Performance Evaluation of CMIP6 GCMs for the Projections of Precipitation Extremes in Pakistan

Zulfiqar Ali
Universiti Teknologi Malaysia - Main Campus Skudai: Universiti Teknologi Malaysia
Mohammad Magdy Hamed
Arab Academy for Science Technology and Maritime Transport College of Engineering and Technology
Mohd Khairul Idlan Muhammad
Universiti Teknologi Malaysia - Main Campus Skudai: Universiti Teknologi Malaysia
Zafar Iqbal
NUST: National University of Sciences and Technology
Shamsuddin Shahid (sshahid@utm.my)
Universiti Teknologi Malaysia https://orcid.org/0000-0001-9621-6452

Research Article

Keywords: Precipitation extremes, CMIP6, evaluation, climate change

Posted Date: April 3rd, 2023

DOI: https://doi.org/10.21203/rs.3.rs-2691336/v1

Version of Record: A version of this preprint was published at Climate Dynamics on May 20th, 2023. See the published version at https://doi.org/10.1007/s00382-023-06831-6.

Abstract

Extreme weather events are more detrimental to human culture and ecosystems than typical weather patterns. A multimodel ensemble (MME) of the top-performing global climate models (GCMs) to simulate 11 precipitation extremes was selected using a hybrid method to project their changes in Pakistan. It also compared the benefits of using all GCMs compared to using only selected GCMs when projecting precipitation extremes for two future periods (2020–2059) and (2060–2099) for four shared socioeconomic pathways (SSPs), SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5. Results showed that EC-Earth3-Veg, MRI-ESM2-0 and NorESM2-MM performed best among GCMs in simulating historical and projecting precipitation extremes. Compared to the MME of all GCMs, the uncertainty in future projections of all precipitation indices using the selected GCMs was significantly smaller. The MME median of the selected GCMs showed increased precipitation extremes over most of Pakistan. The greater increases were in one-day maximum precipitation by 6–12 mm, five-day maximum precipitation by 12–20 mm, total precipitation by 40–50 mm, 95th percentile precipitation events by greater than 30 mm, 99th percentile precipitation events by more than 9 mm, days when precipitation ≥ 4 mm by 0–4 days, days when precipitation ≥ 10 mm by 2–6 days, days when precipitation ≥ 20 mm by 1–3 days, and precipitation intensity by 1 mm/day, consecutive wet days by one day, consecutive dry days by 0–4 days in the northern high elevated areas for SSP5-8.5 in the late future. These results emphasize the greater influence of climate change on precipitation extremes in the northern, high-elevation areas, which provide the majority of the country's water. This emphasizes the necessity to adopt suitable climate change mitigation strategies for sustainable development, particularly in the country's northern regions.

1. Introduction

Extreme weather events severely damage agriculture, livelihoods and properties (Agyekum et al. 2022). However, it is challenging to define extreme weather event as it varies with regional factors (Stephenson et al. 2008). The most recent research uses extreme indices based on the recurrence of a specified amount of precipitation or exceedance of specific thresholds to assess extremes. However, the duration and intensity thresholds used to define extremes are region-specific (Data 2009). For example, the threshold defining heat waves in the middle latitude cannot represent heatwave over the tropics (Perkins et al. 2012). Thus, the Expert Team on Climate Change Detection and Indices proposed twenty-seven extreme indices for the analysis of climatic extremes globally and over specific regions (Sillmann et al. 2013; Larbi et al. 2018; Klutse et al. 2021). These indices provide information about the amplitude and incidence of daily temperature and precipitation extremes and explain whether the climate is more variable or extreme (Tank et al. 2009).

The sector having the highest risk of climate extremes is agriculture and water resources (Ahmed and Schmitz 2011; Ali et al. 2022; di Santo et al. 2022). Climate extremes resulted in crop and cattle losses (Goodland and Anhang 2009), low production of crops (Lal 2004; Hatfield and Prueger 2015), disease eruption and pest infestations (Rosenzweig et al. 2001). Numerous studies attempted to solve the challenges posed by contemporary and future climate extremes (Parry et al. 2007; Stocker et al. 2014; Sillmann et al. 2017). Recently, there has been an increase in both the frequency and intensity of extreme climate events on a global and regional scale (Seneviratne et al. 2012; Stocker et al. 2014; Wang et al. 2022). Particularly, extreme event analysis has indicated increased heavy precipitation events (Edenhofer et al. 2014; Dibaba et al. 2020). According to several studies, annual and seasonal precipitation patterns have changed on a global and local scale (Iqbal et al. 2020; Praveen et al. 2020; Šraj and Bezak 2020; McHale et al. 2021; Heureux et al. 2022). Areas with a variety of topography, such as dry and semiarid regions, are more vulnerable to extreme precipitation events (Qin et al. 2018; Sharafati et al. 2020; Qiu et al. 2022). Pakistan, dominated by a semiarid to an arid climate, is experiencing extreme precipitation increase with a further expected increase in the future (Zahid and Rasul 2011; Samo et al. 2017; Bhatti et al. 2020). Recently, some studies also indicated the dynamic changes in extreme precipitation across the country (Abbas et al. 2018, 2022; Bhatti et al. 2020; Xu et al. 2022a). Increasing precipitation extremes have resulted in various hydrological and meteorological damages in the country (Hassan and Ansari 2015; Mahmood and Jia 2016).

The global circulations models (GCMs) remained a primary tool for investigating climate change and its dynamic mechanism (Flato et al. 2014; Agyekum et al. 2018). The Coupled Model Intercomparison Project (CMIP) was set up to assess the effectiveness of GCMs in simulating past, present, and future climate variables under various conditions. Recently, the CMIP6 has been released, which integrated the representative concentration pathways and shared socioeconomic pathways (SSP) and made projections more authentic (Eyring et al. 2016). CMIP6 GCMs also improve spatial resolution and increase parametrization schemes for climate systems (Tian – Jun et al., 2019). Evaluating past and future climate extremes and understanding the physical processes are the primary focus of the scientific work done for CMIP6 GCMs (Eyring et al. 2016; Marotzke et al. 2017). However, before using GCMs, evaluating their capabilities in reproducing the observed climate conditions is essential. This evaluation reduces errors and provides reliable future projections using the appropriate GCMs (Flato et al. 2014; Agyekum et al. 2018).

The accuracy of CMIP6 models in reproducing global and regional climate extremes has been evaluated in several studies. For example, Kim et al., (2020) identified CMIP6 GCMs performed well in replicating the extreme temperature and precipitation indices. Furthermore, studies revealed that the ensemble mean of GCMs performed robustly in reproducing extreme events during rainy months in East Africa (Akinsanola and Zhou 2019). The two approaches have been widely used for selecting GCMs; past performance and envelope-based approach. In the first approach, the selection is made based on the past performance of GCMs in simulating the historical climate (Raju and D. Kumar 2014; Salman et al. 2018). In the second approach, GCMs provide future projections within a confidence interval is selected (Warszawski et al. 2014). Since the envelope approach does not choose GCMs that can reliably model historical climate, and the past performance method cannot guarantee GCM selection that can consistently simulate future climate, neither method is ideal. Therefore, combining both approaches can solve the problem where initial screening is done based on future projections of GCMs between the upper and lower band of the projection variety, and then the final selection of GCMs is established on historical climate (Lutz et al. 2016).

Many scientists have previously assessed the ability of CMIP6 GCMs to reproduce the weather conditions over Pakistan and its neighbours (Ali et al. 2015; Ahmed et al. 2020; Almazroui et al. 2020; Karim et al. 2020; Abbas et al. 2022). However, the characteristics of precipitation extremes are different in different regions. Some regions may experience increased precipitation but not precipitation extremes (Agyekum et al. 2022). From the available literature review, studies related to the performance evaluation of CMIP6 GCMs in replicating the climate extremes in the study area are lacking. It motivated this study to investigate CMIP6 GCMs and select top-performing GCMs that can simulate the climate extremes in the study area for reliable projections of climatic extremes. The intention is to provide reliable future projections with reduced uncertainties.

This study was designed to select CMIP6 models that best simulate historical distribution and future projections of precipitation extremes indices in Pakistan. Future alteration of precipitation extremes and associated uncertainty was estimated using the best-performing models. This study would help in understanding the capability of CMIP6 models in replicating precipitation indices over Pakistan's diversified and complex regions. This can serve as a starting point for future research on weather extremes in the area. The extreme precipitation estimates can be used to refine the projections for CMIP5 scenarios.

2. Study Area And Data

Pakistan is located in South Asia, between latitude 23.5 ° N to 37.0 °N and longitude 60.5 °E to 78 °E. It has a diverse topography, as shown in Fig. 1. The arid to semiarid climate is observed in the southern and central plains, whereas humid weather is in the northern mountains (Abbas et al. 2014). Pakistan is classified as an arid to a semiarid region with significant variations in temperature and precipitation. It mostly experiences two precipitation patterns: monsoons and westerlies (Khan et al. 2014). Monsoon and westerly systems contributed nearly 95% to the country's annual precipitation (Ullah et al. 2018). The yearly average temperature changes from 0 °C in the far north to 32 °C in the south. The maximum temperature varies between 15 and 35 °C, and the minimum temperature ranges between 0 and 20 °C (Chaudhry et al. 2009; Hamed et al. 2022a).

2.1 Datasets

2.2.1 CMIP6 GCMs

The daily precipitation simulations of CMIP6 GCMs for 1975 – 2014 were used to measure their relative performance in the study area. Twenty CMIP6 GCMs were chosen because of their ability to provide precipitation information for past and projected SSPs. For this study, we used the GCMs found at https://esgf-node.llnl.gov/search/cmip6/. The models' initial variant (r1i1p1f1) was chosen for a fair assessment. The GCMs are summarised in Table S1. Shared Socioeconomic Pathways are a new type of scenario introduced in CMPI6. SSPs consider global financial and demographic shifts and greenhouse gas emissions for their climate simulations. SSP1 and SSP5 indicate more contributions to the health sector, education sector, higher-level institutions and fast economic growth. The critical difference between SSP1 and SSP5 is that earlier implies a speedy move to a sustainable society, and the latter implies fossil-fuelled-based economic growth. SSP3 and SSP4 describe a low-developed economy with a high expansion in population, resulting in the unequal allocation of resources. SSP2 represents the position between SSP1 and SSP3 (Hausfather 2018).

2.2.2 ERA5 dataset

European Centre for Medium – Range Weather Forecasts (ECMWF) developed the ERA – 5 dataset, the fifth edition of the Copernicus Climate Change Service (C3S). Hourly precipitation data were collected from the ERA5 reanalysis for 1975–2014 at a spatial resolution of 0.1° × 0.1°. The GCMs' skills in modelling precipitation indices were evaluated using a reference dataset. Observation data remained challenging due to the shortage of long – term records in developing countries like Pakistan. Therefore, the ERA5 dataset has been used widely in the area (Zittis et al. 2016; Mistry et al. 2022; Syed et al. 2022; Waseem et al. 2022). The data was downloaded from https://cds.climate.copernicus.eu/#!/home.

3. Methodology

This study used 11 ETCCDI extreme precipitation indices as described in Supplementary Table S2. These indices are useful for studying global and regional climate extremes (Heureux et al. 2022; Salehie et al. 2022; Xu et al. 2022b; Khan et al. 2022). Due to the resolution discrepancy between the several accessible GCMs and ERA5 data, bilinear interpolation was used to bring both data sets to a common spatial resolution of 1° × 1°. This technique uses four surrounding points around the targeted point to provide smooth interpolation (Hamed et al. 2022b). The bilinear interpolation for performance evaluation of CMIP6 GCMs have been used worldwide (Chen et al. 2021; Iqbal et al. 2021; Ngoma et al. 2021; Hamed et al. 2022b; Salehie et al. 2022). The models' calculated precipitation extremes varied between the base period and the four SSPs. Similarly, ERA5 precipitation data for the reference period was used to determine all precipitation indices. The steps to achieve the objectives are shown in the flowchart of Fig. 2.

3.1 Ranking of GCMs based on hybrid envelope approach.

The fluctuation in GCM accuracy over time makes it difficult to rank GCMs based on their capacity to simulate over different periods. GCMs performing well in simulating the past climate may not be well in simulating the future. Therefore, a hybrid approach was used in this study to select GCMs that can perform well in simulating the past and projecting the future climate. The researchers recommend a hybrid approach for selecting GCMs due to its efficiency in minimizing historical, future and spatiotemporal uncertainties (Lutz et al. 2016; Salman et al. 2018). In this study, GCMs were screened out by calculating the future projections of 11 precipitation indices by all GCMs for all four SSP scenarios. The 97.5th percentile, median and 2.5th percentile of all GCMs for all indices for all SSPs were calculated till the end of the 21st century. The GCMs showing values between the 95th percentile confidence interval (CI) band for all indices for all scenarios were initially selected.

In the second step, GCMs' skill in replicating the precipitation extremes indices for the historical period was evaluated using Kling – Gupta Efficiency (KGE) metrics. KGE evaluates three statistical metrics as a single measure, i.e., spatial variability ratio, Pearson's correlation and normalized variance, as represented below:

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta-1)^2 + (\gamma-1)^2} \quad (1)$$

$$\beta = \frac{us}{uo}$$

$$\gamma = \frac{\sigma s}{\sigma o} / \frac{us}{uo}$$

where r denotes the Pearson's correlation between GCMs simulations (s) and ERA5 data (o), β denotes the bias stabilized by the standard deviation of observed data, γ is defined as a fraction of variation indicating spatial variability, and u and σ show the mean and standard deviation of GCM (s) simulation and observed data, respectively (o).

Considering the capabilities and sensitivity to extremes, the KGE metric is preferred to quantify GCM's skills (Radcliffe and Mukundan 2017). The KGE is considered a robust spatial assessment metric (Nashwan et al. 2019; Salehie et al. 2022; Sobh et al. 2022). The range of KGE values lies between 1 and ∞. A value of 1 represents the best match. The GCMs performed better than the median for all indexes finally chosen.

3.2 Uncertainties in projected changes

The simulations of the indices using all GCMs and selected GCMs for all SSPs were prepared to compare the uncertainty ranges. Furthermore, spatial maps of the multimodel ensemble (MME) median, 97.5th percentile and 2.5th percentile of all indices based on all GCMs and selected GCMs were prepared to show the difference in the spatial variability in projections by all GCMs and the selected GCMs. In addition, maps showing the median MME of the selected GCMs for all precipitation extreme indices for SSP1-2.6, SSP2-4.5, and SSP5-8.5 in the near and far future were created to illustrate the spatial distribution of absolute changes in precipitation extreme indices over Pakistan.

4. Results

4.1 GCM Ranking

The future projections of all indices using all GCMs for all SSPs were used to assess the consistency in projections. For example, the future projections of two extreme indices, Rx1day and Sdii, using all GCMs for all SSPs for 2020–2099, are shown in Fig. 3. The projections' 2.5th and 97.5th percentile (i.e., 95% CI band) values are presented in Supplementary

Table S3. The table also contains the 95% CI band of the projections of all indices. It shows that the projections of two GCMs, i.e., ACCESS – ESM1 – 5 and FGOALS – g3, were out of the 95% CI band for many indices. Few GCMs also showed projections out of the 95% CI band for one to four indices, but their projections were within the 95% CI band for most indices. Therefore, only two GCMs, ACCESS – ESM1 – 5 and FGOALS – g3, were discarded in the initial screening of GCM selection, considering their unrealistic projections of extreme precipitation.

The initially selected GCMs were further evaluated against the ERA5 precipitation for the historical period (1975 – 2014) using KGE to select the best-performing GCMs. The obtained data are shown in Table S4 of the Supplementary Materials. Then, the KGE values were used to independently rank the GCMs for each index. The rankings of the GCMs in simulating various precipitation indicators are shown in Table 5. The GCMs were finally selected by applying the criteria that it was not ranked below the median rank (below 9th position) in simulating any of the precipitation indices. The process selected EC – Earth3 – Veg, MRI – ESM2 – 0 and NorESM2 – MM. These three GCMs showed consistent projections and also performed best in simulating past climate.

Table 1
Ranking of GCMs for their ability to simulate the studied region's precipitation indices. Numbers in bold are the top 50th percentile, while the final selection GCMs are highlighted in bold.

GCMs	rx1day	rx5day	sdii	r10mm	r20mm	rnnmm	cdd	cwd	r95ptot	r99ptot	prcptot
ACCESS – CM21	13	15	15	14	13	13.5	18	**9**	13	13	14.5
CanESM5	18	18	18	18	18	18	16	17	18	18	18
CMCC – ESM2	**9**	**7**	10	**5**	**6**	**6**	**4**	**7**	**5**	**5**	**6**
EC – Earth3 – Veg – LR	10	**7**	**2**	**6.5**	**8**	**2**	**1**	**1**	**6**	**7**	**3.5**
EC – Earth3 – Veg	**8**	**5**	**1**	**8**	**9**	**6**	**4**	**3**	**7.5**	**8.5**	**7**
EC – Earth3	**6**	**7**	**3**	**9**	10	**8.5**	**8**	**6**	**7.5**	**8.5**	**8**
GFDL – ESM4	**5**	**9**	**4.5**	**4**	**2**	**8.5**	**6**	11	**3**	**3**	**5**
INM – CM4 – 8	15	13	12	16	17	15	14	12	15	14	16
INM – CM5 – 0	17	15	16	15	16	13.5	12	14.5	12	12	13
IPSL – CM6A – LR	**3.5**	**4**	**8**	**2**	**3**	**4**	10	18	**2**	**2**	**2**
KACE – 1–0 – G	16	17	17	17	14	17	15	14.5	17	17	17
MIROC6	12	15	13	13	12	10	**9**	16	10.5	10	10
MPI – ESM1 – 2–HR	**7**	10	11	**6.5**	**4**	11	17	10	10.5	11	**9**
MPI – ESM1 – 2–LR	11	11	**9**	12	11	12	11	**8**	16	16	14.5
MRI – ESM2 – 0	**2**	**1**	**6**	**1**	**1**	**1**	**2**	**4.5**	**1**	**1**	**1**
NorESM2 – LM	14	12	14	11	15	**6**	13	**2**	14	15	11
NorESM2 – MM	**3.5**	**3**	**7**	**3**	**7**	**3**	**4**	**4.5**	**4**	**4**	**3.5**
TaiESM1	**1**	**2**	**4.5**	10	**5**	16	**7**	13	**9**	**6**	12

4.2 Uncertainties using all and selected GCMs

The MME mean and uncertainty in future projections of the indices using all GCMs and selected GCMs were evaluated to show how selected GCMs reduced projection uncertainty. The MME and 95% CI band of the projections of Rx1day and Rx5day using all GCMs and selected GCMs for different SSPs for 2020–2099 are presented in Figs. 5 and 6 as examples. It indicated that the CI band of selected GCMs was much thinner (with less uncertainty) than all GCMs in all cases. Consistent findings across multiple indices point to sizable reductions in uncertainties when employing only some GCMs rather than all of them.

4.3 Projected changes using all and selected GCMs

The spatial changes in precipitation indices using all GCMs and selected GCMs' MME with their 95% CI band values were estimated to compare the relative discrepancy. Figures 6 and 8 show the outcomes for Rx1day and Rx5day, respectively. The results for other indices are presented in supplementary materials (from figure S1 to S9). Figure 6 shows the historical and projected changes in Rx1day based on the MME median, 2.5th and 97.5th percentiles of all GCMs and selected GCMs for two future periods and two SSPs, 1-2.6 and 5-8.5. The MME median of all GCMs and selected GCMs for the historical periods ranged between 5 and 44 mm. Furthermore, the MME median of all GCMs for SSP1-2.6 and SSP5-8.5 remained almost identical in both futures, except for far future in SSP5-8.5. The median MME of the chosen GCMs projected an increase in Rx1day across the board, with a few isolated exceptions in the country's central and southern regions. Contrarily, all GCMs indicated a rise of up to 15 mm in median MME. SSP5-8.5 showed the best prospective increase. The 2.5th and 97.5th percentile changes of Rx1day using all GCMs were much lower and higher, respectively than those estimated using the selected GCMs. The average change for all GCMs in the 2.5th and 97.5th percentile were 2.79 and 11.29, respectively, while it was 0.80 and 6.16 mm, respectively, for the selected GCMs, respectively.

The projected changes in Rx5day based on the MME median, 2.5th and 97.5th percentiles of all GCMs and selected GCMs are presented in Fig. 8. The pattern of MME of all GCMs and selected GCMs for the future periods were like Rx1day. The results indicate less uncertainty range in the MME median of the selected GCMs than all GCMs. The average change (median) for all GCMs was 6.58, while it was 5.77 for the selected GCMs, respectively. The above two figures and the supplementary figures (S1 to S9) revealed the superiority of the GCMs selected in this study for projecting precipitation extremes over Pakistan.

4.4 Projection of precipitation extremes using selected GCMs

The geographical changes in precipitation indices using selected GCMs for three SSPs were estimated to show their future projection changes. The MME median change of the selected GCMs for two future periods, compared with the historical period 1975 – 2014, were estimated for this purpose. Results for Rx1day, Cdd, R95ptot, R10mm and sdii are presented in Figs. 8 to 13. Results for other indexes are included in the appendices (Figures S10 to S14). The anticipated shifts in Rx1day across Pakistan are depicted spatially in Fig. 9. Rx1day will range from – 9 mm to 13 mm for various SSPs, depending on where in the country you are. For all SSPs and future periods, the spatial pattern showed that Rx1day decreased or remained constant in the western arid region while increasing in the northeast high elevated areas. However, there was a large variability in projections for different SSPs in the far future. SSP2-4.5 showed decreased Rx1day over most of the study area, while SSP5-8.5 indicated an increase of 1 to 13 mm over most of the country. However, the discrepancy in the spatial distribution was relatively less for the near future. It was also less between the near and far futures for SSP1-2.6. This indicates a large uncertainty in future projections of Rx1day in the far future for higher SSPs.

Figure 9 indicates the geographical distribution of projected changes in Cdd over the study area. The results revealed a change in Cdd over Pakistan by -15 to 15 days. A decrease in Cdd dominated most regions for all SSPs and future periods. Similarly, a relatively more discrepancy was observed among SSP projections in the far future than in the near future. The change was negative for SSP1-2.6 in the near future (-2.54 days), while it was 1.31 days in the far future.

The opposite pattern was observed in SSP2-4.5 and 5-8.5, with the highest decrease in the future with − 15 and − 13 days, respectively. However, there was an increase of up to 8 days in the northern high elevated areas in the far future for different SSPs.

Projected changes in yearly total precipitation (Prcptot) of more than 1 mm for all SSPs and both future periods are shown in Fig. 10. The results revealed an overall increase in the study area up to 57 mm, especially in the north region. However, a decrease of 11 mm was observed in the south and east in the near future for SSP2-4.5. The most increase was in the northern regions in the far future for SSP5-8.5. While the Prcptot decline was more pronounced in the near future, an increase was more pronounced in the far future across the entire study area. Figure 11 shows the projected changes in R95ptot under three SSPs and future periods. The results showed an overall increase of up to 38 mm in both future periods for all SSPs, except a decrease of 8 mm in the south and east in the near future for SSP2-4.5. However, the highest increase was observed in the north in the far future for SSP5-8.5. Both indices were similar in their pattern of increase and decrease.

Figure 12 presents projected changes in R10mm for three SSPs and two future periods. R10mm increased by two days in both the future and present periods across most of the research area. However, a small decrease of 2 days in the southern and eastern regions along the Indian border was observed in the near future for SSP2-4.5. In the far future, SSP5-8.5 showed the largest 7-day increase in the north. Figure 13 shows projected changes in Sdii. It would slightly change (± 1 mm/day) in the near future for all SSPs, except for a decrease in the central and southern regions for SSP2-4.5. In contrast, precipitation will be more intense (an increase of Sdii by more than 1 mm/day) in the far future, especially for SSP5-8.5.

5. Discussion

The present study evaluated CMIP6 GCMs in replicating the precipitation indices proposed by ETCCDI using a hybrid approach. Past research has mostly focused on evaluating CMIP5 and CMIP6 GCMs and their abilities to stimulate the country's average precipitation and temperature (Ullah et al. 2018; Almazroui et al. 2020; Iqbal et al. 2020; Waseem et al. 2022). No study assessed CMIP6 GCMs' skill in replicating precipitation extremes indices in the study area. In this study, 20 CMIP6 models were used to evaluate their skill in simulating precipitation indices through a hybrid-envelope approach. The envelope approach suggested discarding the Fgoals − g3 and ACCESS − ESM1 − 5 in the initial screening as their projections were out of the 95% CI band for most indices. After comparing ERA5 data from the historical era (1975–2014) with the results of GCM simulations of precipitation indices, the KGE was used to determine a final ranking for the GCMs. Three models, EC-Earth3-Veg, MRI-ESM2-0 and Nor-ESM2-MM, were most successful in consistently simulating the precipitation indices in the future and duplicating extremes of the reference period. The temporal analysis of extreme indices projections using the selected GCMs indicated a more significant improvement in uncertainty reduction than all GCMs. The 95% CI band of selected GCMs was much narrower than all GCMs for all SSPs. Furthermore, the projected spatial changes in indices based on the MME median, 2.5th and 97.5th percentile of selected GCMs showed much less uncertainty than those using all GCMs.

Generally, future projected changes in the median MME of selected GCMs revealed an increase in Rx1day, Prcptot, R95ptot, R10mm and Sdii indices in the most study area in the far future for all SSPs. However, the greatest changes were observed in northern high-elevated areas, followed by southern parts for SSP5-8.5 in the far future. The findings are in line with those of other research efforts (Ali et al. 2015, 2019; Wu et al. 2017; Iqbal et al. 2020; Saddique et al. 2020), which revealed more wet climate in future and further increase in precipitation in northern high elevated areas. However, an increase in the indices may prevail over more frequent floods in the specified regions, such as northern areas. It can damage life, agriculture, food, water resources, and properties.

Furthermore, projected changes in Cdd indicated a decrease in most areas, except in the north for different SSPs in both future periods. The results are aligned with previous studies (Ali et al. 2019; Sajjad and Ghaffar 2019; Reddy and Saravanan 2023). For accurate predictions of future climate extremes in the region, this study recommended the chosen GCMs. Furthermore, the elevated northern region found an overall increase in all precipitation indices for all SSPs. This area provides the majority of the country's fresh water. Hence, findings point to the detrimental effects of climate change on the nation's water supplies. Findings from this study may help policymakers develop adaptation methods to lessen the effects of climate change.

6. Conclusion

The purpose of this research was to identify the best CMIP6 GCMs for forecasting precipitation indicators in Pakistan. As a result, the CMIP6 GCMS were ranked according to their ability to project the heaviest precipitation events. The study revealed EC-Earth3-Veg, MRI-ESM2-0 and Nor-ESM2-MM as the best model for simulating future precipitation extremes consistently and replicating historical precipitation extremes reliably. The results revealed a considerable decline in uncertainties in the projections of all precipitation indices using MME of selected GCMs compared to all GCMs. Most types of extreme precipitation were projected to alter significantly throughout the study's period using the chosen projection method. It was predicted that the northern areas with the highest elevation would experience the greatest increase in extremes, followed by the southern regions. Future periods would have larger rises for SSP5-8.5.

The increased precipitation amount and intensity indicated the noticeable climate change impact in the northern sub-Hymalayan regions, the major source of all major rivers. Flooding may become more common in the future as a result of the predicted wetter climate. This may result in loss of agriculture and damage to infrastructures. Therefore, the results of the study would be helpful for policymakers to combat climate change by developing mitigation strategies. The present study employed 20 GCMs, as those were only available when the study was conducted. More GCMs can be taken into account to find the best possible subset in the future. Besides, GCMs can be selected based on both precipitation and temperature extremes to increase their applicability for a wider range of climate change impact assessments.

Declarations

Funding

The authors received no financial support for the research, authorship, and publication.

Conflict of interest

The authors declare no conflict of interest.

Availability of data:

All the data are available in the public domain at the links provided in the texts.

Availability of code

The codes used for data processing can be provided on request to the corresponding author.

Authors contribution

All authors contributed to the study's conception and design.

References

1. Abbas A, Ullah S, Ullah W et al (2022) Evaluation and projection of precipitation in Pakistan using the Coupled Model Intercomparison Project Phase 6 model simulations. Int J Climatol 42:6665–6684. https://doi.org/https://doi.org/10.1002/joc.7602
2. Abbas F, Ahmad A, Safeeq M et al (2014) Changes in precipitation extremes over arid to semiarid and subhumid Punjab, Pakistan. Theor Appl Climatol 116:671–680. https://doi.org/10.1007/s00704-013-0988-8
3. Abbas F, Sarwar N, Ibrahim M et al (2018) Patterns of climate extremes in the coastal and highland regions of Balochistan, Pakistan. Earth Interact 22:1–23
4. Agyekum J, Annor T, Lamptey B et al (2018) Evaluation of CMIP5 global climate models over the Volta Basin: precipitation. Adv Meteorol 2018
5. Agyekum J, Annor T, Quansah E et al (2022) Extreme precipitation indices over the Volta Basin: CMIP6 model evaluation. Sci Afr 16:e01181. https://doi.org/https://doi.org/10.1016/j.sciaf.2022.e01181
6. Ahmed K, Iqbal Z, Khan N et al (2020) Quantitative assessment of precipitation changes under CMIP5 RCP scenarios over the northern sub-Himalayan region of Pakistan. Environ Dev Sustain 22:7831–7845. https://doi.org/10.1007/s10668-019-00548-5
7. Ahmed M, Schmitz M (2011) Economic assessment of the impact of climate change on the agriculture of Pakistan. Bus Econ Horizons 4:1–12
8. Akinsanola AA, Zhou W (2019) Projection of West African summer monsoon rainfall in dynamically downscaled CMIP5 models. Clim Dyn 53:81–95. https://doi.org/10.1007/s00382-018-4568-6
9. Ali MA, Hassan M, Mehmood M et al (2022) The Potential Impact of Climate Extremes on Cotton and Wheat Crops in Southern Punjab. Pakistan Sustain 14:1609
10. Ali S, Eum H-I, Cho J et al (2019) Assessment of climate extremes in future projections downscaled by multiple statistical downscaling methods over Pakistan. Atmos Res 222:114–133. https://doi.org/https://doi.org/10.1016/j.atmosres.2019.02.009
11. Ali S, Li D, Congbin F, Khan F (2015) Twenty first century climatic and hydrological changes over Upper Indus Basin of Himalayan region of Pakistan. Environ Res Lett 10:14007
12. Almazroui M, Saeed S, Saeed F et al (2020) Projections of Precipitation and Temperature over the South Asian Countries in CMIP6. Earth Syst Environ 4:297–320. https://doi.org/10.1007/s41748-020-00157-7
13. Bhatti AS, Wang G, Ullah W et al (2020) Trend in Extreme Precipitation Indices Based on Long Term In Situ Precipitation Records over Pakistan. Water 12
14. Chaudhry Q-Z, Mahmood A, Rasul G, Afzaal M (2009) Climate change indicators of Pakistan. PAkistan Meterological Dep
15. Chen C-A, Hsu H-H, Liang H-C (2021) Evaluation and comparison of CMIP6 and CMIP5 model performance in simulating the seasonal extreme precipitation in the Western North Pacific and East Asia. Weather Clim Extrem 31:100303. https://doi.org/10.1016/j.wace.2021.100303
16. Data C (2009) Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. World Meteorol Organ
17. di Santo N, Russo I, Sisto R (2022) Climate Change and Natural Resource Scarcity: A Literature Review on Dry Farming. Land 11
18. Dibaba WT, Demissie TA, Miegel K (2020) Drivers and implications of land use/land cover dynamics in Finchaa catchment, northwestern Ethiopia. Land 9:113

19. Edenhofer O, Pichs-Madruga R, Sokona Y, Minx JC (2014) Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change
20. Eyring V, Bony S, Meehl GA et al (2016) Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. Geosci Model Dev 9:1937–1958. https://doi.org/10.5194/gmd-9-1937-2016
21. Flato G, Marotzke J, Abiodun B et al (2014) Evaluation of climate models. In: Climate change 2013: the physical science basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp 741–866
22. Goodland R, Anhang J (2009) Livestock and climate change: What if the key actors in climate change are… cows, pigs, and chickens? Livest Clim Chang what if key actors Clim Chang are. cows, pigs, chickens?
23. Hamed MM, Khan N, Muhammad MKI, Shahid S (2022a) Ranking of Empirical Evapotranspiration Models in Different Climate Zones of Pakistan. Land 11:2168. https://doi.org/10.3390/land11122168
24. Hamed MM, Nashwan MS, Shahid S (2022b) Inter-comparison of Historical Simulation and Future Projection of Rainfall and Temperature by CMIP5 and CMIP6 GCMs Over Egypt. Int J Climatol 42:4316–4332. https://doi.org/10.1002/joc.7468
25. Hassan SA, Ansari M (2015) Hydro-climatic aspects of Indus River flow propagation. Arab J Geosci 8:10977–10982
26. Hatfield JL, Prueger JH (2015) Temperature extremes: Effect on plant growth and development. Weather Clim Extrem 10:4–10. https://doi.org/https://doi.org/10.1016/j.wace.2015.08.001
27. Hausfather Z (2018) Explainer: how 'shared socioeconomic pathways' explore future climate change.Carbon Br19
28. Heureux AMC, Alvar-Beltrán J, Manzanas R et al (2022) Climate Trends and Extremes in the Indus River Basin, Pakistan: Implications for Agricultural Production. Atmos (Basel) 13. https://doi.org/10.3390/atmos13030378
29. Iqbal Z, Shahid S, Ahmed K et al (2020) Evaluation of global climate models for precipitation projection in sub-Himalaya region of Pakistan. Atmos Res 245:105061. https://doi.org/10.1016/j.atmosres.2020.105061
30. Iqbal Z, Shahid S, Ahmed K et al (2021) Evaluation of CMIP6 GCM rainfall in mainland Southeast Asia. Atmos Res 254:105525. https://doi.org/10.1016/j.atmosres.2021.105525
31. Karim R, Tan G, Ayugi B et al (2020) Evaluation of historical CMIP6 model simulations of seasonal mean temperature over Pakistan during 1970–2014. Atmosphere (Basel) 11: https://doi.org/10.3390/atmos11091005
32. Khan F, Ali S, Mayer C et al (2022) Climate change and spatio-temporal trend analysis of climate extremes in the homogeneous climatic zones of Pakistan during 1962–2019. PLoS ONE 17:e0271626
33. Khan SI, Hong Y, Gourley JJ et al (2014) Evaluation of three high-resolution satellite precipitation estimates: Potential for monsoon monitoring over Pakistan. Adv Sp Res 54:670–684. https://doi.org/https://doi.org/10.1016/j.asr.2014.04.017
34. Kim Y-H, Min S-K, Zhang X et al (2020) Evaluation of the CMIP6 multi-model ensemble for climate extreme indices. Weather Clim Extrem 29:100269. https://doi.org/https://doi.org/10.1016/j.wace.2020.100269
35. Klutse NAB, Quagraine KA, Nkrumah F et al (2021) The Climatic Analysis of Summer Monsoon Extreme Precipitation Events over West Africa in CMIP6 Simulations. Earth Syst Environ 5:25–41. https://doi.org/10.1007/s41748-021-00203-y
36. Lal R (2004) Soil carbon sequestration impacts on global climate change and food security. Sci (80-) 304:1623–1627
37. Larbi I, Hountondji FCC, Annor T et al (2018) Spatio-temporal trend analysis of rainfall and temperature extremes in the Vea catchment, Ghana. Climate 6

38. Lutz AF, ter Maat HW, Biemans H et al (2016) Selecting representative climate models for climate change impact studies: an advanced envelope-based selection approach. Int J Climatol 36:3988–4005. https://doi.org/10.1002/joc.4608
39. Mahmood R, Jia S (2016) Assessment of impacts of climate change on the water resources of the transboundary Jhelum River basin of Pakistan and India. Water 8:246
40. Marotzke J, Jakob C, Bony S et al (2017) Climate research must sharpen its view. Nat Clim Chang 7:89–91. https://doi.org/10.1038/nclimate3206
41. McHale MR, Ludtke AS, Wetherbee GA et al (2021) Trends in precipitation chemistry across the U.S. 1985–2017: Quantifying the benefits from 30 years of Clean Air Act amendment regulation. Atmos Environ 247:118219. https://doi.org/https://doi.org/10.1016/j.atmosenv.2021.118219
42. Mistry MN, Schneider R, Masselot P et al (2022) Comparison of weather station and climate reanalysis data for modelling temperature-related mortality. Sci Rep 12. https://doi.org/10.1038/s41598-022-09049-4
43. Nashwan MS, Shahid S, Wang X (2019) Assessment of satellite-based precipitation measurement products over the hot desert climate of Egypt. https://doi.org/10.3390/rs11050555. Remote Sens 11:
44. Ngoma H, Wen W, Ayugi B et al (2021) Evaluation of precipitation simulations in CMIP6 models over Uganda. Int J Climatol 41:4743–4768. https://doi.org/10.1002/joc.7098
45. Parry ML, Canziani O, Palutikof J et al (2007) Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC. Cambridge University Press
46. Perkins SE, Alexander LV, Nairn JR (2012) Increasing frequency, intensity and duration of observed global heatwaves and warm spells.Geophys Res Lett39
47. Praveen B, Talukdar S, Shahfahad et al (2020) Analyzing trend and forecasting of rainfall changes in India using non-parametrical and machine learning approaches. Sci Rep 10:10342. https://doi.org/10.1038/s41598-020-67228-7
48. Qin Y, Li B, Chen Z et al (2018) Spatio-temporal variations of nonlinear trends of precipitation over an arid region of northwest China according to the extreme-point symmetric mode decomposition method. Int J Climatol 38:2239–2249
49. Qiu D, Wu C, Mu X et al (2022) Spatial-temporal Analysis and Prediction of Precipitation Extremes: A Case Study in the Weihe River Basin, China. Chin Geogr Sci 32:358–372. https://doi.org/10.1007/s11769-022-1271-7
50. Radcliffe DE, Mukundan R (2017) PRISM vs. CFSR Precipitation Data Effects on Calibration and Validation of SWAT Models. J Am Water Resour Assoc 53:89–100. https://doi.org/10.1111/1752-1688.12484
51. Raju K, Kumar D (2014) Ranking of global climate models for India using multicriterion analysis. Clim Res 60:103–117
52. Reddy NM, Saravanan S (2023) Extreme precipitation indices over India using CMIP6: a special emphasis on the SSP585 scenario. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-023-25649-7
53. Rosenzweig C, Iglesius A, Yang X-B et al (2001) Climate change and extreme weather events-Implications for food production, plant diseases, and pests
54. Saddique N, Khaliq A, Bernhofer C (2020) Trends in temperature and precipitation extremes in historical (1961–1990) and projected (2061–2090) periods in a data scarce mountain basin, northern Pakistan. Stoch Environ Res Risk Assess 34:1441–1455. https://doi.org/10.1007/s00477-020-01829-6
55. Sajjad H, Ghaffar A (2019) Observed, simulated and projected extreme climate indices over Pakistan in changing climate. Theor Appl Climatol 137:255–281. https://doi.org/10.1007/s00704-018-2573-7

56. Salehie O, bin Ismail T, Hamed MM et al (2022) Projection of Hot and Cold Extremes in the Amu River Basin of Central Asia using GCMs CMIP6. https://doi.org/10.1007/s00477-022-02201-6. Stoch Environ Res Risk Assess
57. Salman SA, Shahid S, Ismail T et al (2018) Selection of climate models for projection of spatiotemporal changes in temperature of Iraq with uncertainties. Atmos Res 213:509–522. https://doi.org/10.1016/j.atmosres.2018.07.008
58. Samo SR, Bhatti N, Saand A et al (2017) Temporal analysis of temperature and precipitation trends in Shaheed Benazir Abad Sindh, Pakistan. Eng Technol Appl Sci Res 7:2171–2176
59. Seneviratne S, Nicholls N, Easterling D et al (2012) Changes in climate extremes and their impacts on the natural physical environment
60. Sharafati A, Pezeshki E, Shahid S, Motta D (2020) Quantification and uncertainty of the impact of climate change on river discharge and sediment yield in the Dehbar river basin in Iran. J Soils Sediments 20:2977–2996. https://doi.org/10.1007/s11368-020-02632-0
61. Sillmann J, Kharin VV, Zhang X et al (2013) Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. J Geophys Res Atmos 118:1716–1733
62. Sillmann J, Thorarinsdottir T, Keenlyside N et al (2017) Understanding, modeling and predicting weather and climate extremes: Challenges and opportunities. Weather Clim Extrem 18:65–74. https://doi.org/https://doi.org/10.1016/j.wace.2017.10.003
63. Sobh MT, Nashwan MS, Amer N (2022) High Resolution Reference Evapotranspiration for Arid Egypt: comparative analysis and evaluation of empirical and artificial intelligence models. Int J Climatol 1–21. https://doi.org/10.1002/joc.7894
64. Šraj M, Bezak N (2020) Comparison of time trend- and precipitation-informed models for assessing design discharges in variable climate. J Hydrol 589:125374. https://doi.org/https://doi.org/10.1016/j.jhydrol.2020.125374
65. Stephenson DB, Diaz HF, Murnane RJ (2008) Definition, diagnosis, and origin of extreme weather and climate events. Clim Extrem Soc 340:11–23
66. Stocker T, Plattner G-K, Dahe Q (2014) IPCC climate change 2013: the physical science basis-findings and lessons learned. In: EGU General Assembly Conference Abstracts. p 17003
67. Syed Z, Ahmad S, Dahri ZH et al (2022) Hydroclimatology of the Chitral River in the Indus Basin under Changing Climate.Atmos.13
68. Tank AMK, Zwiers FW, Zhang X (2009) WMO guidelines on extremes guidelines on analysis of extremes in a changing climate in support of informed decisions.Clim data Monit52
69. Tian-Jun Z, Li-Wei ZOU, Xiao-Long C (2019) Commentary on the coupled model intercomparison project phase 6 (CMIP6). Adv Clim Chang Res 15:445
70. Ullah S, You Q, Ullah W, Ali A (2018) Observed changes in precipitation in China-Pakistan economic corridor during 1980–2016. Atmos Res 210:1–14. https://doi.org/https://doi.org/10.1016/j.atmosres.2018.04.007
71. Wang J, Xin L, Wang X, Jiang M (2022) The Impact of Climate Change and Grain Planting Structure Change on Irrigation Water Requirement for Main Grain Crops in Mainland China. Land 11
72. Warszawski L, Frieler K, Huber V et al (2014) The inter-sectoral impact model intercomparison project (ISI–MIP): project framework. Proc Natl Acad Sci 111:3228–3232
73. Waseem S, Muhammad I, Rehan L et al (2022) Performance evaluation and comparison of observed and reanalysis gridded precipitation datasets over Pakistan.Theor Appl Climatol4100
74. Wu J, Zha J, Zhao D (2017) Evaluating the effects of land use and cover change on the decrease of surface wind speed over China in recent 30 years using a statistical downscaling method. Clim Dyn 48:131–149

75. Xu C, Fu H, Yang J, Wang L (2022a) Assessment of the Relationship between Land Use and Flood Risk Based on a Coupled Hydrological–Hydraulic Model: A Case Study of Zhaojue River Basin in Southwestern China. Land 11
76. Xu H, Chen H, Wang H (2022b) Future changes in precipitation extremes across China based on CMIP6 models. Int J Climatol 42:635–651
77. Zahid M, Rasul G (2011) Frequency of Extreme Temperature & Precipitation Events in Pakistan 1965–2009. Sci Int 23:313–319
78. Zittis G, Hadjinicolaou P, Fnais M, Lelieveld J (2016) Projected changes in heat wave characteristics in the eastern Mediterranean and the Middle East. Reg Environ Chang 16:1863–1876

Figures

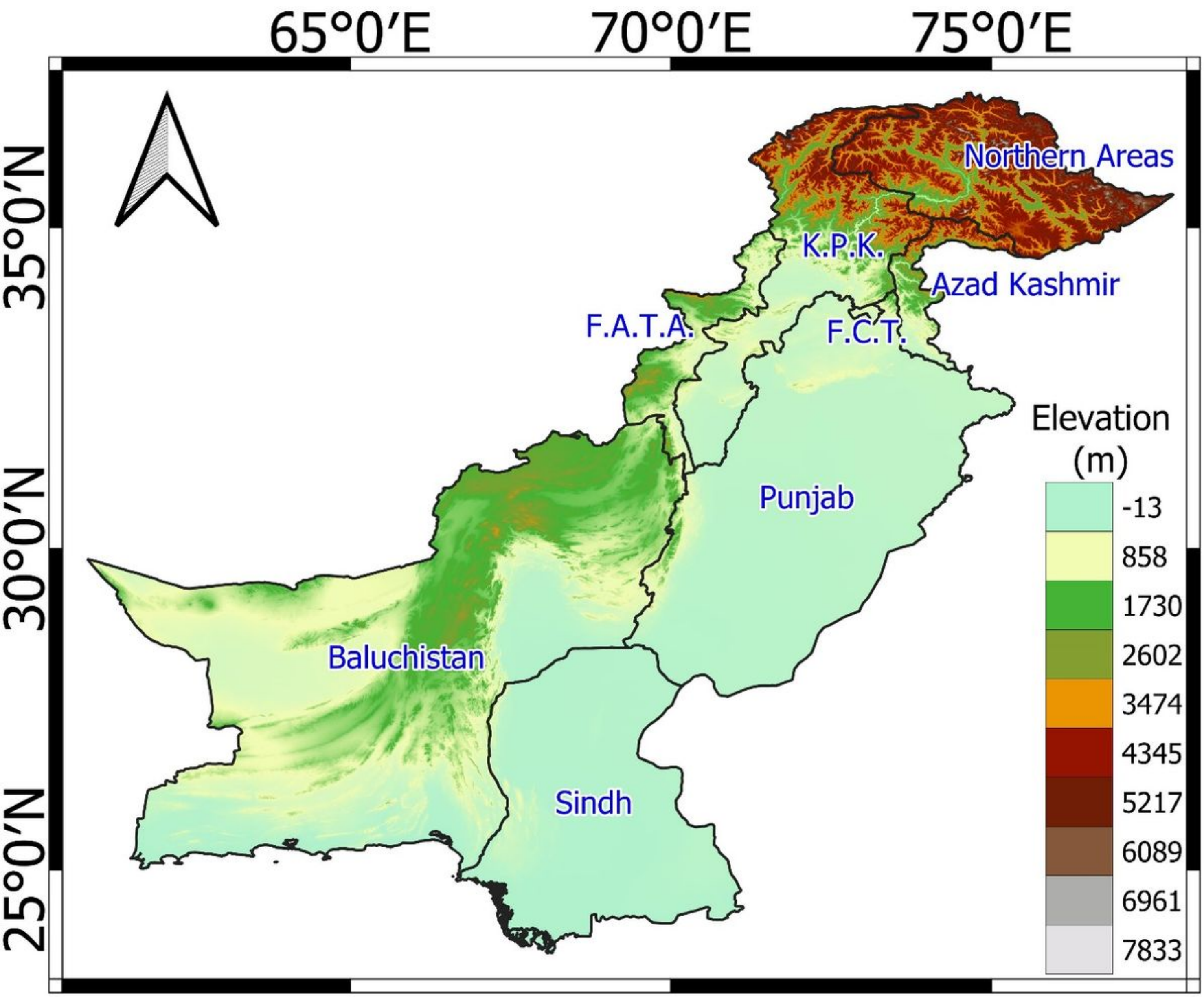

Figure 1

Map of the study area

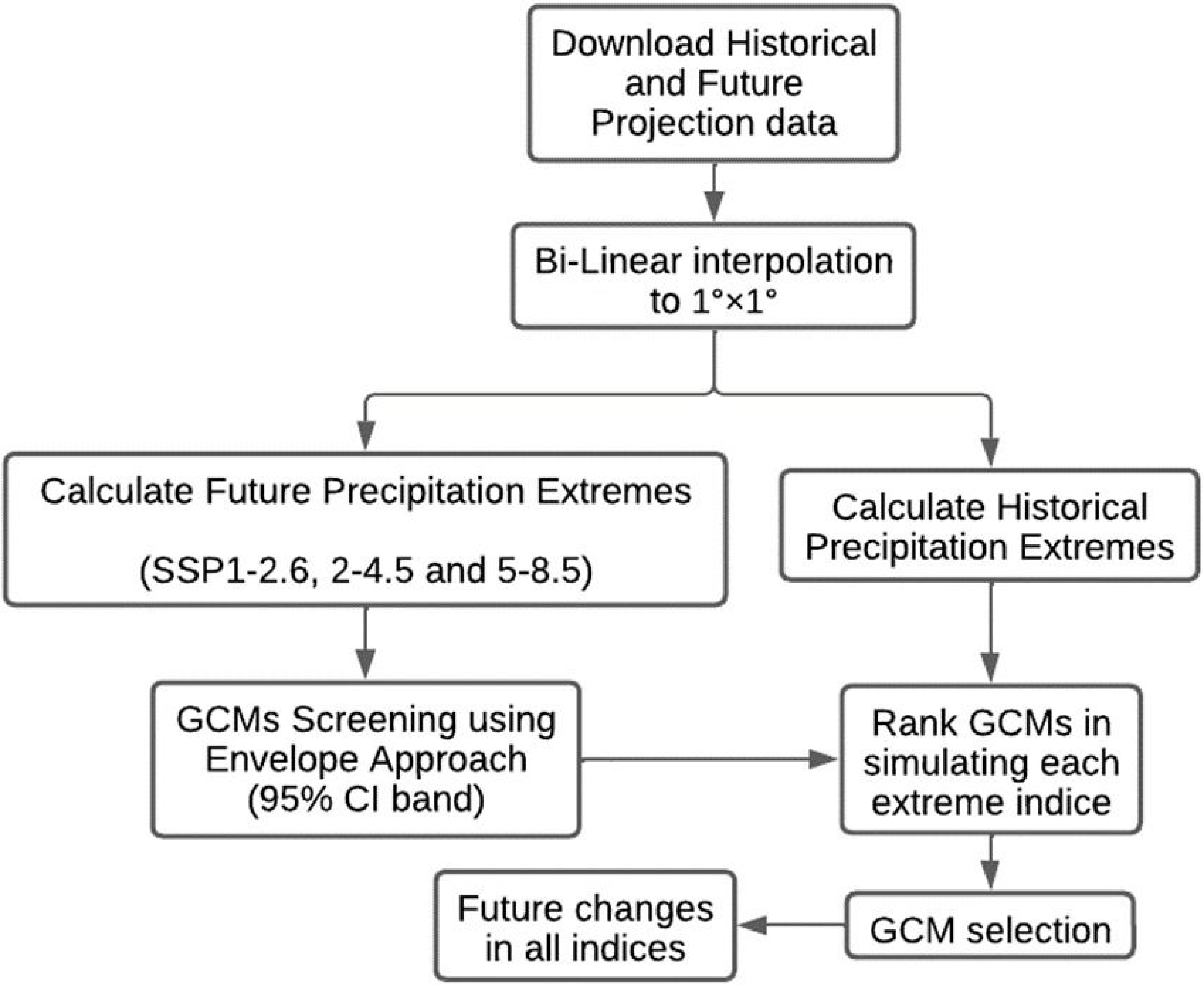

Figure 2

Procedures used in the research.

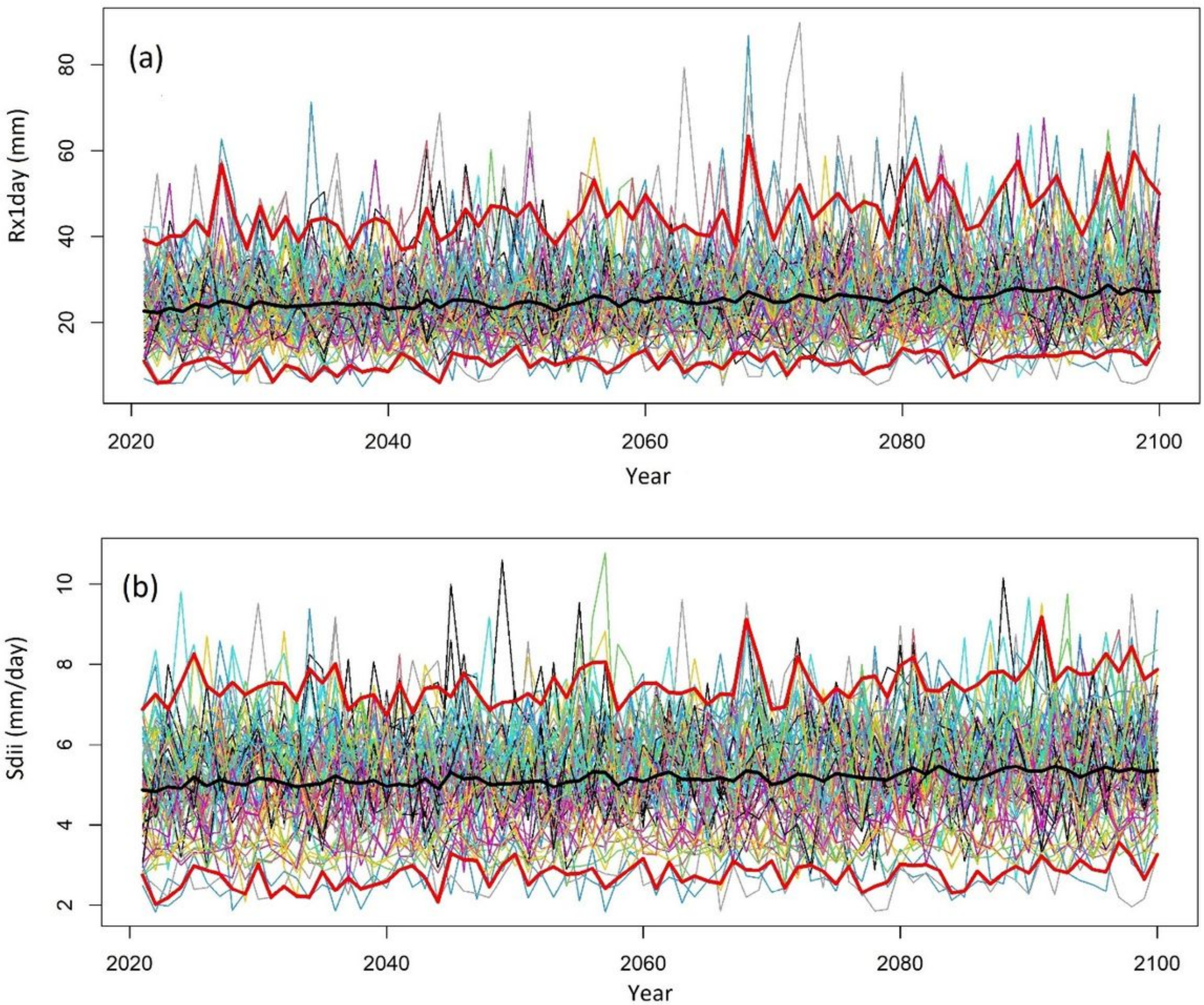

Figure 3

Future projections of (a) one-day maximum precipitation (Rx1day) and (b) Simple daily intensity index (Sdii) by all GCMs for all SSPs.

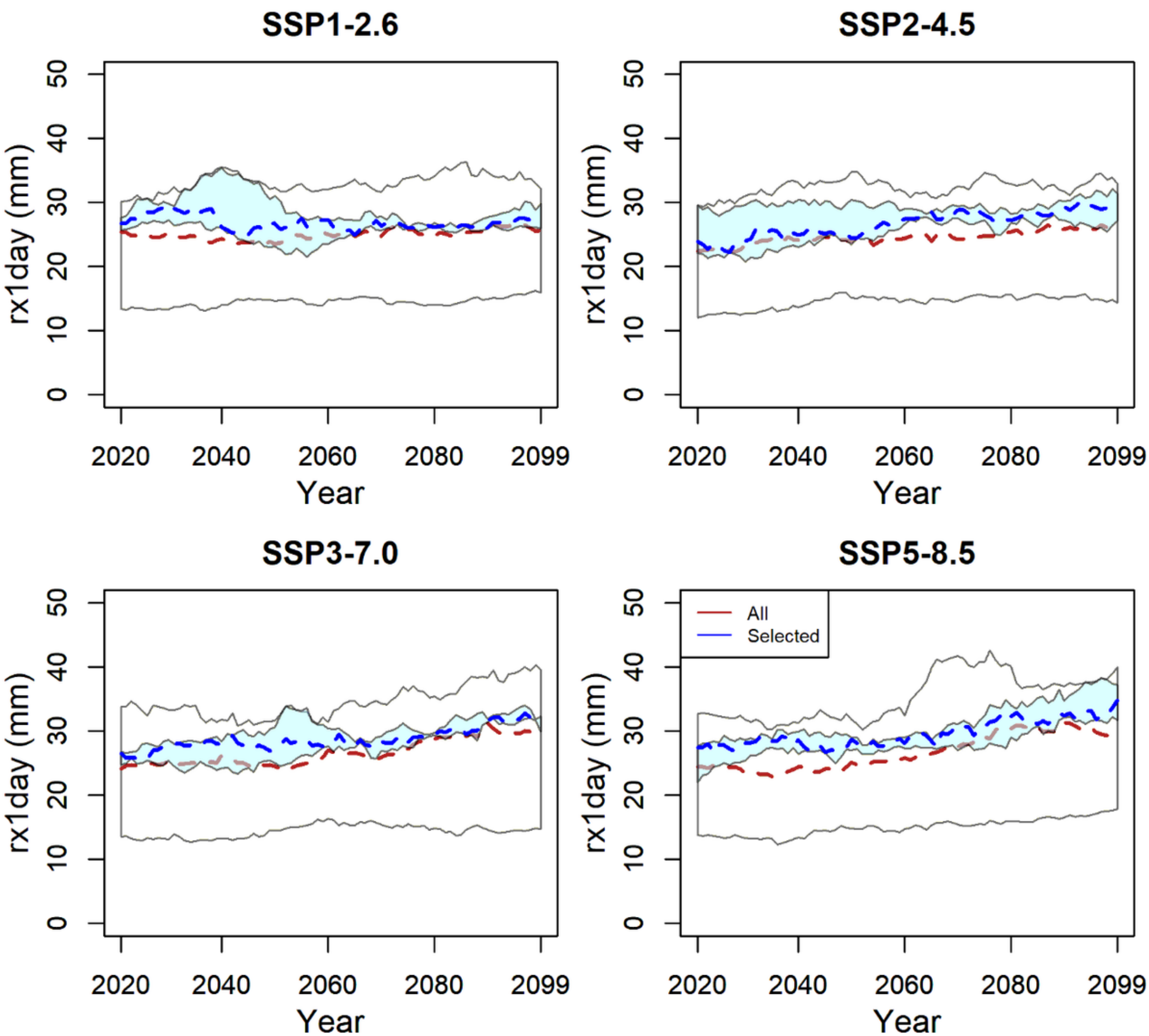

Figure 4

Temporal evaluation of annual mean Rx1day (mm) for all GCMs (yellow) and selected GCMs (blue) for different SSPs: (first row) SSP1-2.6 and SSP2-4.5 and (second row) SSP3-7.0 and SSP5-8.5. The shaded portion indicates a 95% confidence interval band.

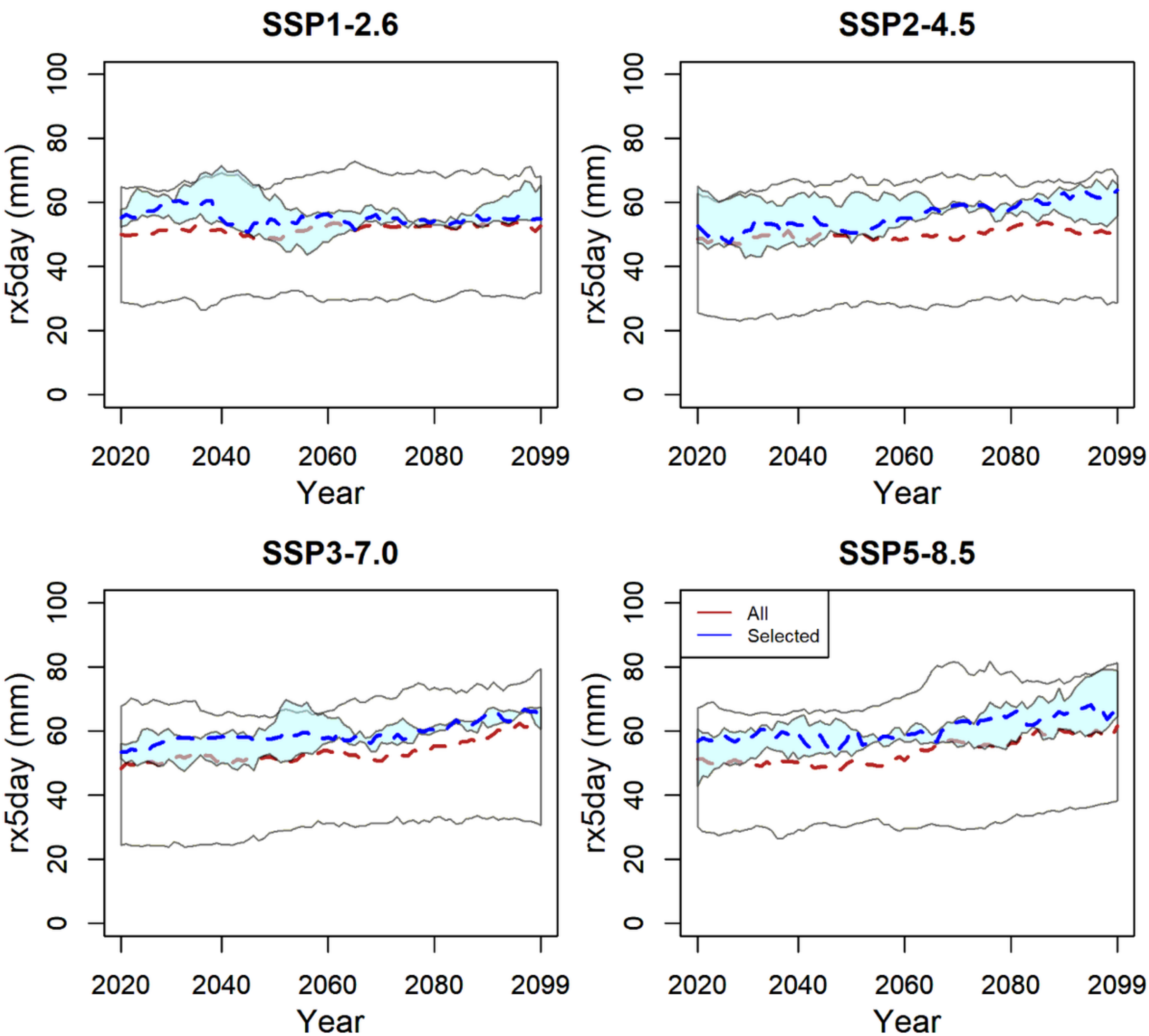

Figure 5

Consistent with Figure 4, but with Rx5day (mm).

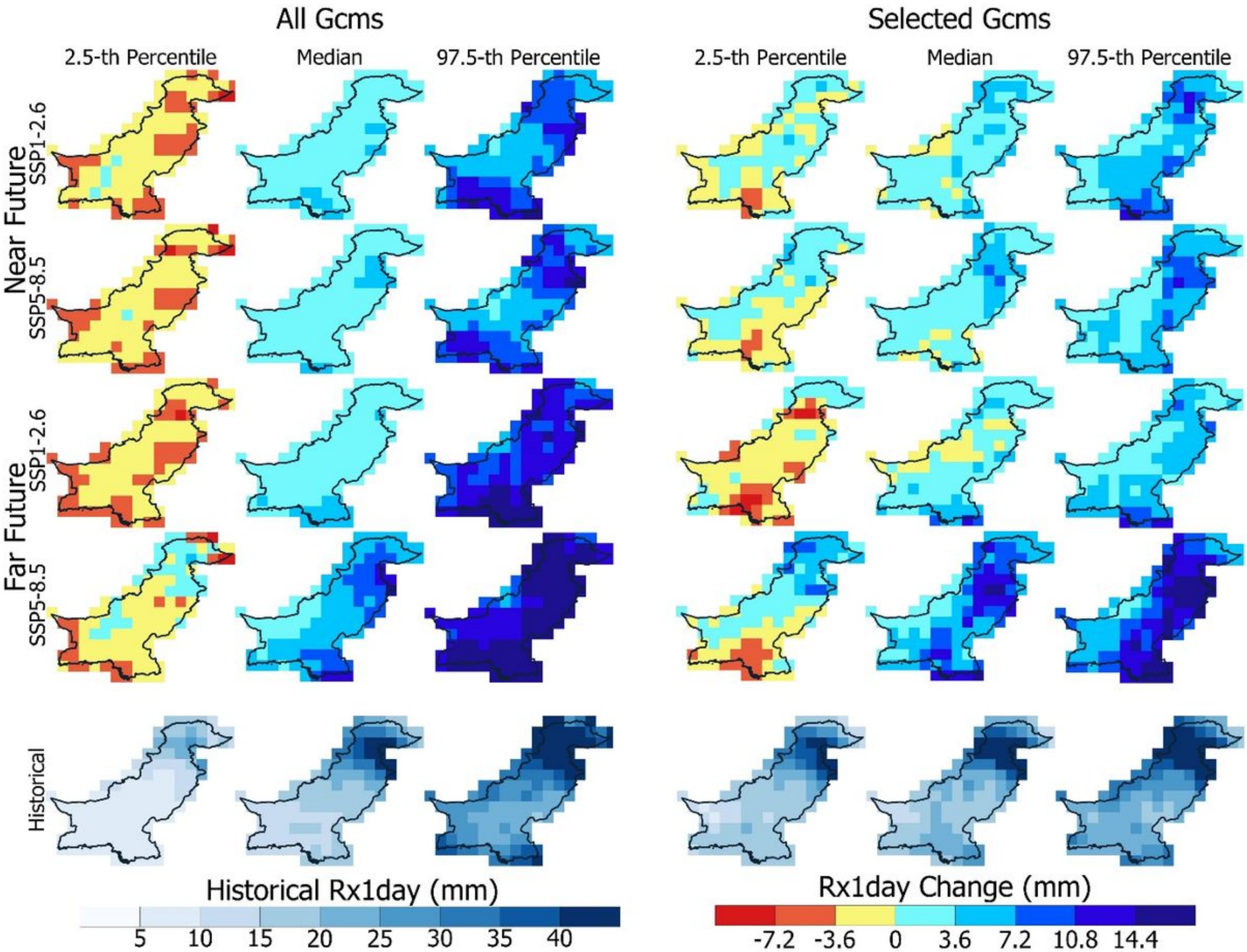

Figure 6

Spatial changes in Rx1day (mm) in the study area indicating 97.5th percentile, median and 2.5th percentile of all GCMs and selected GCMs for the historical period and in the near (2020−2059) and far (2060−2099) futures for SSP1-2.6 and SSP5-8.5.

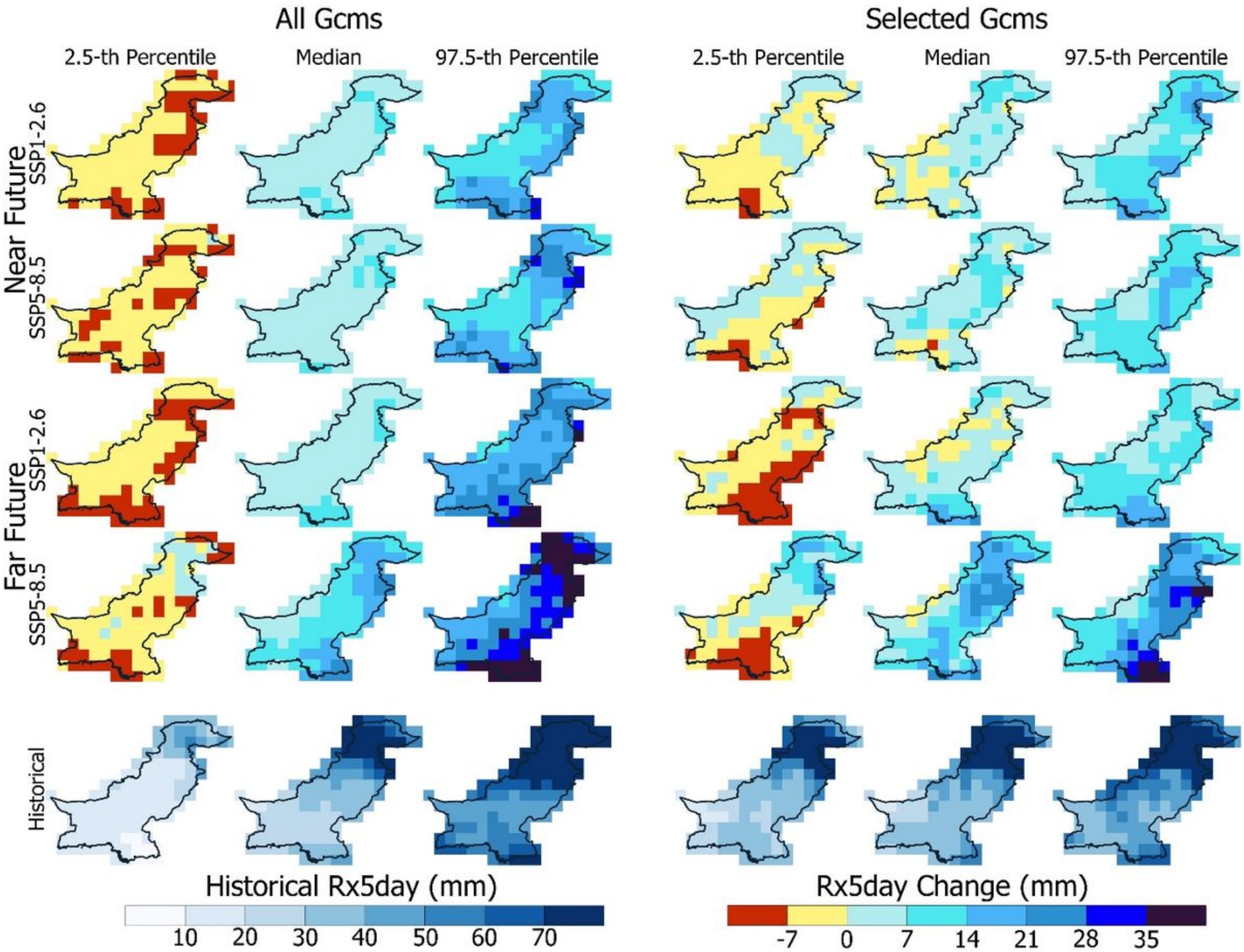

Figure 7

Consistent with Figure 6, but with Rx5day (mm).

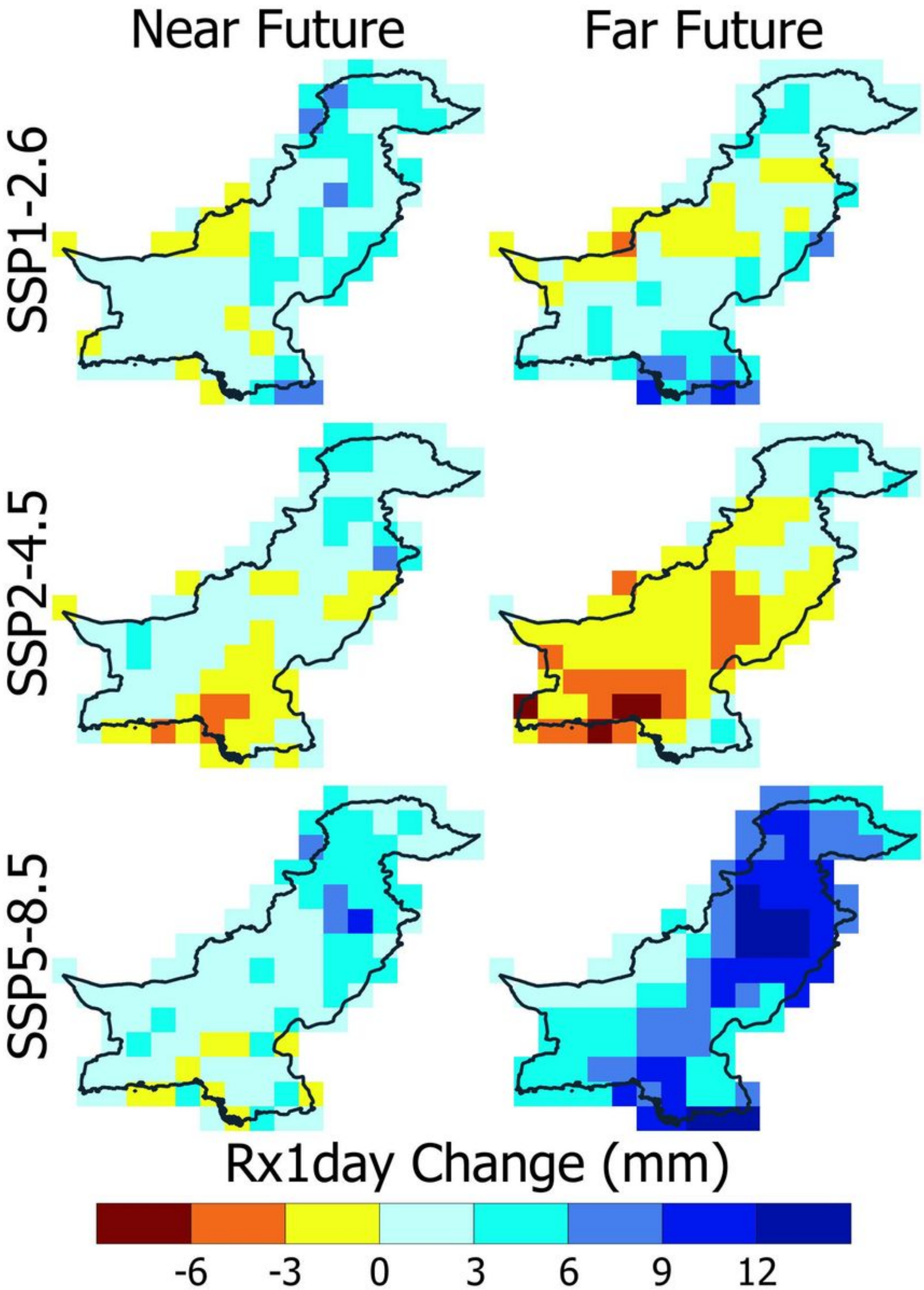

Figure 8

Spatial distribution of changes in Rx1day (mm) in study area indicating Median MME of selected GCMs in the period of (2020–2059) and (2060–2099) for different SSPs.

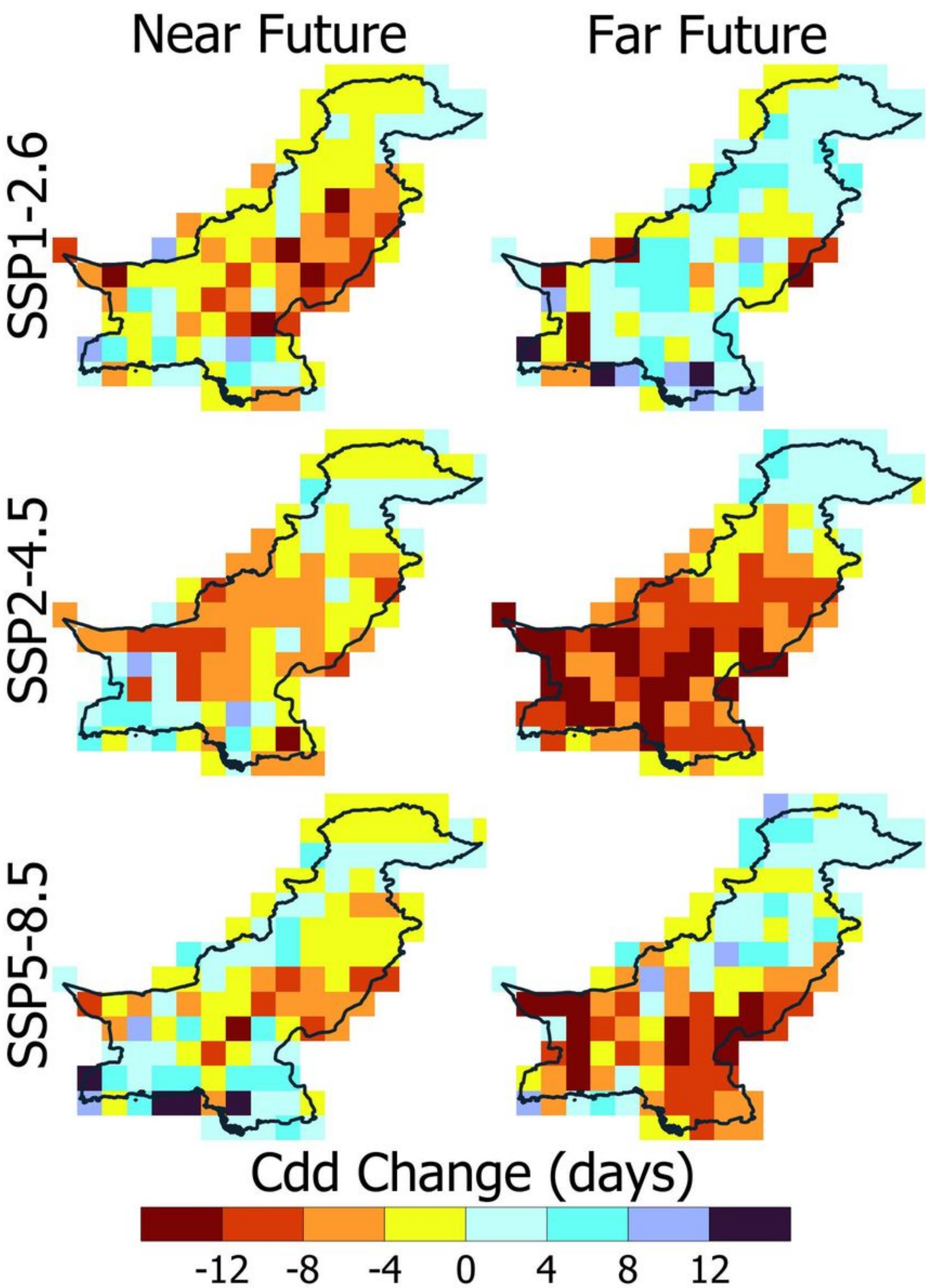

Figure 9

Consistent with Figure 8, but with Cdd (day).

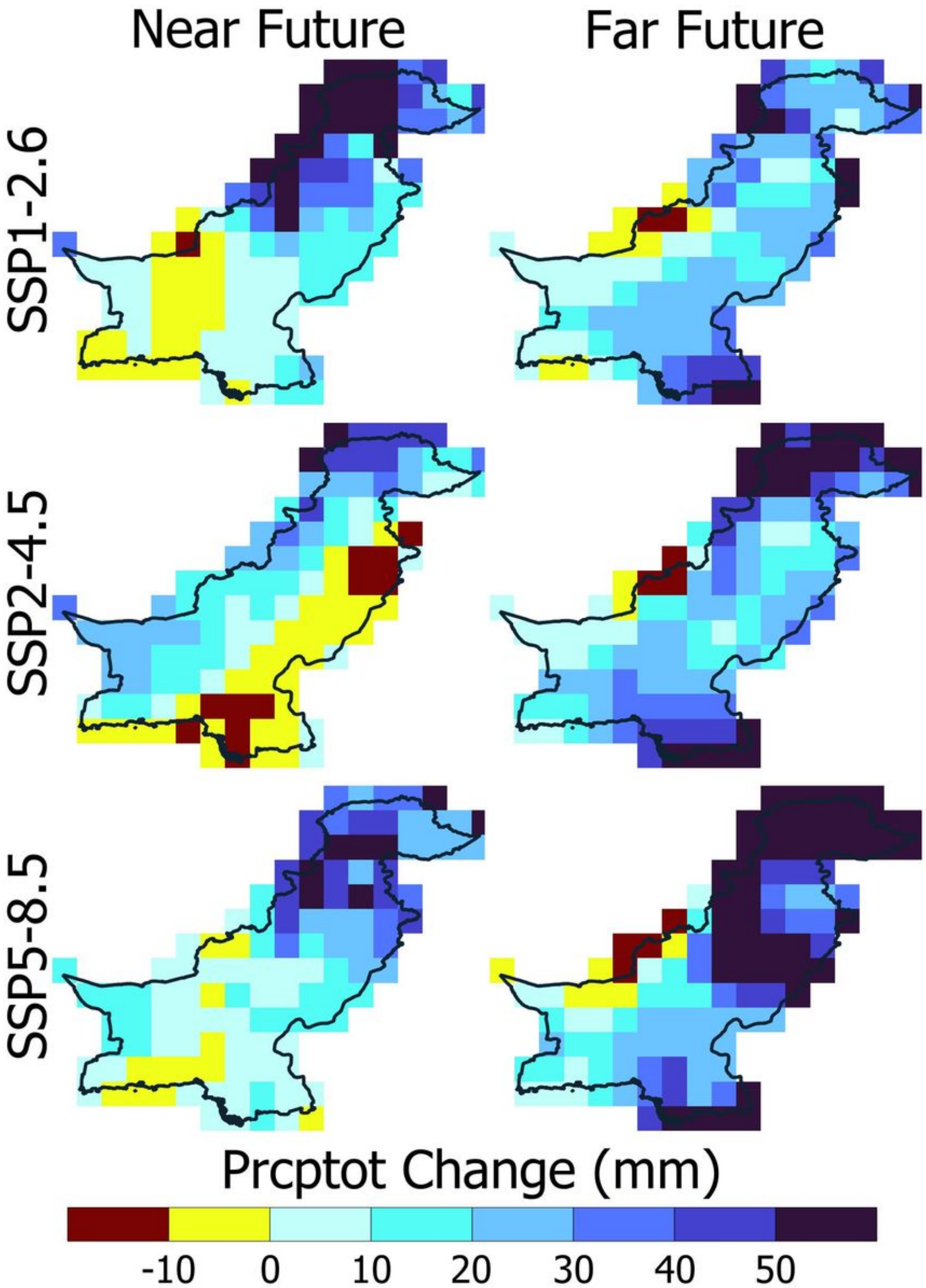

Figure 10

Consistent with Figure 8, but with Prcptot (mm)

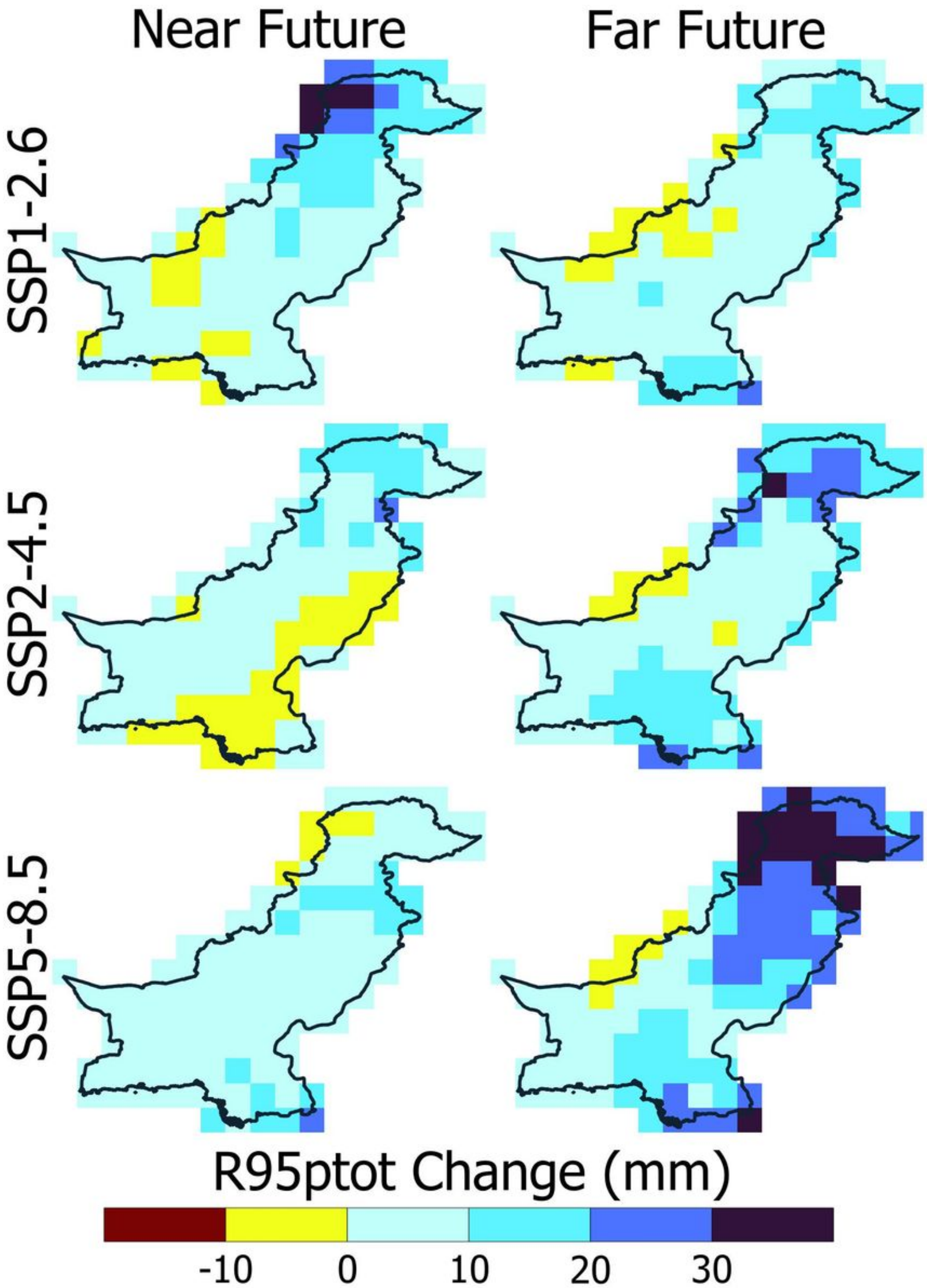

Figure 11

Consistent with Figure 8, but with R95ptot (mm)

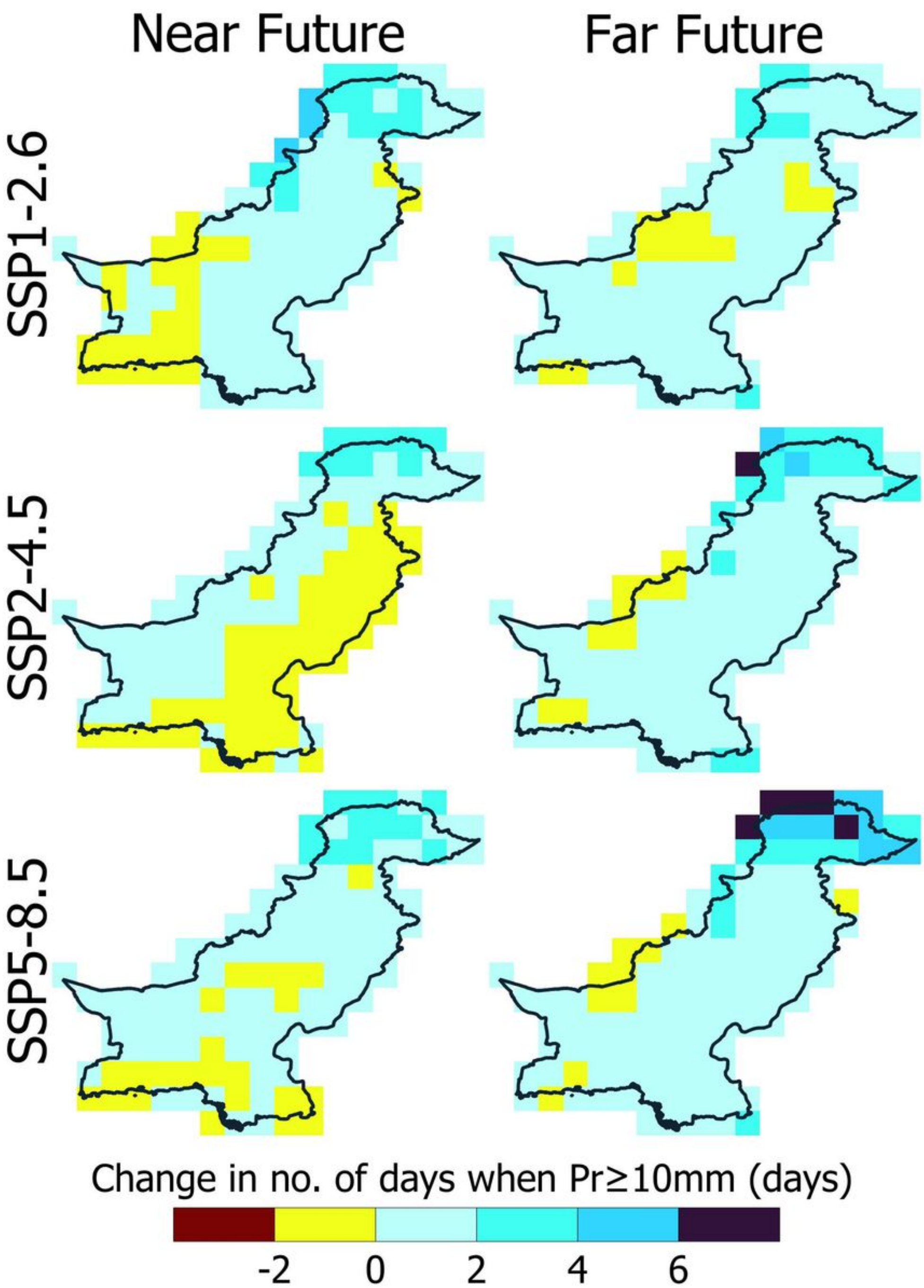

Figure 12

Consistent with Figure 8, but with R10mm (day)

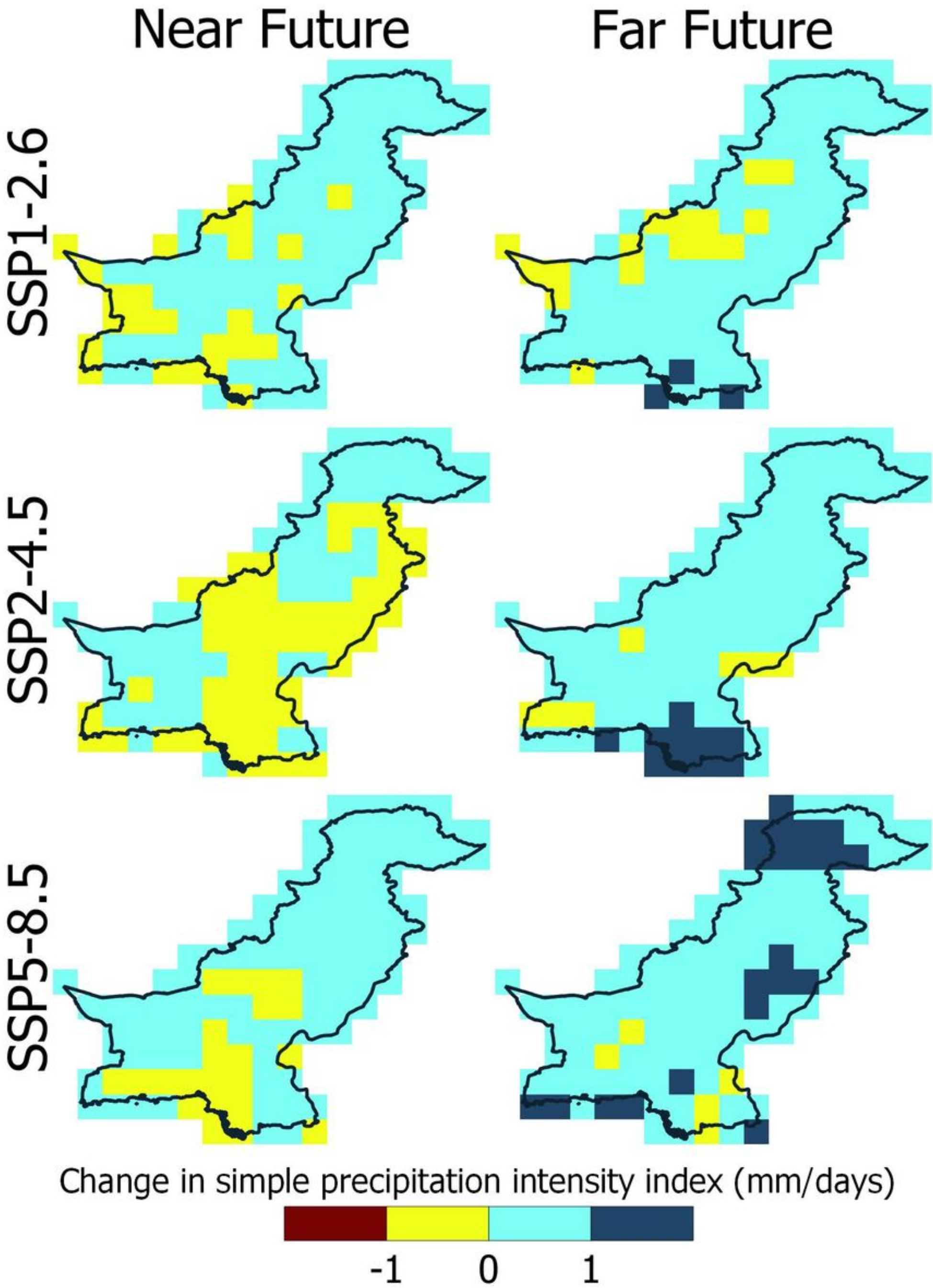

Figure 13

Consistent with Figure 8, but with Sdii (mm/day)

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Supplemetrytables.docx