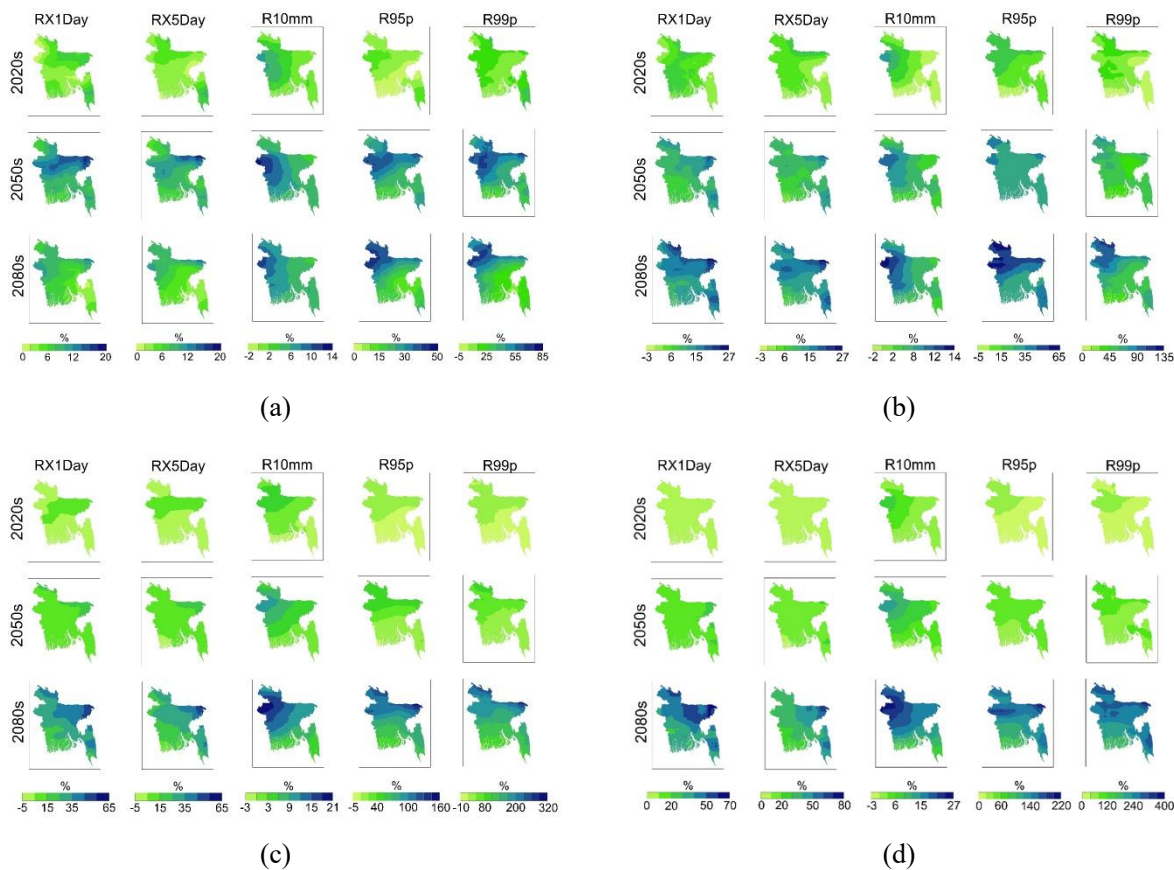


Figure 7: Spatial plot showing percentage change of Multi-Model Ensemble Mean under (a) SSP1-2.6 scenario, (b) SSP2-4.5 scenario, (c) SSP3-7.0 scenario, and (d) SSP5-8.5 scenario of RX1day, RX5day, R10mm, R95p, and R99p for Near Future (2020s), Mid Future (2050s) and Far Future (2080s).

Under the highest radiative forcing (SSP5-8.5), RX1day and RX5day increase by up to 70% and 80%, respectively, by the end of the century. The spatial distribution clearly highlights the northeastern and northern regions as primary hotspots for these absolute extremes, directly compounding the existing flash-flood risks inherent to the northeastern haor basin. The number of heavy precipitation days (R10mm) shows a more muted progression, increasing by up to 27% under SSP5-8.5, mostly in the west and northwest. Percentile indices, Very Wet Days (R95p) and Extremely Wet Days (R99p), display monumental percentage increases. While mid-century shifts under SSP1-2.6 are moderate, far-future surges are extreme. R99p exhibits up to a 320% increase under SSP3-7.0 and an alarming 400% increase under SSP5-8.5. The highest concentrations of these extreme percentile events migrate toward the northwest and northern territories as the century progresses.

4.2.3 Annual Precipitation and Extreme Contributions

The final spatial cluster assesses how the proportion of extreme rainfall influences total annual yields (PRCPTOT, R95pTOT, R99pTOT).

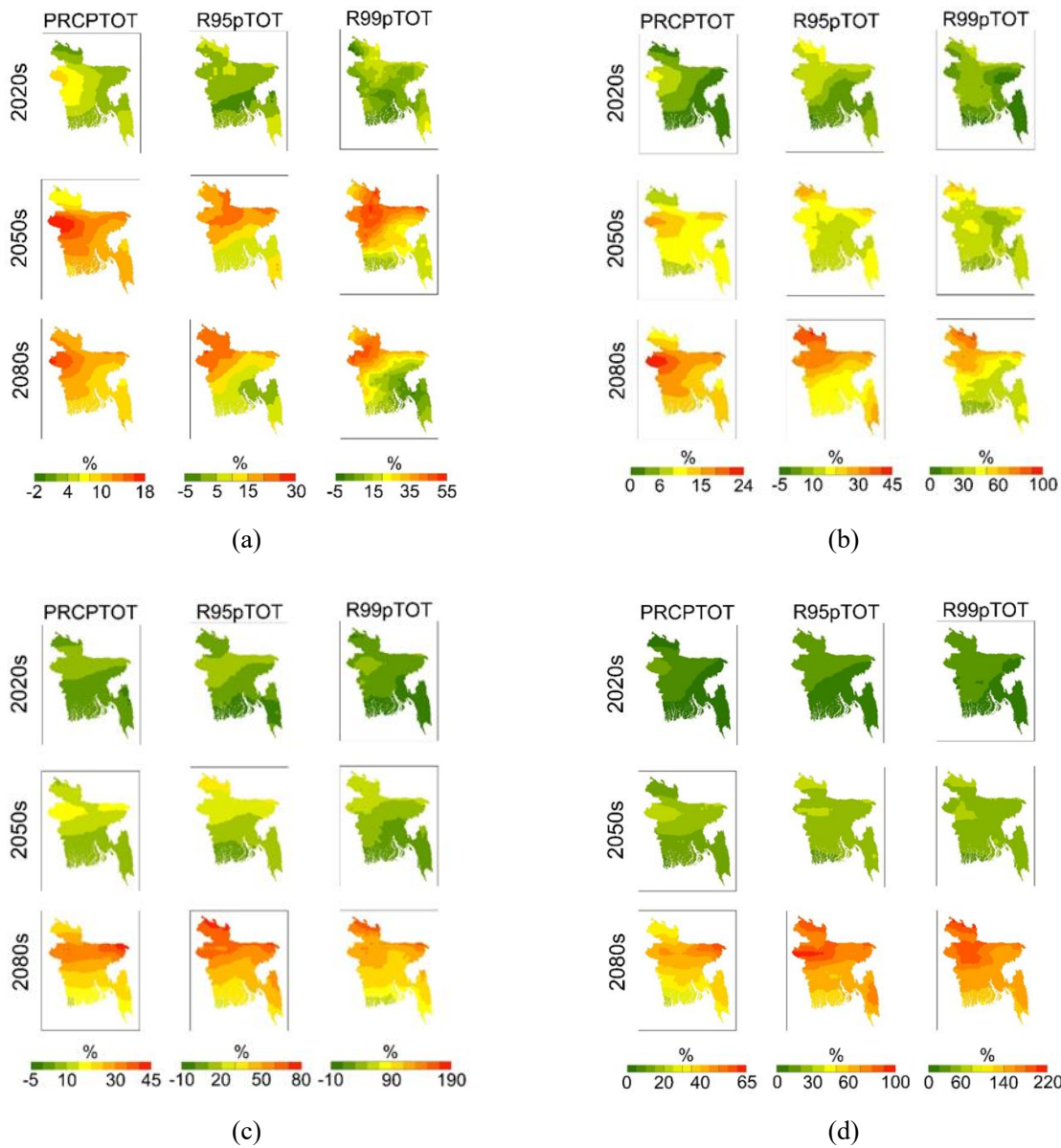


Figure 8: Spatial plot showing percentage change of Multi-Model Ensemble Mean under (a) SSP1-2.6 scenario, (b) SSP2-4.5 scenario, (c) SSP3-7.0 scenario, and (d) SSP5-8.5 scenario of PRCPTOT, R95pTOT and R99pTOT for Near Future (2020s), Mid Future (2050s) and Far Future (2080s).

Total annual precipitation (PRCPTOT) exhibits an expanding positive anomaly across all scenarios. Under SSP5-8.5, PRCPTOT is projected to increase by up to 65% by the 2080s, an anomaly largely anchored in the northwestern quadrant. Crucially, the fractional contributions of very wet (R95pTOT) and extremely wet (R99pTOT) days outpace the baseline PRCPTOT growth. By the 2080s, R99pTOT climbs by up to 100% under SSP2-4.5, up to 190% under SSP3-7.0, and peaks at an increase of 220% under SSP5-8.5. Spatially, this establishes a severe hydrological paradox for the historically dry northwestern region. While this region is projected to receive substantially more total annual rainfall by the century's end, the vast majority of this increase will be delivered in intense, extreme percentile bursts (R95p and R99p) rather than stable, evenly distributed seasonal precipitation.

397 From the spatial plots, it is clearly evident that the change in the climate indices indicates a wetter and warmer
398 climate in the future, with the change taking place slowly throughout the century and reaching its maximum near
399 the end of the century.

400 **4.3 Probability Distribution Functions**

401 Probability distribution functions (PDFs) illustrate the likelihood of specific climate index values occurring,
402 smoothed using a generalized extreme value distribution. In this study, PDFs isolate the shifting mean values
403 and variances between the historical baseline (black line) and four future SSP scenarios (Figure 9-11). A
404 rightward shift in the distribution indicates an increase in the mean value, while a lowering of the peak and
405 widening of the curve (a "fatter tail") indicates increased variability and a higher probability of extreme outliers.

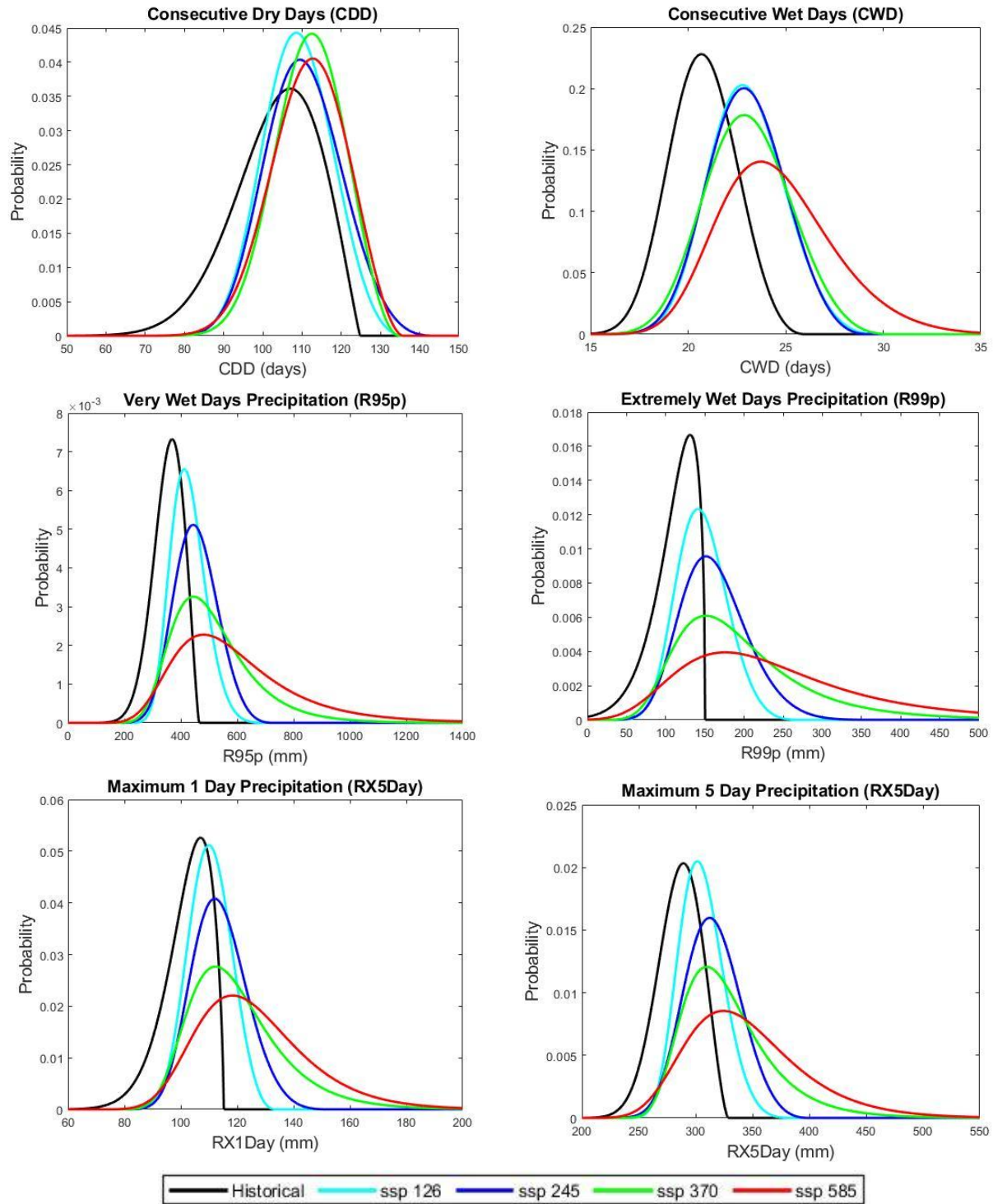


Figure 9: Probability Distribution Functions of CDD, CWD, R95p, R99p, RX1day and RX5day.

The PDFs for Consecutive Dry Days (CDD) show a slight rightward shift, with the peak moving from a historical baseline of roughly 105 days to approximately 110-115 days under the most extreme scenario, SSP5-8.5. Consecutive Wet Days (CWD) display a much more pronounced shift; the historical peak probability occurs at 21 days, but under SSP585, the mean shifts to 24 days, with the right tail stretching well beyond 30 days. The peak probability for CDD rises from 0.035 in baseline to 0.04 under SS5-8.5 while CWD peak drops significantly

from 0.23 to 0.14 under SSP5-8.5, indicating a much wider variance in both dry and wet spell lengths in the future.

The absolute extreme indices, Maximum 1-Day Precipitation (RX1day) and Maximum 5-Day Precipitation (RX5day), both exhibits pronounced rightward shifts. The historical peak of 290 mm shifts to 340 mm under SSP5-8.5, with the extreme right tail extending up to 500 mm with the probability dropping from 0.02 to below 0.01.

Percentile indices R95p (Very Wet Days) and R99p (Extremely Wet Days) show some of the most dramatic shifts in variance in the dataset. The historical peak for R95p sits at 380 mm, but SSP5-8.5 flattens the curve entirely, pushing the peak to 480 mm and extending the right tail beyond 1,200 mm. The R99p index mirrors this; its historical peak of 130 mm shifts to 180 mm, and its probability peak drops from 0.017 to just 0.004 under SSP5-8.5. This severe flattening of the curve reflects a massive increase in the likelihood of historically unprecedented extreme rainfall anomalies.

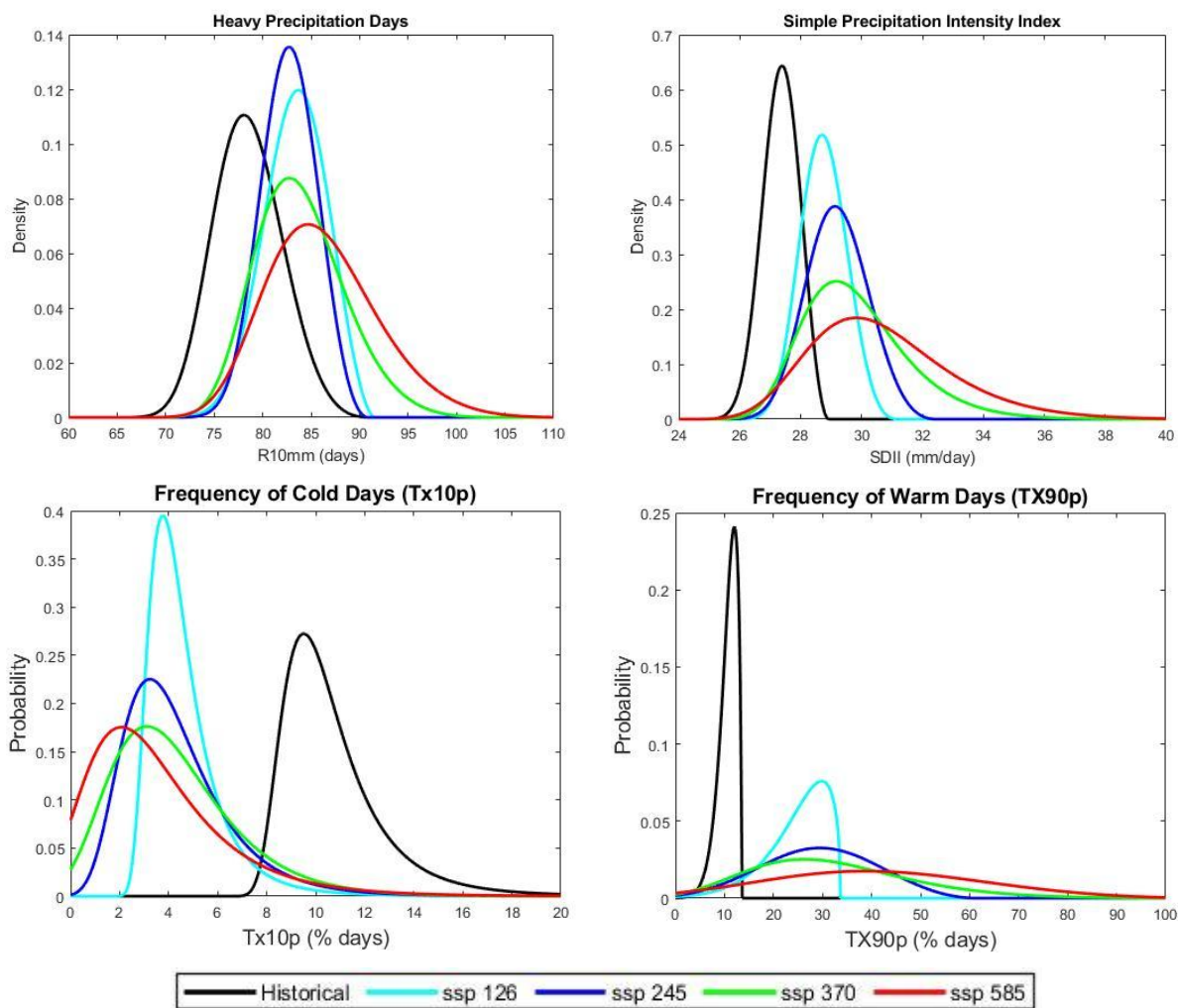


Figure 10: Probability Distribution Functions of R10mm, SDII, TX10p and TX90p.

The intensity metrics echo the widening variance seen in the duration extremes. The Number of Heavy Precipitation Days (R10mm) shifts from a peak of 78 days historically to 86 days under SSP5-8.5, with the distribution widening to include probabilities up to 110 days. The Simple Precipitation Intensity Index (SDII) follows suit, with its historical peak at 27 mm/day shifting to 30 mm/day under SSP5-8.5. Crucially, the peak

probability density for SDII collapses from 0.65 historically to 0.18 under SSP585, as the curve flattens and extends out to 38 mm/day, underscoring a vast increase in day-to-day rainfall intensity fluctuations.

Temperature PDFs present the most severe deviations from the baseline. The Frequency of Cold Days (TX10p) demonstrates a stark leftward shift, moving from a historical peak of 10% down to less than 2% under SSP5-8.5, effectively compressing the probability of cold days to near zero. Conversely, the Frequency of Warm Days (TX90p) exhibits an extreme rightward shift. The sharp, tightly bound historical peak at 12% warm days degrades into a highly dispersed, flattened curve under SSP5-8.5 that spans continuously from 20% to nearly 100%, peaking broadly around 60-70%. This demonstrates a fundamental transition to a highly variable, persistently hotter baseline climate.

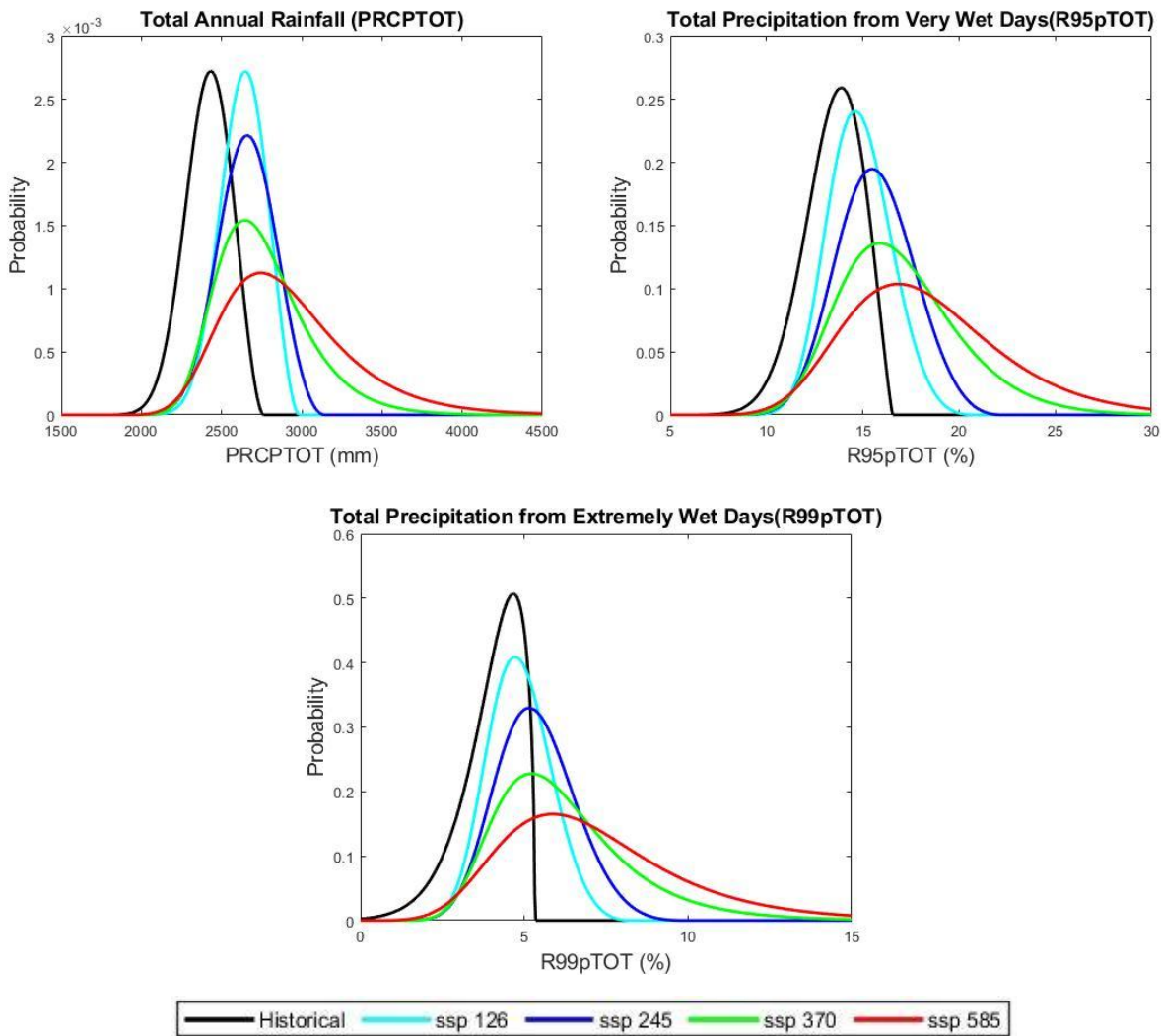


Figure 11: Probability Distribution Functions of PRCPTOT, R95pTOT and R99pTOT.

Total Annual Rainfall (PRCPTOT) shifts rightward from a historical peak of 2,400 mm to 2,800 mm under SSP5-8.5, with the rightward tail stretching up to 4,500 mm. The distributions for R95pTOT and R99pTOT verify that this total annual increase is heavily driven by extreme events. The fractional contribution of R99pTOT shifts from a historical mode of 4% to 6% under SSP5-8.5, while its right tail extends out to 15%. The peak

probability for R99pTOT similarly drops from 0.5 to 0.15 under SSP5-8.5, demonstrating that extreme events will claim a highly variable, but definitively larger, share of the total annual water budget.

5. Discussion

The spatiotemporal and probability distribution function (PDF) analyses of the CMIP6 multi-model ensemble reveal a fundamental shift in the climate baseline of Bangladesh toward more volatile, wetter, and warmer conditions. Transitioning from historical baselines to future Shared Socioeconomic Pathways (SSPs) highlights profound regional disparities in how extreme precipitation and temperature hazards will manifest, directly challenging existing hydro-morphological baselines and adaptive infrastructure design.

One of the most significant and descriptive findings of this study is the projected geographic shift in extreme precipitation. Historically, the northwestern region of Bangladesh has been characterized by recurrent droughts and a long-term declining trend in annual, monsoon, and winter rainfall, as observed by Upal (2019). However, the far-future spatial plots under SSP3-7.0 and SSP5-8.5 demonstrate that this historically dry region will experience the highest percentage increases in extremely wet days (R99p) and consecutive wet days (CWD).

While total annual precipitation (PRCPTOT) in the northwest is projected to increase, the rightward flattening of the R95p and R99p PDFs indicates that this excess water will be delivered almost exclusively through high-intensity, short-duration extreme events rather than stable seasonal rainfall. Recent contemporary CMIP6 analyses by Mishu et al. (2025) corroborate these statistical shifts, indicating that precipitation extremes will exhibit high regional variability and increasingly skew toward flood-inducing events. Further research by Nazrul et al. (2025) and Mirzaei et al. (2024) utilizing CMIP6 ensembles confirms this spatial intensification, projecting significant increases in extreme rainfall under high-emission scenarios (SSP5-8.5) that pose severe risks for the country's water and agricultural security.

In contrast to the northwest, the northeastern haor basin already receives the highest historical rainfall in the country. The MME mean projections indicate that this region will serve as the primary hotspot for absolute extreme precipitation events, specifically Maximum 1-day (RX1day) and Maximum 5-day (RX5day) rainfall. The projected 70% to 80% escalations in these absolute extremes by the 2080s under SSP5-8.5 severely compound the region's existing vulnerability to pre-monsoon flash floods.

These results physically corroborate earlier regional climate model studies. For instance, Nowreen et al. (2010) utilized the PRECIS model to project significant future increases in both RX1day and RX5day alongside an overarching rightward shift in extreme rainfall probabilities over the haor basin. More recent assessments evaluating CMIP6 multi-model ensembles similarly underscore that rising RX1day and RX5day metrics will dramatically amplify flood risks, particularly in these northeastern borderlands. As highlighted by the World Bank's 2024 Climate Risk Profile, northern and eastern divisions are projected to be nearly twice as likely to experience extreme 1-day cumulative precipitation events by midcentury under high-emission pathways (World Bank, 2011).

The temperature indices reflect an aggressive and unmitigated thermal transition. The PDF analysis demonstrates a near-total collapse of the cold day frequency (TX10p) alongside an explosive 600% to 700% surge in warm days (TX90p) under high-emission scenarios. This severe divergence, occurring as early as the 2040s, supports the highly sensitive regional warming trajectories previously identified in the region. Khan et al. (2020) observed that even at specific global warming levels of 1.5 °C and 2.0 °C, Bangladesh experiences acute upward changes in warm indices and corresponding downward trends in cold indices.

Recent projections utilizing CMIP6 models echo these findings, demonstrating that annual maximum temperatures (TXx) and minimum temperatures (TNn) could rise by over 5 °C under SSP5-8.5 by the late 21st century, leading to prolonged heatwaves and elevated nighttime temperatures. Independent assessments by Das et al. (2022) confirm this trajectory, noting that the thermal expansion across the country will be profound and sustained.

The transition toward prolonged wet spells (CWD) and intensified multi-day precipitation (RX5day) places unprecedented hydraulic stress on existing flood defense mechanisms and coastal polders. In the southwest coastal region, this shifting hydrological baseline directly impacts the efficacy of tidal river management systems. As total annual rainfall becomes increasingly concentrated into extreme percentile bursts, hydro-morphological assessments must account for higher peak discharges and elevated riverbank erosion potentials. Understanding the localized intensity of these RX5day and R99p hotspots is specifically vital for calibrating and evaluating the solutions outlined in the Bangladesh Delta Plan 2100. As extreme weather variability exacerbates the nation's infrastructural vulnerabilities, aligning these localized extreme index projections with the broader developmental and waterlogging mitigation goals of BDP 2100 is critical for ensuring long-term resilience.

While the robust multi-model ensemble limits individual model bias, the divergence of the SSP trends post-2060 underscores the inherent uncertainty of global emission trajectories. As noted by Knutti et al. (2010) and Brunner et al. (2020), combining projections from multiple climate models involves uncertainties related to internal climate variability and model response. Future assessments utilizing dynamic downscaling with finer parameterization schemes (Zhu et al., 2021) will be critical to further refining the physical processes governing these regional extremes. Furthermore, addressing systematic wet biases that still persist in some CMIP6 configurations over South Asia remains a crucial priority for refining regional projections moving forward.

6. Conclusion:

This study projected future precipitation and temperature extremes across Bangladesh using a multi-model ensemble (MME) of 13 CMIP6 General Circulation Models. By evaluating thirteen core ETCCDI indices over a historical baseline (1981-2010) and three future time slices (2020s, 2050s, and 2080s) under four Shared Socioeconomic Pathways (SSPs), the research establishes a definitive shift toward a warmer, wetter, and increasingly volatile climate baseline. The spatiotemporal and probability distribution analyses yield several critical insights:

- **Intensification of Extreme Precipitation:** The climate is shifting toward a regime where extreme, short-duration events dominate the annual water budget. The intensity of single rainfall events (SDII) and the frequency of heavy precipitation days (R10mm) will increase significantly, with the contribution of extremely wet days (R99pTOT) amplifying by up to 220% under high-emission scenarios (SSP5-8.5) by the 2080s.
- **The Northwestern Hydrological Paradox:** Historically the driest region, the northwest is projected to experience the nation's highest percentage increases in total annual precipitation (PRCPTOT) and consecutive wet days (CWD). However, this increase is driven almost entirely by extreme percentile bursts, indicating heightened spatial volatility rather than stabilized seasonal water availability.
- **Amplified Haor Basin Flood Risks:** While the northwest sees the highest relative percentage changes, the absolute rainfall extremes (RX1day and RX5day) will peak in the northeastern haor basin. This localized intensification directly heightens the vulnerability to, and expected frequency of, severe pre-monsoon flash floods.

- **Unmitigated Thermal Shifts:** The thermal baseline will transition aggressively. Across all scenarios, the frequency of cold days (TX10p) trends toward near-zero occurrences by the end of the century. Simultaneously, the frequency of warm days (TX90p) expands drastically, completely altering the historical temperature probability distribution.

Given Bangladesh's acute climate vulnerability, these projections present immediate challenges for national infrastructure. The pronounced lengthening of wet spells and the concentration of annual rainfall into extreme anomalies necessitate the recalibration of regional hydraulic structures and flood defense mechanisms. Integrating these high-resolution extreme indices into the adaptive planning frameworks of the Bangladesh Delta Plan 2100 will be essential for mitigating escalating flash-flood risks in the northeast and managing altered, extreme water yields in the northwest.

While the CMIP6 multi-model ensemble successfully mitigates individual model biases, uncertainties remain regarding future emission trajectories and internal climate variability. Future research must prioritize dynamic downscaling to better resolve localized physical processes and incorporate season-specific assessments to capture Bangladesh's profound intra-annual variability, ultimately refining the predictive tools available for proactive disaster management.

References

- Adil, L., Eckstein D., Kunzzel, V and Schafer, L. (2025) Global Climate Risk Index 2026: Who Suffers Most from Extreme Weather Events? Germanwatch e.V.
- Ahmed, A.S.M.S. and Kim I.K., 2003. Patterns of daily rainfall in Bangladesh during the summer monsoon season: Case studies at three stations. *Physical Geography*, 24: 295-318
- Alam, S., Hasan, F., Debnath, M., & Rahman, A. (2023). Morphology and land use change analysis of lower Padma River floodplain of Bangladesh. *Environmental Monitoring and Assessment*, 195(7), 886. <https://doi.org/10.1007/s10661-023-11461-w>
- Almazroui M et al (2021) Assessment of CMIP6 Performance and Projected Temperature and Precipitation Changes Over South America. *Earth Systems and Environment* (2021) 5:155-183
- Basak, J.K., Titumir, R.A.M. and Dey, N.C., 2013. Climate Change in Bangladesh: A Historical Analysis of Temperature and Rainfall Data. *Journal of Environment*, 2(2): 41-46
- Basher MA, Stiller-Reeve MA, Islam AKMS, Bremer S (2017) Assessing climatic trends of extreme rainfall indices over northeast Bangladesh. *Theor Appl Climatol* 134:441-452
- Bourdeau-Goulet, S.-C., & Hassanzadeh, E. (2021). Comparisons between CMIP5 and CMIP6 models: Simulations of climate indices influencing food security, infrastructure resilience, and human health in Canada. *Earth's Future*, 9, e2021EF001995.
- Brunner L, Pendergrass AG, Lehner F, Merrifield AL, Lorenz R, Knutti R (2020) Reduced global warming from CMIP6 projections when weighting models by performance and independence. *Earth Syst Dyn* 11:995-1012
- Chen HP, Sun JQ. (2015) Assessing model performance of climate extremes in China: an intercomparison between CMIP5 and CMIP3. *Clim Change* 129:197-211
- Chen, Z., Zhou, T., Zhang, L., Chen, X., Zhang, W., & Jiang, J. (2020). Global land monsoon precipitation changes in CMIP6 projections. *Geophysical Research Letters*, 47(14), e2019GL086902
- Chowdhury, M.H.K., and Debsarma, S.K. (1992) Climate change in Bangladesh - A statistical review. Report of IOC-UNEP Workshop on Impacts of Sea Level Rise due to Global Warming, NOAMI, November 16-19, 1992, Dhaka, Bangladesh. Intergovernmental Oceanographic Commission.
- Collins, M., et al. (2014) Section 12.3.1.3 The New Concentration Driven RCP Scenarios, and their Extensions, in: Chapter 12: Long-term Climate Change: Projections, Commitments and Irreversibility. IPCC AR5 WG1 2013, pp. 1045-1047
- Compo GP, Sardeshmukh PD et al (2013) Independent confirmation of global land warming without the use of station temperatures. *Geophys Res Lett* 40:3170-3174
- Das, S., Islam, A., & Kamruzzaman, M. (2022). Assessment of climate change impact on temperature extremes in a tropical region with the climate projections from CMIP6 model. *Climate Dynamics*, 60. <https://doi.org/10.1007/s00382-022-06416-9>
- Debsarma, S.K. (2003) Intra-annual and inter-annual variation of rainfall over different regions of Bangladesh. In: Proceedings of SAARC Seminar on Climate Variability in the South Asian Region and its Impacts, SMRC, December 20-24, 2002, Dhaka, Bangladesh. Dhaka, SAARC Meteorological Research Centre
- Diffenbaugh NS et al (2017) Quantifying the influence of global warming on unprecedented extreme climate events. *Proc Natl Acad Sci* 114:4881-4886
- Di Luca, A., Pitman, A. J., & de Elía, R. (2020). Decomposing temperature extremes errors in CMIP5 and CMIP6 models. *Geophysical Research Letters*, 47(14), 1-10
- Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J., Taylor, K.E., 2016. 575 Overview of the coupled model Intercomparison project phase 6 (CMIP6) experimental 576 design and organization. *Geosci. Model Dev. (GMD)* 9, 1937-1958
- Fan X, Miao CY, Duan QY, Shen CW, Wu Y (2020) The performance of CMIP6 versus CMIP5 in simulating temperature extremes over the global land surface. *J Geophys Res-Atmos* 125(18):e2020JD033031

- Fan X, Duan Q, Shen C, Wu Y, Xing C (2021) Evaluation of historical CMIP6 model simulations and future projections of temperature over the Pan-Third Pole region. *Environmental Science and Pollution Research* (2022) 29:26214-26229
- Field, C. B., and Coauthors, Eds., 2012: *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation*. Cambridge University Press, 582 pp
- Giorgi, F., Raffaele, F., Coppola, E., 2019. The response of precipitation characteristics to global warming from climate projections. *Earth Syst. Dynam.* 10, 73-89. Dio:10.5194/esd-10-73-2019
- Gou J, Miao C, Duan Q, Tang Q, Di Z, Liao W, Wu J, Zhou R (2020) Sensitivity analysis-based automatic parameter calibration of the variable infiltration capacity (VIC) model for streamflow simulations over China. *Water Resour Res* 56:e2019WR025968
- Grose MR, Narsey S, Delage FP et al (2020) Insights from CMIP6 for Australia's future climate. *Earth's Future* 8(5):e2019EF001469
- Gudmundsson, L., Bremnes, J. B., Haugen, J. E. & Engen-Skaugen, T. (2012) Technical Note: Downscaling RCM precipitation to the station scale using statistical transformations – A comparison of methods. *Hydrol. Earth Syst. Sci.* 16, 3383-3390
- Gusain, A., Ghosh, S., & Karmakar, S. (2020). Added value of CMIP6 over CMIP5 models in simulating Indian summer monsoon rainfall. *Atmospheric Research*, 232, 104680
- Haque, M.Z., Quayyam, H.A., Hossian, M.M., and Islam, M.S. (1992) Occurrence of grain sterility in different rice crops. In: Islam, A.K.M.N., Fattah, Q.A., Muttaqi, I.A., and Aziz, A. eds. *Plant Science and Man: problems and Prospects*. Proc. Intl. Bot. Conf., January 10-12, 1991, Bangladesh Bot. Soc., Dhaka, Bangladesh. Dhaka, Bangladesh Bureau of Statistics (BBS), pp. 117-124.
- Hausfather, Z. (2019). CMIP6: The next generation of climate models explained. *Carbon Brief*, December 2. Retrieved from <https://www.carbonbrief.org/cmip6-the-next-generation-of-climate-models-explained>
- IPCC (2018) Summary for policymakers. In: *Global warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways* (World Meteorological Organization, Geneva, Switzerland, 32 pp)
- Islam AKMS, Hasan MA (2012) Climate induced changes of precipitation extremes over Bangladesh. *ICEAB 2012*
- Kamal ASMM, Hossain F, Shahid S (2021) Spatiotemporal changes in rainfall and droughts of Bangladesh for 1.5 and 2 °C temperature rise scenarios of CMIP6 models. *Theoretical and Applied Climatology* (2021) 146:527-542
- Karmakar, S. (2003) Trends in the annual frequency of cyclonic disturbances and storms in the Bay of Bengal. In: *Proceedings of SAARC Seminar on Climate Variability in the South Asian Region and its Impacts*, SMRC, December 20-24, 2002, Dhaka, Bangladesh. Dhaka, SAARC Meteorological Research Centre.
- Karmakar S., and Shrestha M.L. (2000) *Recent Climate Change in Bangladesh*. SMRC Series, no. 4. Dhaka, SAARC Meteorological Research Centre.
- Karmakar, S., and Nessa, J. (1997) Climate change and its impacts on natural disasters and south-west monsoon in Bangladesh and the Bay of Bengal. *Journal of Bangladesh of Academy of Sciences*, 21(2), pp. 127-136.
- Khan MJU, Islam AS, Das MK, Mohammed K, Bala SK, Islam GT (2019) Observed trends in climate extremes over Bangladesh from 1981 to 2010. *Clim Res* 77(1):45-61
- Khan MJU, Islam AK, Bala SK, Islam GT (2020) Changes in climate extremes over Bangladesh at 1.5 °C, 2 °C, and 4 °C of global warming with high-resolution regional climate modeling. *Theoretical and Applied Climatology* (2020) 140:1451-1466
- Kharin, V.V., Zwiers, F.W., Zhang, X., Wehner, M., 2013. Changes in temperature and precipitation extremes in the CMIP5 ensemble. *Climatic Change* 119, 345-357
- Kim, Y.-H., Min, S.-K., Zhang, X., Sillmann, J., & Sandstad, M. (2020). Evaluation of the CMIP6 multi-model ensemble for climate extreme indices. *Weather and Climate Extremes*, 29, 100269
- Knutti R, Furrer R, Tebaldi C, Cermak J, Meehl GA (2010) Challenges in combining projections from multiple climate models. *J Clim* 23:2739-2758
- Kumar D, Kodra E, Ganguly AR. (2014) Regional and seasonal intercomparison of CMIP3 and CMIP5 climate model ensembles for temperature and precipitation. *Clim Dyn* 43:2491-518

- Li Y, Yan D, Peng H, Xiao S (2021) Evaluation of precipitation in CMIP6 over the Yangtze River Basin. *Atmos Res* 253:105406
- Lovino MA, Pierrestegui MJ, Müller OV, Berbery EH, Müller GV, Pasten M (2021) Evaluation of historical CMIP6 model simulations and future projections of temperature and precipitation in Paraguay. *Clim Change* 164(3):46
- McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J., and White, K.S., (2001). "Climate Change 2001: Impacts, Adaptation and Vulnerability". Intergovernmental Panel on Climate Change (IPCC), Work Group II Input to the Third Assessment Report Cambridge University Press: Cambridge
- Merrifield, A. L., Brunner, L., Lorenz, R., Medhaug, I., & Knutti, R. (2020). An investigation of weighting schemes suitable for incorporating large ensembles into multi-model ensembles. *Earth System Dynamics*, 11(3), 807-834
- Mia, N. M. (2003) Variations of temperature in Bangladesh. In: Proceedings of SAARC Seminar on Climate Variability in the South Asian Region and its Impacts, SMRC, December 20-24, 2002, Dhaka, Bangladesh. Dhaka, SAARC Meteorological Research Centre.
- Mirzaei, M., Shirmohammadi, A., Ruiz-Barradas, A., Olson, L. J., & Negahban-Azar, M. (2025). Climate change effects on the spatial and temporal distribution of extreme precipitation in the Mid-Atlantic region. *Urban Climate*, 61, 102382. <https://doi.org/https://doi.org/10.1016/j.uclim.2025.102382>
- Mishra V, Bhatia U, Tiwari AD (2020) Bias-corrected climate projections for South asia from Coupled Model Intercomparison Project-6. *Scientific Data* 7:338 <https://doi.org/10.1038/s41597-020-00681-1>
- Mishu, R., Mallick, J., Akter, M., Fattah, M., Kamruzzaman, M., Salam, M., Pal, S., & Islam, A. (2025). Spatial and temporal variability of future extreme precipitation in Bangladesh using CMIP6 models. *Journal of Water and Climate Change*, 16, 1281-1309. <https://doi.org/10.2166/wcc.2025.415>
- Moss; et al. (2008). Towards New Scenarios for Analysis of Emissions, Climate Change, Impacts, and Response Strategies. Geneva: Intergovernmental Panel on Climate Change. p. 132.
- Nazrul, F., Karim, R., Pavan, W., & Kamruzzaman, M. (2025). Future Climate Extremes in Bangladesh: Insights from a Multi-Model Ensemble of CMIP6 Simulations. *Earth Systems and Environment*, 10, 1369-1388. <https://doi.org/10.1007/s41748-025-00681-4>
- Nowreen S et al (2012) An indicator of climate change in the south west region of Bangladesh. *Int J Clim Chang Impacts Response* 4(3): 47-60
- Nowreen S, Murshed SB, Islam AKMS, Bhaskaran B, Hasan MA (2010) Changes of rainfall extremes around the haor basin areas of Bangladesh using multi-member ensemble RCM. *Theor Appl Climatol*, Springer Nature 119:363-377
- O'Neill BC, Tebaldi C, Vuuren DPV, Eyring V, Friedlingstein P, Hurtt G, Sanderson BM (2016) The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geosci Model Dev* 9(9):3461-3482
- Pai, D. S. et al. (2014) Development of a new high spatial resolution ($0.25^\circ \times 0.25^\circ$) Long Period (1901-2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam* 65, 1-18
- Pascoe, C., Lawrence, B. N., Guilyardi, E., Juckes, M., & Taylor, K. E. (June 2019). Designing and Documenting experiments in CMIP6. *Geoscientific model Development discussions* (pp. 1-27)
- Petrie R, Denvil S, Ames S et al (2021) Coordinating an operational data distribution network for CMIP6 data. *Geosci Mod Dev* 14:629-644
- Piao S et al (2010) The impacts of climate change on water resources and agriculture in China. *Nature* 467:43-51
- Piani, C., Haerter, J. O. & Coppola, E. (2010) Statistical bias correction for daily precipitation in regional climate models over Europe. *Theor. Appl. Climatol.* 99, 187-192
- Rahman, A., & Alam, S. (2024). EXPLORING MOISTURE FLUX AVAILABILITY ABOVE THE SEA FOR EXPLORING MOISTURE FLUX AVAILABILITY ABOVE THE SEA FOR. 7th International Conference on Civil Engineering for Sustainable Development (ICCESD 2024), March.
- Randall, D. A., Wood, R. A., Bony, S., Colman, R., Fichet, T., Fyfe, J., et al. (2007). Climate models and their evaluation. In *Climate change 2007: The physical science basis. Contribution of working group I to the fourth assessment report of the IPCC (FAR)* (pp. 589-662). Cambridge University Press

696 Rashid HE (1991) Geography of Bangladesh (Second). University Press, Dhaka, Bangladesh

697 Riahi K, Van Vuuren DP, Kriegler E, Edmonds J, O'Neill BC, Fujimori S et al (2017) The shared socioeconomic
698 pathways and their energy, land use, and greenhouse gas emissions implications: an overview. *Glob Environ*
699 *Changw* 42:153-168

700 Sakib, M. S., Alam, S., Shampa, Murshed, S. B., Kirtunia, R., Mondal, M. S., & Chowdhury, A. I. A. (2023). Impact
701 of Urbanization on Pluvial Flooding: Insights from a Fast Growing Megacity, Dhaka. *Water*, 15(21).
702 <https://doi.org/10.3390/w15213834>

703 Seddon AWR, Macias-Fauria M, Long PR, Benz D, Willis KJ (2016) Sensitivity of global terrestrial ecosystems to
704 climate variability. *Nature* 531:229-232

705 Seneviratne, S. I., & Hauser, M. (2020). Regional climate sensitivity of climate extremes in CMIP6 versus CMIP5
706 multimodel ensembles. *Earth's Future*, 8(9), e2019EF001474

707 Shah, H. L. & Mishra, V. (2016) Hydrologic Changes in Indian Sub-Continental River Basins (1901-2012). *J.*
708 *Hydrometeorol.* 17, 2667-2687

709 Shahid S (2009) Spatio-temporal variability of rainfall over Bangladesh during the time period 1969-2003. *Asia Pac*
710 *J Atmos Sci* 45:375-389

711 Shahid S (2011) Trends in extreme rainfall events of Bangladesh. *Theor Appl Climatol* 104(3-4):489-499

712 Sheffield, J., Goteti, G. & Wood, E. F. (2006) Development of a 50-year high-resolution global dataset of
713 meteorological forcings for land surface modeling. *J. Clim.* 19, 3088-3111

714 Sheffield, J., Barrett, A. P., Colle, B., Nelun Fernando, D., Fu, R., Geil, K. L., et al. (2013). North American climate
715 in CMIP5 experiments. Part I: Evaluation of historical simulations of continental and regional climatology.
716 *Journal of Climate*, 26(23), 9209-9245

717 Sillmann, J., Kharin, V. V., Zhang, X., Zwiers, F. W., & Bronaugh, D. (2013). Climate extremes indices in the CMIP5
718 multimodel ensemble: Part 1. Model evaluation in the present climate. *Journal of Geophysical Research - D:*
719 *Atmospheres*, 118(4), 1716-1733

720 SMRC (2009) Understanding the rainfall climatology and detection of extreme weather events in the SAARC region:
721 Part II- Utilization of RCM data. SAARC Meteorological Research Centre (SMRC), Dhaka

722 Srivastava, A. K., Rajeevan, M. & Kshirsagar, S. R. (2009) Development of a high resolution daily gridded
723 temperature data set (1969 - 2005) for the Indian region. *Atmos. Sci. Lett.* 10, 249-254

724 Stouffer, R. J., Eyring, V., Meehl, G. A., Bony, S., Senior, C., Stevens, B., & Taylor, K. E. (2017). CMIP5 scientific
725 gaps and recommendations for CMIP6. *Bulletin of the American Meteorological Society*, 98(1), 95-105

726 Syed, A. and Amin, A.M., 2016. Geospatial modeling for investigating spatial pattern and change trend of temperature
727 and rainfall. *Climate*, 4(21). doi:10.3390/cli4020021

728 Taylor KE, Stouffer RJ, Meehl GA. (2012) An overview of CMIP5 and the experiment design. *Bull Amer Meteorol*
729 *Soc* 93:485-98

730 Upal (2019) Analysis of Spatio-Temporal Rainfall Variability over Bangladesh. *Journal of Climate Change*, Vol. 6,
731 No. 1 (2020), pp. 7-14.

732 van Vuuren DP, Edmonds J, Kainuma M et al (2011) The representative concentration pathways: an overview. *Clim*
733 *Change* 109(1):5-31

734 Warrick, R.A., Bhuiya, A.H., and Mirza, M.Q. (1994) The Greenhouse Effect and Climate Change: Briefing
735 Document No. 1. Dhaka, Bangladesh Unnayan Parishod (BUP), pp. 17-20

736 Wazneh, H., Arain, M. A., & Coulibaly, P. (2020). Climate indices to characterize climatic changes across southern
737 Canada. *Meteorological Applications*, 27(1), e1861

738 Weyant J, Azar C, Kainuma, M, Kejun J, Nakicenovic N, Shukla, P.R.; La Rovere E, Yohe G. (2009). Report of 2.6
739 Versus 2.9 Watts/m2 RCP Evaluation Panel. Geneva, Switzerland: IPCC Secretariat.

740 World Bank. (2011). Climate Change Knowledge Portal. Climate Change Knowledge Portal.
741 <https://climateknowledgeportal.worldbank.org/>

742 Wright DB, Knutson TR, Smith JA (2015) Regional climate model projections of rainfall from U.S. landfalling
743 tropical cyclones. *Climate Dyn* 45(11):3365-3379

744 Zhang LX, Chen XL, Xin XG (2019) Short commentary on CMIP6 scenario model intercomparison project
745 (ScenarioMIP). *Clim Change Res* 15:519-525

746 Zhu X, Lee S, Wen X, Ji Z, Lin L, Wei Z, Zheng Z, Xu D, Dong W (2021) Extreme climate changes over three major
747 river basins in China as seen in CMIP5 and CMIP6. *Climate Dynamics* (2021) 57:1187-1205