Theoretical and Applied Climatology
https://doi.org/10.1007/s00704-018-2455-z

ORIGINAL PAPER

Historical simulations and climate change projections over India by NCAR CCSM4: CMIP5 vs. NEX-GDDP

Sandeep Sahany[1] · Saroj Kanta Mishra[1] · Popat Salunke[1]

Received: 19 April 2017 / Accepted: 6 March 2018

Abstract

A new bias-corrected statistically downscaled product, namely, the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), has recently been developed by NASA to help the scientific community in climate change impact studies at local to regional scale. In this work, the product is validated over India and its added value as compared to its CMIP5 counterpart for the NCAR CCSM4 model is analyzed, followed by climate change projections under the RCP8.5 global warming scenario using the two datasets for the variables daily maximum 2-m air temperature (T_{max}), daily minimum 2-m air temperature (T_{min}), and rainfall. It is found that, overall, the CCSM4-NEX-GDDP significantly reduces many of the biases in CCSM4-CMIP5 for the historical simulations; however, some biases such as the significant overestimation in the frequency of occurrence in the lower tail of the T_{max} and T_{min} still remain. In regard to rainfall, an important value addition in CCSM4-NEX-GDDP is the alleviation of the significant underestimation of rainfall extremes found in CCSM4-CMIP5. The projected T_{max} from CCSM4-NEX-GDDP are in general higher than that projected by CCSM4-CMIP5, suggesting that the risks of heat waves and very hot days could be higher than that projected by the latter. CCSM4-NEX-GDDP projects the frequency of occurrence of the upper extreme values of historical T_{max} to increase by a factor of 100 towards the end of century (as opposed to a factor of 10 increase projected by CCSM4-CMIP5). In regard to rainfall, both CCSM4-CMIP5 and CCSM4-NEX-GDDP project an increase in annual rainfall over India under the RCP8.5 global warming scenario progressively from the near term through the far term. However, CCSM4-NEX-GDDP consistently projects a higher magnitude of increase and over a larger area as compared to that projected by CCSM4-CMIP5. Projected daily rainfall distributions from CCSM4-CMIP5 and CCSM4-NEX-GDDP suggest the occurrence of events that have no historical precedents. Worth noting is that the extreme daily rainfall values projected by CCSM4-NEX-GDDP are two to three times larger than that projected by CCSM4-CMIP5.

1 Introduction

Climate change projections are essential on a wide range of space and time scales in order to plan adaptation and mitigation strategies so as to minimize the potential risks. The assessment reports produced by the Intergovernmental Panel on Climate Change (IPCC) serve as a good starting point to have a global as well as regional picture of climate change and their likely impacts. The latest in this series is the Assessment Report 5 (AR5) that was released in 2014. The AR5 is based on the results from the latest set of model simulations provided by the Coupled Model Intercomparison Project Phase (CMIP5; Taylor et al. 2012). The CMIP5 set of simulations includes a wider variety of experiments and more advanced climate models at higher resolutions as compared to its predecessor CMIP3. Since the CMIP5 model outputs are made freely available to the scientific community, they are used world over in numerous ways for a variety of decision-making exercises.

One of the first studies for India using the CMIP5 data was done by Chaturvedi et al. (2012) followed by other studies (e.g., Sooraj et al. 2015; Saha et al. 2014; Sabeerali et al. 2015). Using CMIP5 data, Chaturvedi et al. (2012) made projections of temperature and precipitation over India for various Representative Concentration Pathways (RCP) global warming scenarios. For the RCP6.0 and RCP8.5 scenarios,

✉ Sandeep Sahany
ssahany@cas.iitd.ac.in

[1] Centre for Atmospheric Sciences, Indian Institute of Technology Delhi, Hauz Khas, New Delhi 110016, India

Published online: 13 March 2018

they projected the mean warming over India to be in the range of 1.7–2 °C by 2030s (2021–2050) and around 3.3–4.8 °C by 2080s (2070–2099) relative to the pre-industrial (PI) levels. They projected that the annual precipitation over India would increase by 4 to 5% by 2030s and by 6 to 14% by 2080s compared to the 1961–1990 baseline period, and also found an increase in the frequency of extremes during the last few decades of the century. They found that far-term precipitation projections were more robust than the short-term ones (due to less disagreement between models in far-term projections).

In a seminal study by Knutti et al. (2013), the authors reported that the CMIP5 models showed a better agreement with observations than CMIP3. They also reported that although there are a large number of models in CMIP5, they are not completely independent of each other since many of these models are branched-out versions of a common ancestor. They used a distance metric to evaluate the CMIP models by estimating normalized distance of the model simulations from observations and reanalysis data. Their metric showed that from the CMIP5 set of models 3 (CESM1-CAM5, CESM1-BGC, and CCSM4) out of the top 5 models happen to be from the National Center for Atmospheric Research (NCAR).

Although CMIP5 models provide a global picture of climate change projections, owing to their coarser resolution, they sometimes prove to be of limited use while assessing regional climate change that requires much higher spatial resolutions than those provided by most of the global coupled models. This deficiency in the CMIP5 models is partially solved by downscaling the coarser model data to finer spatial resolutions. The downscaling is done either by using dynamical models (such as that done in the Coordinated Regional Downscaling Experiment [CORDEX]) or by statistical techniques. In the past, there have been few studies on using statistical downscaling and bias correction methods to post-process climate model outputs, both at regional as well as global scales, for impact assessment studies (e.g., Themeßl et al. 2011). Themeßl et al. (2011) used an ensemble of seven statistical downscaling and error-correction methods on regional climate simulation data over the Alpine region. They reported a significant reduction in error characteristics of the model-simulated rainfall by application of the statistical downscaling and error correction, and recommended the usability of these methods over other regions. Chen et al. (2013) compared the performance of six bias correction methods for hydrological modeling over North America, and reported that the distribution-based methods were better than the mean-based ones. In the Indian context, Salvi et al. (2011) applied the quartile-based bias correction method to model-simulated temperature, and reported that it worked quite well in getting rid of the biases.

Recently, the National Aeronautics and Space Administration (NASA) came up with a global, high-resolution, bias-corrected statistically downscaled product using CMIP5 outputs. The product is called as the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP) dataset (Thrasher et al. 2012; dataset URL: https://nex.nasa.gov/nex/projects/1356/). Given the availability of this new dataset, it is important to validate the downscaled product over different regions of the world and use it to assess climate change. In one of the first studies using this dataset, Ahmadalipour et al. (2017) used it for drought projections over various regions of the USA, and reported that there could be more frequent and intense summer droughts across the Contiguous United States under global warming.

Analysis presented in Mishra et al. (2017) showed that CCSM4 is one of the best-performing global climate models over the Indian region, in line with the conclusions drawn by Knutti et al. (2013). Taking this into consideration, and the fact that the NCAR CCSM4 is a community model with a large user base spread across the world, we chose this model for historical validation and climate change projections presented in this paper. It is to be noted that if one's primary objective is to make climate change projections over a certain region, then using only one model is definitely not advisable, since the uncertainty in climate change projections due to model uncertainty cannot be conveyed if one uses just one model. However, the primary objectives of this work are (i) for the historical climate investigate (by comparing with observations) how effective is the bias-corrected statistically downscaled NCAR CCSM4 data (from NEX-GDDP) in alleviating the existing biases in the CCSM4 model outputs from CMIP5 over the Indian region, and (ii) keeping the historical performance in hindsight compare the climate change projections for the RCP8.5 global warming scenario from the two datasets over the Indian region to analyze the similarities and differences. It is to be noted that we have used the RCP8.5 scenario since it is still widely used as the worst-case scenario for climate change studies, and to the best of our knowledge, it is yet to be formally ruled out as an unlikely scenario in spite of mitigation strategies being planned by some of the nations with highest emissions.

2 Data used

In this analysis, we have used the India Meteorological Department (IMD) gridded daily maximum 2-m air temperature (T_{max}) and daily minimum 2-m air temperature (T_{min}) at 1° resolution (1.0° × 1.0°) (Srivastava et al. 2009), and precipitation at quarter degree resolution (0.25° × 0.25°) (Pai et al. 2014) over the Indian land for the period 1975–2005. The CMIP5 (Taylor et al. 2012) datasets are available from the Earth System Grid Federation (ESGF) (https://esgf-index1.ceda.ac.uk/search/cmip5-ceda). For the historical simulations, the coupled atmosphere-ocean model is used and is forced by the estimated changes in the historical atmospheric composition due to factors such as volcanoes, greenhouse gases (GHGs), and aerosols. The historical simulations were performed for the period 1850–2005. In this study, we have used 31 years (1975–2005) of daily and monthly means of surface air temperature (maximum and minimum), and precipitation from CMIP5.

The NEX-GDDP dataset is a set of global, high-resolution, bias-corrected data that has been statistically downscaled from the CMIP5 model outputs. It uses a statistical downscaling technique called as the Bias-Corrected Spatial Disaggregation (BCSD) method (Wood et al. 2002, 2004; Maurer and Hidalgo 2008; Thrasher et al. 2012). The algorithm first compares the model outputs with the corresponding observations for the same period, and then uses the information related to the biases in the historical climate to correct the future climate projections. It also uses the finer-scale features from observations to interpolate the coarser climate model outputs to higher resolutions (0.25° × 0.25°). For observed estimates required for bias correction and statistical downscaling, the dataset used to produce NEX-GDDP is called as the Global Meteorological Forcing Dataset (GMFD) for land surface modeling, available from the Terrestrial Hydrology Research Group at Princeton University (Sheffield et al. 2006). This dataset blends reanalysis data with observations. Daily maximum temperature, daily minimum temperature, and daily precipitation, at quarter degree horizontal resolution, from 1950 to 2005 were used for the development of NEX-GDDP.

3 Results

In the following, first the CMIP5 and corresponding NEX-GDDP data for CCSM4 is validated against IMD observations. Following this, the climate change projections over India under the RCP8.5 global warming scenario is assessed using CCSM4-CMIP5 and CCSM4-NEX-GDDP for the near-term (2010–2039), mid-term (2040–2069), and far-term (2070–2099) time scales.

3.1 Historical simulations

In the following, the historical simulations from CCSM4-CMIP5 and CCSM4-NEX-GDDP are validated against IMD observations for T_{max}, T_{min}, and rainfall.

3.1.1 Historical simulations of T_{max} and T_{min}

In this section, the historical simulations from the CCSM4 model, both from CMIP5 and NEX-GDDP, are compared with observations from IMD. Since the NEX-GDDP produces only three variables, namely, daily maximum temperature, daily minimum temperature, and rainfall, these three variables are compared from the two datasets for CCSM4. In Fig. 1 the climatological (1975–2005) mean T_{max} and the mean T_{min} are compared with IMD observations. In Fig. 1 (a1), one can see that the mean T_{max} shows a spatial maxima over the southern parts and northwestern parts of India, and a spatial minima over the northernmost parts of India. The T_{max} values are not as high as one may expect because of the fact that the native resolution of the IMD temperature dataset is quite coarse (1° × 1°).

From Fig. 1 (b1), one can see that there is an underestimation of the mean T_{max} in the CSSM4-CMIP5, and the negative bias is especially large over the northernmost parts of India including the Himalayan region. It is to be noted that the biases over the Himalayan region must be treated with some caution since the observation density is also quite less over that region as compared to other parts of India. CCSM4-CMIP5 gets the spatial minima in T_{max} right over the northernmost parts of India, but the spatial maxima has errors. From Fig. 1 (c1), one can see that the mean T_{max} values from CCSM4-NEX-GDDP are much closer to observations, both in terms of magnitude and spatial pattern. The spatial maxima are rightly placed over the southern and northwestern parts of India, and the spatial minima over the northernmost parts of India.

Next, the simulations of the mean T_{min} from CCSM4-CMIP5 and CCSM4-NEX-GDDP are validated. From Fig. 1 (a2), one can see that the mean T_{min} has a spatial maxima over the southeastern parts and a spatial minima over the northernmost parts of India. CCSM4-CMIP5 gets the spatial pattern right but significantly underestimates the temperatures over the northernmost parts of India (see Fig. 1 (b2)). From Fig. 1 (c2), one can see that the spatial patterns are captured quite well by CCSM4-NEX-GDDP but the spatial minima over the northernmost parts of India is still underestimated. The bias, however, is smaller than that in CCSM4-CMIP5.

In Fig. 2, the probability distribution function (PDF) of T_{max} and T_{min} over India (without any spatial averaging) is shown from IMD observations, CCSM4-CMIP5, and CCSM4-NEX-GDDP for the period 1975–2005. From Fig. 2a, one can see that both CCSM4-CMIP5 and CCSM4-NEX-GDDP overestimate the frequency of occurrence in the low-temperature regime (< 20 °C) of T_{max}. Most of this could be coming from the Himalayan region where the mean T_{max} is significantly underestimated (see Fig. 1), but as noted earlier, this portion of the PDF in observations is also comparatively less reliable due to low measurement density over the Himalayan region. In the 20–40 °C range, both CCSM4-CMIP5 and CCSM4-NEX-GDDP match quite well with observations, the latter showing a better match. In the upper extreme of the distribution, both CCSM4-CMIP5 and CCSM4-NEX-GDDP have some values that are higher than observed, the former having more of them.

Figure 2b is similar to Fig. 2a, but for T_{min}. One can see similar features in the PDF as those seen in Fig. 2a. Both

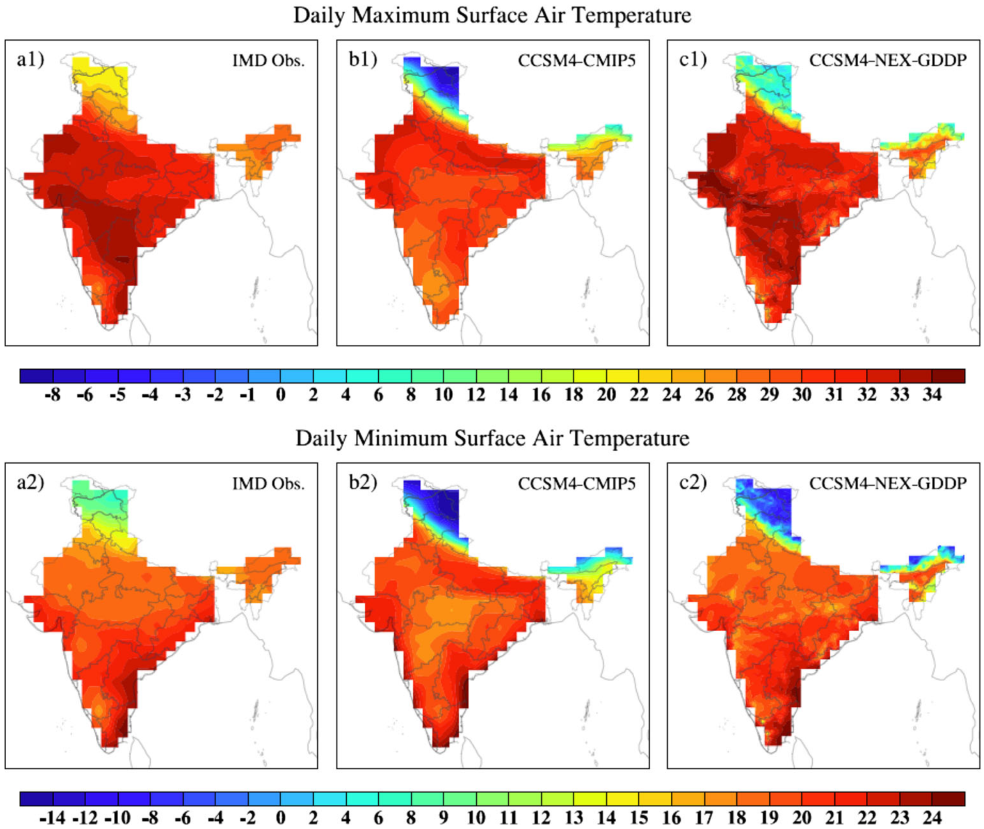

Fig. 1 Climatological (1975–2005) mean pattern of the daily maximum 2-m air temperature from a1 IMD, b1 CCSM4-CMIP5, and c1 CCSM4-NEX-GDDP. Climatological mean pattern of the daily minimum 2-m air temperature from a2 IMD, b2 CCSM4-CMIP5, and c2 CCSM4-NEX-GDDP

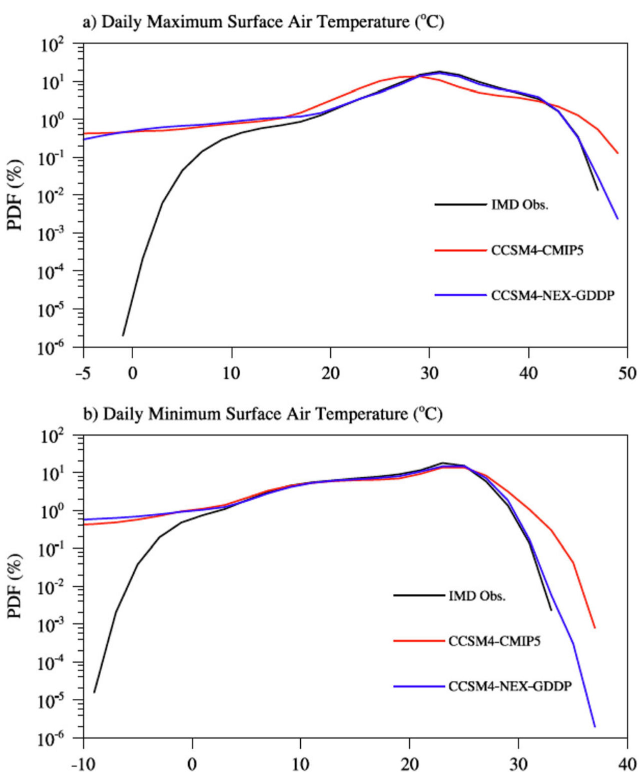

Fig. 2 Probability distribution functions over India for the period 1975–2005 computed from IMD observations, CCSM4-CMIP5, and CCSM4-NEX-GDDP for **a** daily maximum 2-m air temperature, and **b** daily minimum 2-m air temperature

CCSM4-CMIP5 and CCSM4-NEX-GDDP overestimate the frequency of occurrence in the lower extreme of the distribution, most likely due to the large negative bias in the mean T_{min} seen over the Himalayan region in Fig. 1 (b2–c2). In the temperature range of around 5–30 °C, there is an excellent match between the observations and both CCSM4-CMIP5 and CCSM4-NEX-GDDP. In the upper extreme of the distribution, similar to what was seen in Fig. 2a, both CCSM4-CMIP5 and CCSM4-NEX-GDDP have some values that are higher than observed, and here also the former has more of them.

3.1.2 Historical rainfall

In Fig. 3, the climatological (1975–2005) mean annual rainfall over India from IMD, CCSM4-CMIP5, and CCSM4-NEX-GDDP is shown. From Fig. 3a, one can see the broad features of the annual mean rainfall over India with spatial maxima over the northeastern parts, and Western Ghats; high rainfall over central and eastern states and foothills of Himalayas; and the dry regions of northwest and peninsular India. From Fig. 3b, one can see that CCSM4-CMIP5 gets the spatial maxima over northeast India and the spatial minima over northwestern parts of India right, but does not get the spatial maxima over the Western Ghats. It also fails to simulate the dry regions over peninsular India. From Fig. 3c, one can see that most of the

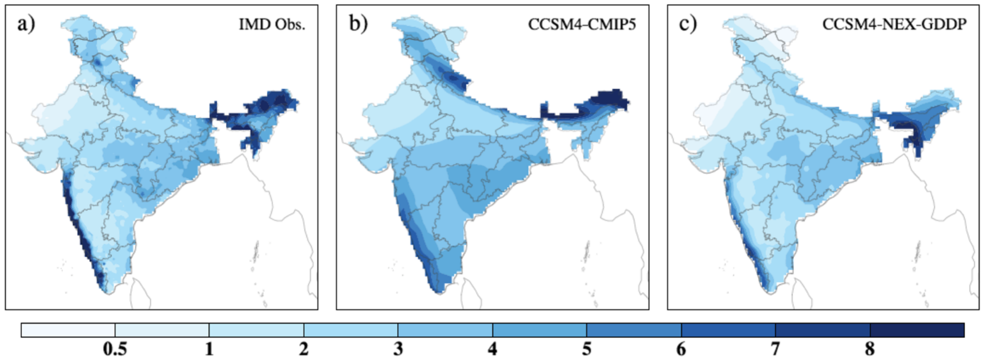

Fig. 3 Climatological (1975–2005) mean pattern of rainfall (mm/day) from **a** IMD observations, **b** CCSM4-CMIP5, and **c** CCSM4-NEX-GDDP

biases in CCSM4-CMIP5 get corrected in CCSM4-NEX-GDDP, with the Western Ghats maxima and dry regions over peninsular India appearing more prominently.

In Fig. 4, the PDF of daily rainfall over India from IMD observation, CCSM4-CMIP5, and CCSM4-NEX-GDDP is shown. One can see from the figure that the frequency of occurrence in the first bin (0–10 mm/day) is almost 90% in observations as well as CCSM4-CMIP5 and CCSM4-NEX-GDDP. This is due to the inclusion of non-rainy days in the distribution. In the low rainfall regime (0–50 mm/day), both CCSM4-CMIP5 and CCSM4-NEX-GDDP agree quite well with the observations. In the rainfall regime above this, CCSM4-CMIP5 underestimates the frequency of occurrence, with the degree of underestimation increasing with higher daily rainfall bins, thus showing significant underestimation of observed rainfall extremes. CCSM4-NEX-GDDP, however, matches quite well with the observed distribution, including extremes.

3.2 Climate change projections

In the following, T_{max}, T_{min}, and rainfall over India from CCSM4-CMIP5 and CCSM4-NEX-GDDP are projected for three time scales, namely, the near term (2010–2039), the mid term (2040–2069), and the far term (2070–2099) under the RCP8.5 global warming scenario.

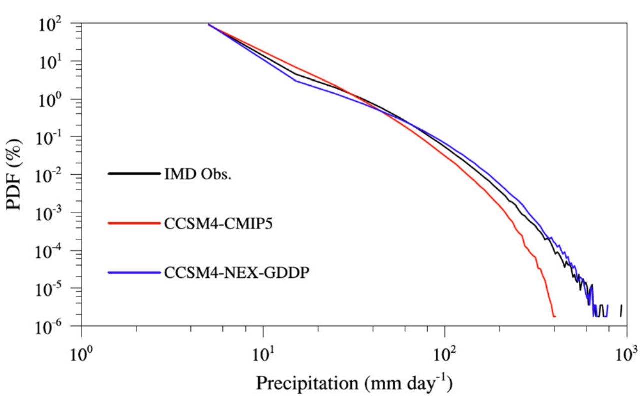

Fig. 4 Probability distribution functions over India for the period 1975–2005 computed from IMD observations, CCSM4-CMIP5, and CCSM4-NEX-GDDP for daily rainfall in bins of 10 mm/day

3.2.1 Projections of T_{max} and T_{min}

In Fig. 5, the projections of mean T_{max} over India under the RCP8.5 global warming scenario from CCSM4-CMIP5 and CCSM4-NEX-GDDP are shown for the near term, mid term, and far term. From Fig. 5 (a1–a3 and b1–b3), one can see an increase in T_{max} with time progressively from the near term to mid term, and then to the far term, in both CCSM4-CMIP5 and CCSM4-NEX-GDDP. Due to bias correction and statistical downscaling in CCSM4-NEX-GDDP, one can see that in general the values are higher than that simulated by CCSM4-CMIP5, thus suggesting that the potential risks of heat waves and extreme temperatures are higher than that projected by the latter. From Fig. 5 (b1–b3), one can also see that statistical downscaling brings out the finer-scale spatial structures in CCSM4-NEX-GDDP such as the higher temperatures over northwestern and peninsular India. However, notably, if one were to look at the change in T_{max} for the three time periods from CCSM4-CMIP5 and CCSM4-NEX-GDDP (see Fig. 5 (c1–c3 and d1–d3)), one finds that the magnitudes as well as the spatial pattern of changes are not very different.

Figure 6 is similar to Fig. 5, just that here the projections for mean T_{min} is shown in place of T_{max}. One can see from Fig. 6 that there is a progressive increase in mean T_{min} from the near term through the far term, similar to that seen in mean T_{max}. Similar to Fig. 5, one can see the finer spatial patterns in CCSM4-NEX-GDDP as compared to CCSM4-CMIP5 (see Fig. 6 (a1–a3, b1–b3)). If one were to look at the changes in mean T_{min} for the three time slices, one finds that both CCSM4-CMIP5 and CCSM4-NEX-GDDP show a similar spatial pattern and similar magnitude of changes. The spatial maxima in the warming signal of around 1.5 °C in the near term, around 3 °C in the mid term, and around 5 °C in the far term can be seen in the northernmost parts of India. Comparing Figs. 5 (d3) and Fig. 6 (d3), one can see that CCSM4-NEX-GDDP projects an increase in the mean T_{max} in the far term by around 2.5 °C over the northernmost parts of India whereas the corresponding increase in the mean T_{min} is around 5 °C, suggesting a decrease in the diurnal range of temperature.

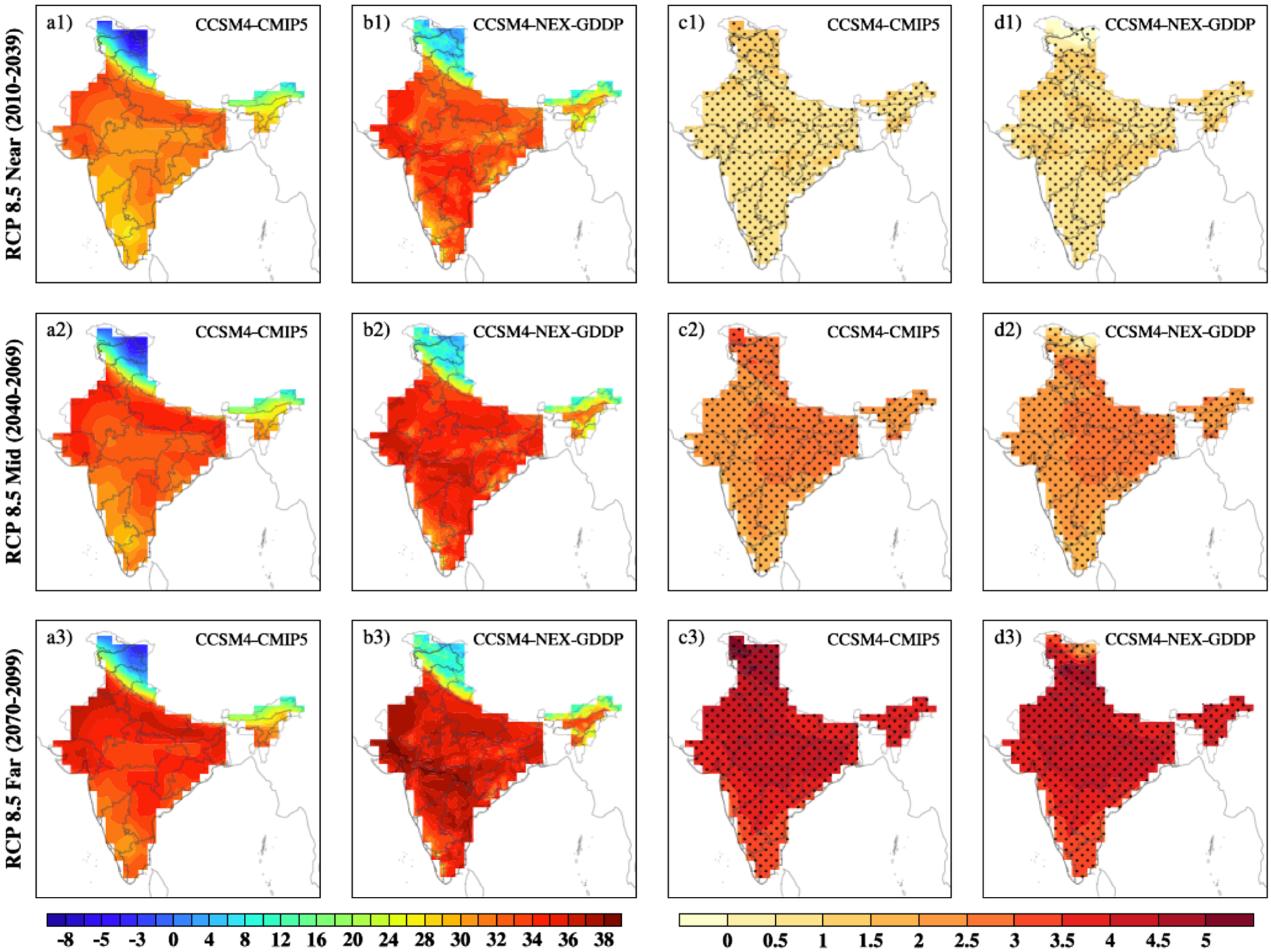

Fig. 5 Projections of mean daily maximum 2-m air temperature under the RCP8.5 global warming scenario for CCSM4-CMIP5 a1 near term, a2 mid term, and a3 far term; for CCSM4-NEX-GDDP b1 near term, b2 mid term, and b3 far term. Projections of changes in the mean daily maximum 2-m air temperature under the RCP8.5 global warming scenario as compared to the baseline period (1975–2005) for CCSM4-CMIP5 c1 near term, c2 mid term, and c3 far term; for CCSM4-NEX-GDDP d1 near term, d2 mid term, and d3 far term. Stippling indicates grid points that have changes significant at the 99% level

In Fig. 7, the probability distribution function of T_{max}, and T_{min} for historical and RCP8.5 projections from CCSM4-CMIP5 and CCSM4-NEX-GDDP is shown for near term, mid term, and far term. From Fig. 7 (a1), one can see that based on CCSM4-CMIP5, the left tail of the distribution ($T_{max} < \sim 15$ °C) is not much affected due to climate change, but there are important changes in the rest of the distribution. In the lower-mid range (~ 15 to ~ 30 °C), there is a reduction in the frequency of occurrence progressively from the near term through the far term. In the upper-mid range (~ 30 to ~ 40 °C), there is an increase in the frequency of occurrence progressively from the near term through the far term. In the right tail of the distribution (> ~ 40 °C), there is a significant increase in the occurrence probability to the extent that in the far term the frequency of occurrence of the most extreme values increases by a factor of 10 as compared to the historical climate. In Fig. 7 (b1), the corresponding PDFs from CCSM4-NEX-GDDP is shown. Similar to what was seen in Fig. 7 (a1), one can see that the left tail of the distribution is not much affected due to climate change, but there are important changes in the rest of the distribution, with a reduction in the frequency of occurrence progressively from the near term through the far term in the lower-mid range, and an increase in the frequency of occurrence progressively from the near term through the far term in the upper-mid range. In the right tail of the distribution, however, there is a much larger increase in the occurrence probability projected by CCSM4-NEX-GDDP as compared to that projected by CCSM4-CMIP5. As per CCSM4-NEX-GDDP, the frequency of occurrence of the most extreme values are projected to increase by a factor of 100 in the far term as compared to the historical climate (as opposed to a factor of 10 increase projected by CCSM4-CMIP5).

In Fig. 7 (a2–b2), the probability distribution functions similar to Fig. 7 (a1–b1) are shown, but for T_{min}. From Fig. 7 (a2), one can see that the left tail of the distribution is not much affected due to climate change. In the mid range, there is

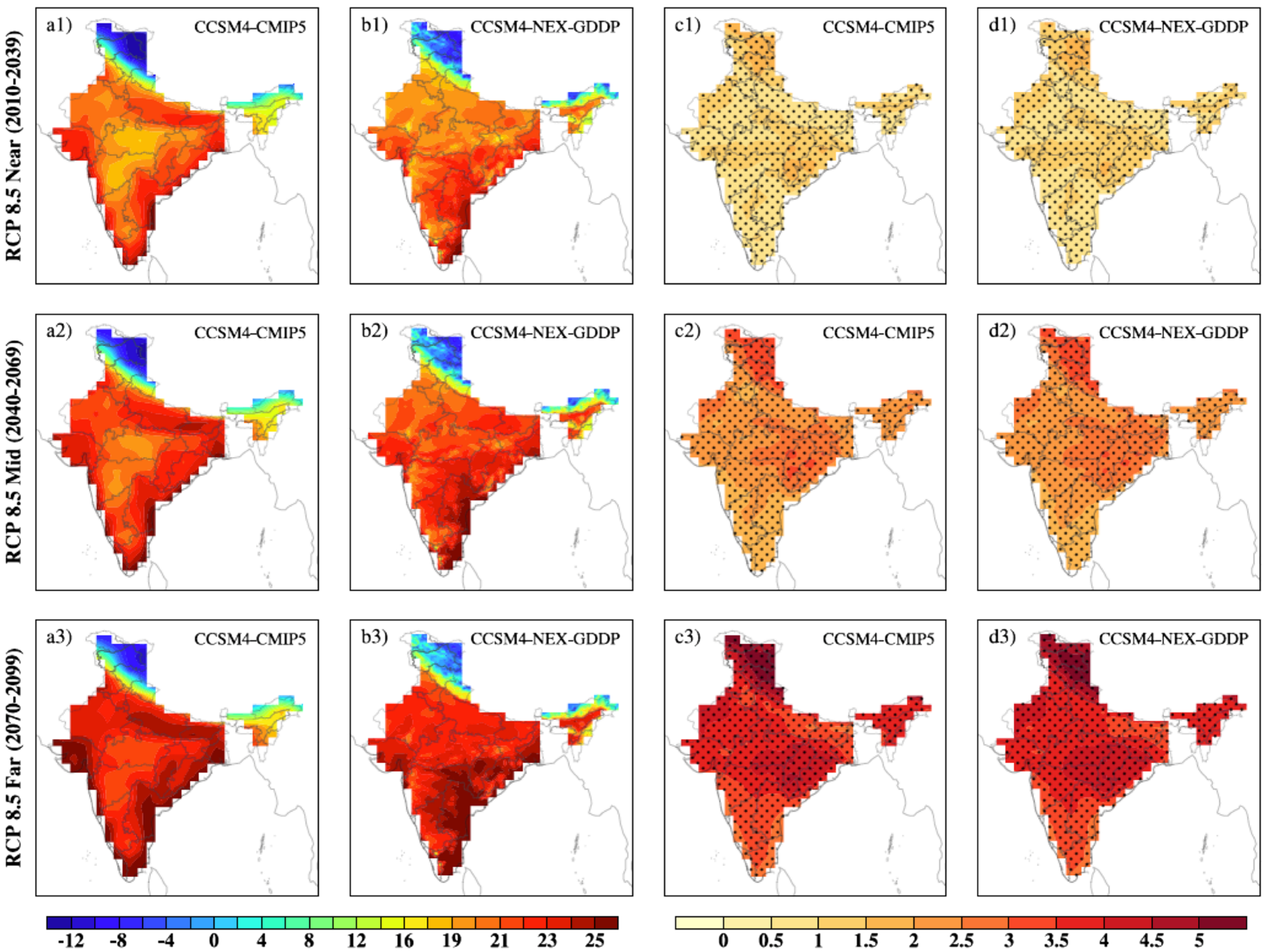

Fig. 6 Projections of mean daily minimum 2-m air temperature under the RCP8.5 global warming scenario for CCSM4-CMIP5 a1 near term, a2 mid term, and a3 far term; for CCSM4-NEX-GDDP b1 near term, b2 mid term, and b3 far term. Projections of changes in the mean daily minimum 2-m air temperature under the RCP8.5 global warming scenario as compared to the baseline period (1975–2005) for CCSM4-CMIP5 c1 near term, c2 mid term, and c3 far term; for CCSM4-NEX-GDDP d1 near term, d2 mid term, and d3 far term. Stippling indicates grid points that have changes significant at the 99% level

a small progressive decrease in the frequency of occurrence from the near term through the far term, but the largest changes occur in the right tail of the distribution. One can see that under the RCP8.5 scenario, there is a progressive increase from the near term through the far term in the frequency of occurrence of the upper extreme values. One can also see that as per the CCSM4-CMIP5 projections, the highest values of T_{min} in the near term are unprecedented in the historical, and those in the mid term and far term are even higher than the near term. CCSM4-NEX-GDDP also projects an increase in occurrence frequency in the upper extremes of T_{min} in the near term through the far term; however, the projected frequency is less than that suggested by CCSM4-CMIP5.

3.2.2 Projections of rainfall

In Fig. 8, the annual mean rainfall projections over India from CCSM4-CMIP5 and CCSM4-NEX-GDDP are shown for the three time scales, namely, the near term, the mid term, and the far term, under the RCP8.5 global warming scenario. From Fig. 8 (a1–a3, b1–b3), one can see that there is a steady increase in annual rainfall over many parts of India from near term through the far term in both CCSM4-CMIP5 and CCSM4-NEX-GDDP, although the actual values in the latter are less over many parts (e.g., central India, peninsular India, and Himalayan foothills) due to bias correction of the existing positive biases in CCSM4-CMIP5. The changes in annual rainfall can be more clearly seen from Fig. 8 (c1–c3, d1–d3). In the near term (see Fig. 8 (c1–d1)), significant positive changes are projected over a smaller area and of lower magnitude by CCSM4-CMIP5 as compared to CCSM4-NEX-GDDP. In the mid term (see Fig. 8 (c2–d2)), both CCSM4-CMIP5 and CCSM4-NEX-GDDP show an increase in the area with significant positive changes and also an increase in magnitude, with the latter projecting a larger area and higher magnitude of positive changes. In the far term (see Fig. 8 (c3–

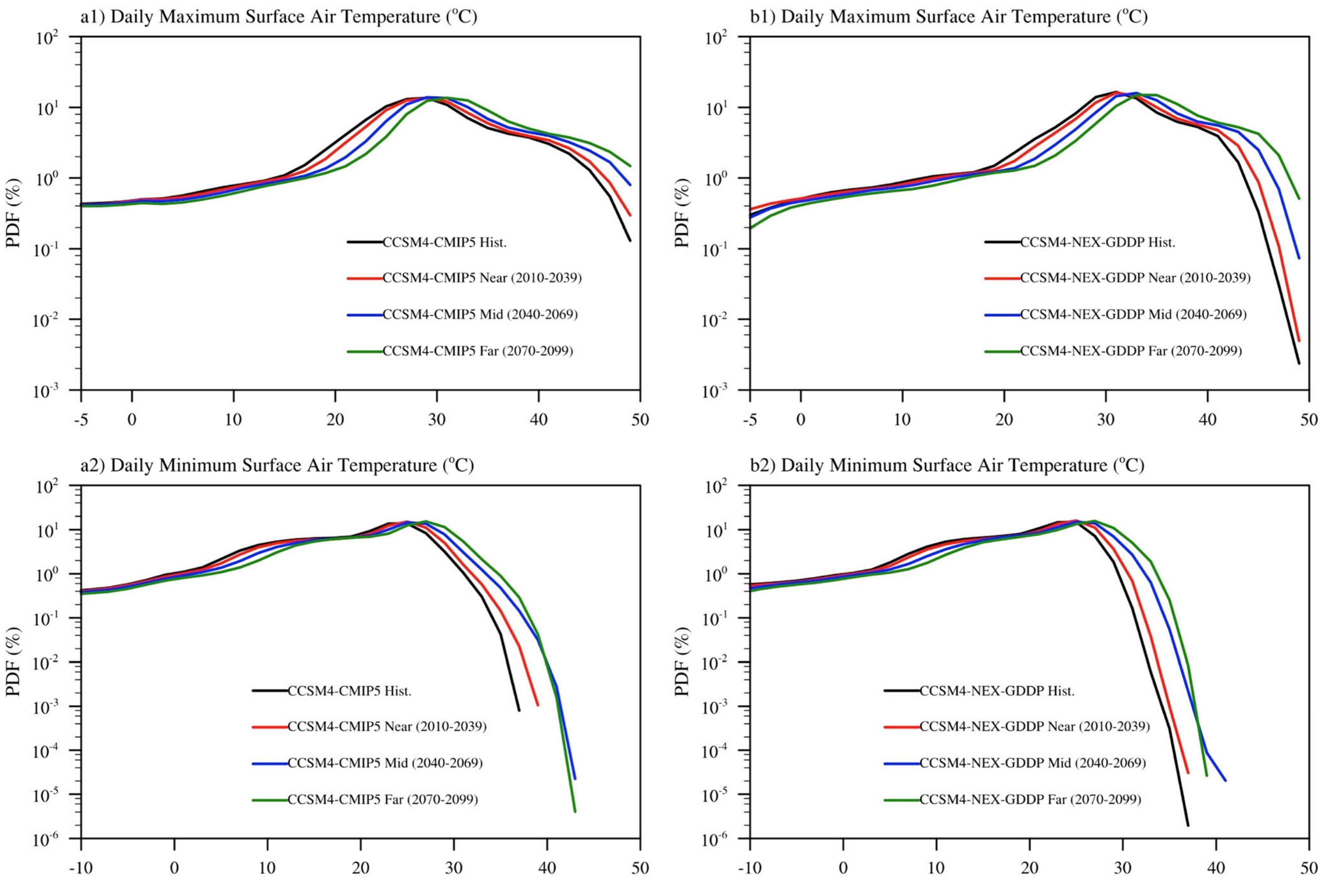

Fig. 7 Probability distribution functions of historical simulations and projections under the RCP8.5 global warming scenario from CCSM4-CMIP5 and CCSM4-NEX-GDDP for near term, mid term, and far term for a1, b1 daily maximum 2-m air temperature, and a2, b2 daily minimum 2-m air temperature

d3)), both CCSM4-CMIP5 and CCSM4-NEX-GDDP show a further increase in the area with significant positive changes and also a further increase in magnitude, with the latter projecting a larger area and higher magnitude of positive changes. By the end of the century, the largest increase (by around 25%) is projected in the northeastern states of India, and an increase by ~ 15% in the southern, central, and eastern states of India. Over the northwestern parts of India, although there is a small positive projected increase from the near term through the far term in both CCSM4-CMIP5 and CCSM4-NEX-GDDP, the changes are not significant.

In Fig. 9, the probability distribution functions of precipitation for historical and RCP8.5 projections from CCSM4-CMIP5 and CCSM4-NEX-GDDP are shown for near term, mid term, and far term. Comparing the projections from CCSM4-CMIP5 and CCSM4-NEX-GDDP with their corresponding historical distributions, one can see that there is an increase in the frequency of occurrence of high values of daily rainfall progressively from the near term through the far term. Both CCSM4-CMIP5 and CCSM4-NEX-GDDP project the occurrence of events that are unprecedented in the past. The extreme values projected by CCSM4-NEX-GDDP, however, are two to three times larger than that projected by CCSM4-CMIP5, thus suggesting more severe floods.

4 Summary and discussion

In this paper, for the NCAR CCSM4 model, we first evaluated the added value of the bias-corrected statistically downscaled product from NASA, namely, NEX-GDDP, as compared to the corresponding model simulation from CMIP5 for the historical period. Following this, we used the two datasets to project the daily maximum 2-m air temperatures, daily minimum 2-m air temperatures, and rainfall over the Indian region under the RCP8.5 global warming scenario for the near-term, mid-term, and far-term future.

The observed T_{max} spatially peaks over the southern parts and northwestern parts of India, and has a spatial minimum over the northernmost parts of India. Historical simulations from CCSM4-CMIP5 show a large negative bias over the northernmost parts of India including the Himalayan region. Overall, T_{max} values from CCSM4-NEX-GDDP are much closer to observations, both in terms of magnitude and spatial pattern, due to the effect of both bias correction and statistical

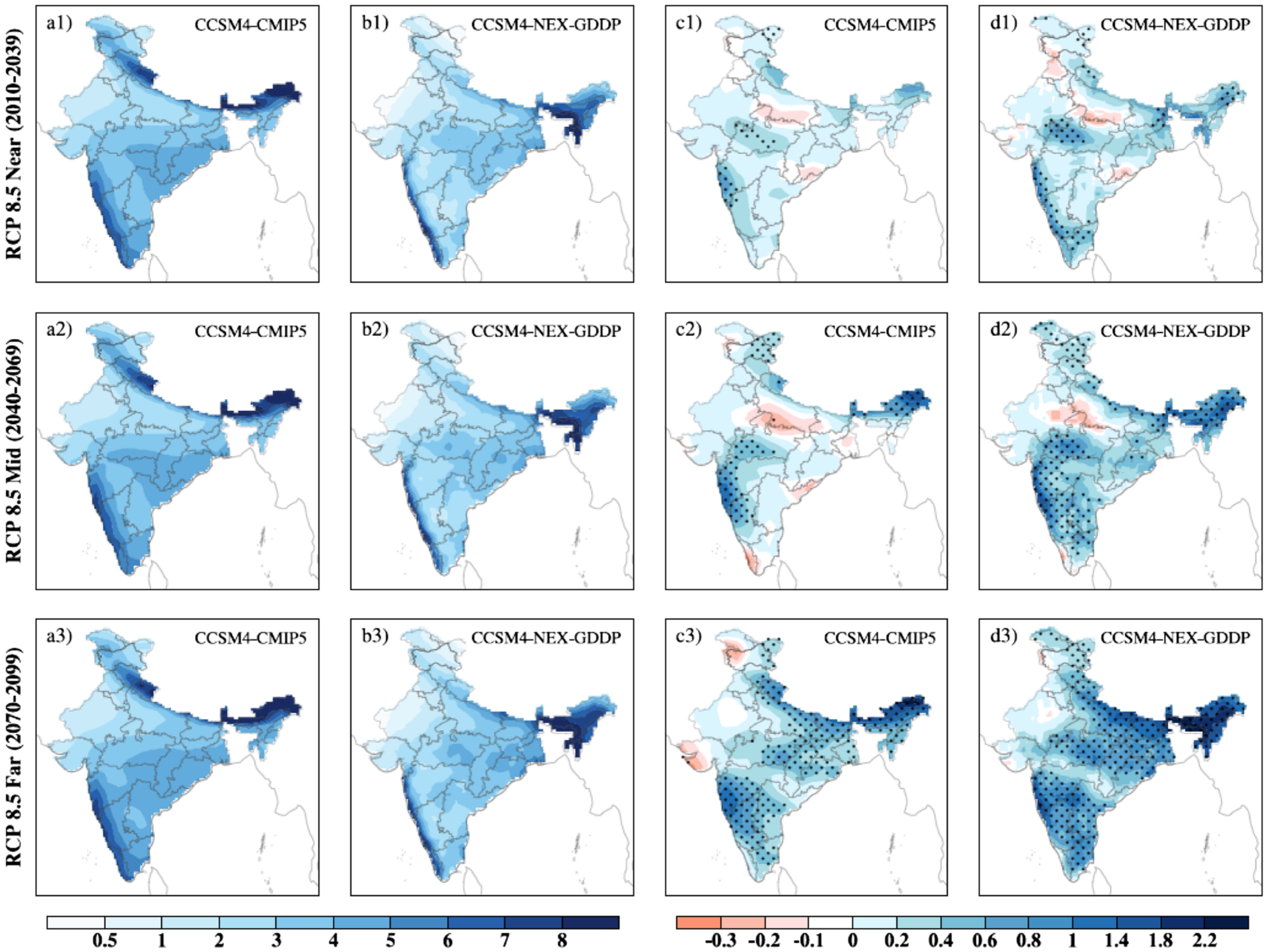

Fig. 8 Projections of annual rainfall (mm/day) under the RCP8.5 global warming scenario for CCSM4-CMIP5 a1 near term, a2 mid term, and a3 far term; for CCSM4-NEX-GDDP b1 near term, b2 mid term, and b3 far term. Projections of changes in the annual rainfall (mm/day) under the RCP8.5 global warming scenario as compared to the baseline period (1975–2005) for CCSM4-CMIP5 c1 near term, c2 mid term, and c3 far term; for CCSM4-NEX-GDDP d1 near term, d2 mid term, and d3 far term. Stippling indicates grid points that have changes significant at the 99% level

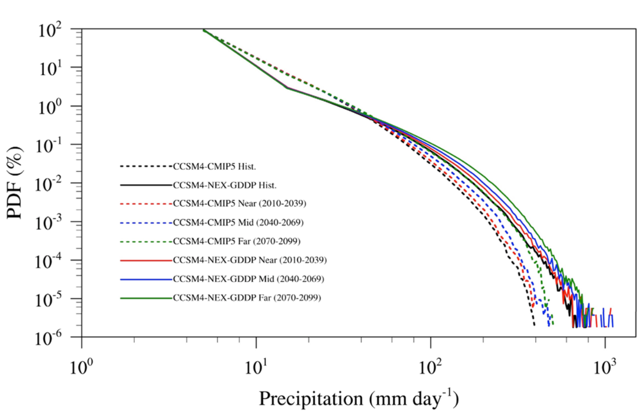

Fig. 9 Probability distribution function of rainfall for the historical and RCP8.5 projections for near term, mid term, and far term from CCSM4-CMIP5 and CCSM4-NEX-GDDP

downscaling. Analysis of the probability distribution functions showed that both CCSM4-CMIP5 and CCSM4-NEX-GDDP overestimated the frequency of occurrence in the low-temperature regime. This could most likely be due to the significant underestimation of T_{max} over the Himalayan region. Due to bias correction and statistical downscaling, it was seen that CCSM4-NEX-GDDP matches quite well with observations, and one would expect that the corresponding projections may be more reliable than that from CCSM4-CMIP5. The projected T_{max} over India under the RCP8.5 global warming scenario shows an increase from the near term through the far term, in both CCSM4-CMIP5 and CCSM4-NEX-GDDP. The projected T_{max} from CCSM4-NEX-GDDP are, in general, higher than that projected by CCSM4-CMIP5. This suggests that the risks of heat waves and extreme temperatures could be higher than those projected by CCSM4-CMIP5. However, the magnitude and spatial pattern of change in T_{max} are not very different in the two sets of projections for all the three time periods. Analysis of projected PDFs from the two sets shows that the left tail of the distribution will not be affected much due to climate change, although important changes are projected for the rest of the distribution. Frequency of occurrence in the lower-mid range of the distribution is projected to reduce, and the frequency of occurrence in the upper-mid range of the distribution is projected to increase, progressively from the near term through the far term. Both CCSM4-CMIP5 and CCSM4-NEX-GDDP project an increase in the frequency of occurrence in the right tail of the distribution (upper extremes); however, there is a much larger increase projected by the latter. As compared to the historical climate, CCSM4-NEX-GDDP projects the frequency of occurrence of the most extreme values to increase by a factor of 100 in the far term (as opposed to a factor of 10 increase projected by CCSM4-CMIP5).

The observed T_{min} spatially peaks over the southeastern parts and shows a spatial minimum over the northernmost parts of India. The T_{min} over the northernmost parts of India is underestimated by both CCSM4-CMIP5 and CCSM4-NEX-GDDP; however, the latter has lower bias. From the PDF analysis, similar to T_{max}, both CCSM4-CMIP5 and CCSM4-NEX-GDDP are found to overestimate the frequency of occurrence in the lower extreme of the distribution, most likely due to the significant underestimation of T_{min} over the Himalayan region. Similar to T_{max}, projections of T_{min} also show a progressive increase from the near term through the far term. The spatial maxima in the warming signal is over the northernmost parts of India, with around 1.5 °C increase in the near term, around 3 °C increase in the mid term, and around 5 °C increase in the far term. CCSM4-NEX-GDDP projects an increase in T_{max} in the far term by around 2.5 °C over the northernmost parts of India, but the corresponding increase in T_{min} is projected to be around 5 °C, thus suggesting a higher increase in the number of warm nights as compared to the increase in the number of hot days. One should also note that the significant increase in temperatures over the northernmost parts of India that includes the Himalayas has strong implications for the snow cover and hence water supply management and agriculture downstream. Similar to the projected PDFs of T_{max}, projected PDFs of T_{min} show that the left tail of the distribution is not much affected due to climate change. In the mid range, there is a small progressive decrease in the frequency of occurrence from the near term through the far term. The largest changes, however, occur in the right tail of the distribution. As compared to the historical distribution, there is a progressive increase from the near term through the far term in the frequency of occurrence of the upper tail values. Projections from CCSM4-NEX-GDDP suggest that the occurrence frequency of the upper extremes in T_{min} (very warm nights) in the near term through the far term would be less than that projected by CCSM4-CMIP5.

In regard to rainfall, IMD data shows a spatial maximum in annual mean rainfall over the northeastern parts, and Western Ghats; high rainfall over central and eastern states and foothills of Himalayas; and dry regions over northwest and peninsular India. The spatial maxima over northeast India and minima over northwestern parts of India are captured by CCSM4-CMIP5, but it fails to simulate the maxima over the Western Ghats, and also the dry peninsular India. Corresponding spatial patterns in CCSM4-NEX-GDDP, however, are much closer to observations. Analysis of PDFs of daily rainfall shows that both CCSM4-CMIP5 and CCSM4-NEX-GDDP agree quite well with observations in the low rainfall regime (0–50 mm/day). Beyond this rainfall regime, CCSM4-CMIP5 underestimates the frequency of occurrence. The negative bias increases with higher rainfall bins, with observed rainfall extremes being significantly underestimated. However, CCSM4-NEX-GDDP matches quite well with the observed distribution, including extremes. A steady increase in annual rainfall is projected over many parts of India progressively from the near term through the far term in both CCSM4-CMIP5 and CCSM4-NEX-GDDP under the RCP8.5 scenario. However, the actual magnitude of rainfall over many parts (e.g., central India, peninsular India, and Himalayan foothills) is less in the latter due to appropriate correction of the positive biases in CCSM4-CMIP5. In general, both CCSM4-CMIP5 and CCSM4-NEX-GDDP project an increase in annual rainfall over India under the RCP8.5 global warming scenario progressively from the near term through the far term. CCSM4-NEX-GDDP, however, projects a higher magnitude of increase and over a larger area as compared to that projected by its CMIP5 counterpart. According to the current projections, the largest increase (by around 25%) would occur over the northeastern states of India by the end of the century. Over the southern, central, and eastern states of India, an increase of around 15% is projected by the end of the century. Analysis of projected PDFs of daily rainfall from CCSM4-CMIP5 and CCSM4-NEX-GDDP suggests the occurrence of events that are unprecedented in the past. Importantly, the extreme values projected by CCSM4-NEX-GDDP are much larger than that projected by its CMIP5 counterpart.

Thus, overall it is found that NEX-GDDP serves the purpose it has been designed for, i.e., to help the scientific community in climate change impact studies at local to regional scales. Analysis carried out in this paper for the specific case of the NCAR CCSM4 model shows that many of the biases in the CMIP5 simulations, especially in the extremes of temperature and rainfall, get corrected in CCSM4-NEX-GDDP. In addition, statistical downscaling has helped to bring out finer spatial structures in temperature and rainfall that were not as prominent in CCSM4-CMIP5. This builds confidence that the climate change projections using NEX-GDDP could be more reliable than its CMIP5 counterpart, and hence more suitable for climate change impact studies at local and regional scales. However, one must take into account the following important caveats in bias correction and statistical downscaling while using this product: (i) correction factors used in the bias correction process do not take into account the potential change in the relationship between the observed and modeled distributions under climate change, and (ii) the relationship between the large scale and local scale used in the statistical downscaling process is assumed to be time invariant, but in reality it may vary under climate change. Finally, it is important to note that the current work has not analyzed the uncertainty in the climate change projections in the two datasets, since the focus of the paper was only on the NCAR CCSM4 model. In order to analyze the uncertainty information associated with the climate change projections presented here, one needs to consider all available models in the two datasets.

Acknowledgments The authors sincerely thank the anonymous reviewer and the editor for the helpful suggestions that have significantly helped in improving the paper. The DST Centre of Excellence in Climate Modeling at IIT Delhi, and the Science and Engineering Research Board (for research grant ECR/2015/000229) are thankfully acknowledged for support. The use of the CMIP5 outputs and IMD dataset are thankfully acknowledged. We thankfully acknowledge the use of the NEX-GDDP dataset prepared by the Climate Analytics Group and NASA Ames Research Center using the NASA Earth Exchange, and distributed by the NASA Center for Climate Simulation (NCCS).

References

Ahmadalipour A, Moradkhani H, Svoboda M (2017) Centennial drought outlook over the CONUS using NASA-NEX downscaled climate ensemble. Int J Climatol 37:2477–2491. https://doi.org/10.1002/joc.4859

Chaturvedi RK, Joshi J, Jayaraman M, Bala G, avindranath NHR (2012) Multi-model climate change projections for India under representative concentration pathways. Curr Sci 103(7):791–802

Chen J, Brissette FP, Chaumont D, Braun M (2013) Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America. Water Resour Res 49:4187–4205. https://doi.org/10.1002/wrcr.20331

Knutti R, Masson D, Gettelman A (2013) Climate model genealogy: generation CMIP5 and how we got there. Geophys Res Lett 40: 1194–1199. https://doi.org/10.1002/grl.50256

Maurer EP, Hidalgo HG (2008) Utility of daily vs. monthly large-scale climate data: an intercomparison of two statistical downscaling methods. Hydrol Earth Syst Sci 12:551–563

Mishra SK, Sahany S, Salunke P (2017) CMIP5 vs. CORDEX over the Indian region: how much do we benefit from dynamical downscaling? Theor Appl Climatol. https://doi.org/10.1007/s00704-017-2237-z

Pai DS, Sridhar L, Rajeevan M, Sreejith OP, Satbhai NS, Mukhopadhyay B (2014) Development of high spatial resolution (0.25° × 0.25°) 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

Sabeerali CT, Rao SA, Dhakate AR, Salunke K, Goswami BN (2015) Why ensemble mean projection of south Asian monsoon rainfall by CMIP5 models is not reliable? Clim Dyn 45(16):1–174. https://doi.org/10.1007/s00382-014-2269-3

Saha A, Ghosh S, Sahana AS, Rao EP (2014) Failure of CMIP5 climate models in simulating post-1950 decreasing trend of Indian monsoon. Geophys Res Lett 41(20):7323–7330

Salvi K, Kannan S, Ghosh S (2011) Statistical downscaling and bias correction for projections of Indian rainfall and temperature in climate change studies, in 2011 International Conference on Environmental and Computer Science, vol. 19, IACSIT Press, Singapore, pp 7–11

Sheffield J, Goteti G, Wood EF (2006) Development of a 50-yr high-resolution global dataset of meteorological forcings for land surface modeling. J Clim 19(13):3088–3111

Sooraj KP, Terray P, Mujumdar M (2015) Global warming and the weakening of the Asian summer monsoon circulation: assessments from the CMIP5 models. Clim Dyn 45(1–2):233–252

Srivastava AK, Rajeevan M, Kshirsagar SR (2009) Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. Atmos Sci Lett 10:249–254. https://doi.org/10.1002/asl.232

Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of CMIP5 and the experiment design. Bull Am Meteorol Soc 93:485–498

Themeßl MJ, Gobiet A, Heinrich G (2011) Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. Clim Chang 112:449–468. https://doi.org/10.1007/s10584-011-0224-4

Thrasher B, Maurer EP, McKellar C, Duffy PB (2012) Technical note: bias correcting climate model simulated daily temperature extremes with quantile mapping. Hydrol Earth Syst Sci 16(9):3309–3314

Wood AW, Maurer EP, Kumar A, Lettenmaier DP (2002) Long-range experimental hydrologic forecasting for the eastern United States. J Geophys Res Atmospheres 107:4429. https://doi.org/10.1029/2001JD000659

Wood AW, Leung LR, Sridhar V, Lettenmaier DP (2004) Hydrologic implications of dynamical and statistical approaches to downscaling climate model outputs. Clim Chang 15:189–216