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RESEARCH REPORT

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PREFACE

It is our pleasure to present this report on the APEC Climate Center (APCC)'s research activities in 2013, which has been a very productive year for our Center.

APCC has expanded its research scope, in response to regional societal and scientific needs. While building expertise in climate prediction remains a priority, we are extending our reach to include policy-relevant climate applications and value-added climate information products.

APCC has accelerated efforts to better our service to the region. As one of the main services provided by APCC, the MME 3-month prediction information has been productively applied by scientists in developing countries that are unable to produce their own prediction information. Furthermore, in order to better prepare for climate-related hazards in a timely manner, APCC launched its 6-month MME prediction service in September 2013. We also began to release forecasts of the Boreal Summer Intraseasonal Oscillation (BSISO), starting from July 2013, as the world's first operational BSISO forecast service. Our researchers also achieved great success in publishing their papers in noted academic journals. Dr. Ok-Yeon Kim, for example, published a paper in *Climate Dynamics* and her research was later selected as one of the Research Highlights by another distinguished journal, *Nature Climate Change*. The following research report provides more information about our research outcomes from 2013.

We will continue to promote the best use of our research outcomes in various scientific and application areas. Our successes and achievements would not have been possible without the support of our valued partners. In this regard, I extend my thanks to you and I hope you enjoy this 2013 Research Report.

Chin-Seung Chung
Director, APEC Climate Center

CONTENTS

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RESEARCH REPORT 2013-07

Simple Statistical Bias Correction for Climate Change Applications

Dr. Prasanna Venkatraman | Climate Change Research Team

ABSTRACT

This study makes use of temperature and precipitation from CMIP5 climate model output projections for climate change applications (agricultural application). Bias correction of temperature and precipitation from CMIP5 GCM simulation results with respect to observation is discussed in detail. The non-linear statistical bias correction is a suitable bias correction method for climate change data because it is simple and does not add artificial uncertainties to the impact assessment of climate change scenarios for application studies (agricultural production) in future projections. The simple statistical bias correction uses observational constraints on the GCM baseline, and the projected results are scaled with respect to the changing magnitude in future scenarios, varying from model to model. Two types of bias correction techniques are shown here. (1) A simple bias correction using a percentile-based quantile-mapping algorithm and (2) a simple but improved bias correction method, a cumulative distribution function (CDF; Weibull distribution function) based quantile-mapping algorithm, are done. This study shows that the percentile-based quantile matching method gives results similar to the CDF (Weibull) based quantile matching method. The usefulness of the quantile matching method for climate change application is elucidated with the regression-based agricultural yield projection scenarios using CMIP5 precipitation and temperature data sets.

1. INTRODUCTION

The bias correction of temperature and precipitation data from Coupled Model Intercomparison Project Phase 5 (CMIP5) climate models for climate change applications is the focus of this study. Generally, the bias correction is carried out to remove systematic errors caused by physics and parameterization schemes used in the climate models. The presence of biases in the data seriously limits their use in climate change applications, and it can result in a range of uncertainties in the projected climate (IPCC 2001a, b; IPCC 2007; IPCC 2007a, b; van der Linden and Mitchell 2009). The general circulation model (GCM) simulated temperature and precipitation output cannot be used for climate impact studies without some form of prior bias correction, if realistic scenarios are to be produced. The errors in the GCM temperature or precipitation are generally a bias in the mean and in the variance.

Climate modelers customarily present future global or regional temperature or precipitation projections in terms of the relative changes in the statistics. As a result, several techniques to correct potential bias in precipitation and temperature have been developed. Some use (a) monthly correction factors based on the ratio between present-day simulated values and observed values (Durman et al. 2001), (b) linear or nonlinear transformation functions that consider changes in the mean and the variance of the observed and simulated time series (Leander and Buishand 2007; Leander et al. 2008), or (c) probability distribution transfer functions derived from observed and simulated cumulative distribution functions (cdfs), which is also referred to as "quantile mapping" or "histogram equalization" (Piani et al. 2010). Generally, quantile mapping shows better performance, particularly at high quantiles, which is favorable for climate change applications.

A realistic representation of temperature and precipitation fields in future climate projections from climate models is crucial for impact and vulnerability assessment studies. Hence, crop modelers use bias correction techniques for impact assessment studies. Often, bias correction involves some form of consistent empirical adjustments between the observed and simulated variables. These methods are given a wide range of names in the literature: statistical downscaling, quantile mapping, histogram equalizing, rank matching, and others. In this study, we perform a simple statistical bias correction.

In applying a baseline-derived correction to simulations of projected climate, we must assume either that the correction still holds for the projected climate or that the bias does not change in the future climate, so we can reconstruct the projected climate by calculating the trend in the future projection and add to the bias corrected time series. This assumption is the most fundamental for many bias correction methods. In this study, we develop a simple, robust, and practical statistical bias correction method, which we apply to the climate change impact on sustainable agricultural production in the future. The main objective of this paper is to give attention to the bias correction of temperature and precipitation. A relatively simple percentile-based bias correction technique adjusting both the bias in the mean and the bias in the variability has performed quite well when compared with the sophisticated CDF (Weibull distribution function) based bias correction technique. Bias correction has led to a better reproduction of simulated climate that corresponds quite well with those obtained using observed precipitation and temperature.

2. DATA SOURCES

2.1 Rainfall data

The representative all-India Summer Monsoon Rainfall (AISMR) index, calculated from the JJAS mean rainfall data set area averaged from Climate Research Unit (CRU) precipitation (Jones et al., 1999) data for the period 1901-2000, is used in this study. The index is also compared with the area weighted monthly rainfall series for India as a whole (Parthasarathy et al. 1995), prepared from data of 306 rain-gauge stations provided by the India Meteorological Department (IMD), uniformly distributed over the country (also used as observed rainfall index data) for the period 1901-2000, available from the website of the Indian Institute of Tropical Meteorology (IITM) [http://www.tropmet.res.in/].

2.2 Temperature data

The temperature index is also calculated from the JJAS mean data set area averaged from CRU temperature (Jones et al., 1999) data for the period 1901-2000 used in the study. Apart from the rainfall index, a long series of IITM temperature indexes (Pant and Rupa Kumar, 1997; Kothawale and Rupakumar, 2005), prepared from a network of 121 stations provided by the India Meteorological Department (IMD), uniformly distributed over the country for the period 1901-2000, available from the website of the IITM, were also used in this study.

2.3 CMIP5 model data set

The transient climate change simulations of 12 Atmosphere-Ocean General Circulation Models (AOGCMs) have been used in the present study. These climate change simulations are part of the suite of simulations performed for the CMIP5 intercomparison studies as well as the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5). The main centers of development of the 12 models used in the study, along with their acronyms, are listed in Table 1. The technical details of the above AOGCMs, including resolution and different climate model components (Atmospheric Model, Ocean Model, and Land Model), are summarized in Table 1. The 12 models have been used to simulate global climate representing the present climate (historical) and the likely future change with RCP4.5 and RCP8.5 forcing. Monthly data of precipitation and temperature are utilized in this study. The lengths of the data for each model run are nominally 200 years of simulation to correspond to the present climate of 1901-2100.

2.4 Kharif food grain yield data set for India

Kharif food grain yield data for India for agricultural years 1966-1967 to 2009-2010 (June 1 to May 31, a complete financial year) have been collected from the publication, *Agricultural Statistics at a Glance 2010*, compiled by the Directorate of Economics & Statistics of the Department of Agriculture Cooperation (DES 2010), which is a mirror of progress in the agriculture sector at the national level as well as across the states.

The food grain yield has exhibited an increasing trend since the early 1970s, mainly because of expanded use of high-yield varieties of crops and changing crop patterns and agricultural practices, as mentioned by Krishna Kumar et al. 2004. Hence, the time series of the aggregate kharif food grain yield and rabi food grain yield has been de-trended to see the inter-annual variability in the yields and is used as an index of food grain yield.

3. METHODOLOGY

3.1 Bias correction methodology

In this section, the method used to calculate the bias correction for precipitation and temperature is described in detail. The methodology described in the following section is applied to the simulated monthly temperature and precipitation data from interpolated CMIP5 data on to CRU (Jones et al. 1999) 1-degree × 1-degree grid data.

Both temperature and precipitation will be corrected by two different independent quantile mapping methods, namely the (a) percentile-based bias correction method and (b) CDF (Weibull distribution function) based bias correction method. The bias correction will lead to an improvement in precipitation and temperature statistics. Differences in the CMIP5 model-simulated field will be decreased significantly in both the historical (baseline) and the projected climate, which will provide a better yield projection.

The bias correction is performed for the historical period 1901-2000 for each model, and the bias corrected precipitation and temperature data are projected for the future in RCP4.5 and RCP8.5 scenarios by adding the linear trend calculated at each grid point.

1) Simple percentile-based quantiles

Quantiles are points taken at regular intervals from the cumulative distribution function (CDF) of a random variable. Dividing ordered data into q essentially equal-sized data subsets is the motivation for q-quantiles; the quantiles are the data values marking the boundaries between consecutive subsets. Put another way, the k^{th} q-quantile for a random variable is the value x such that the probability that the random variable will be less than x is at most k/q, and the probability that the random variable will be more than x is at least $(q - k)/q = 1 - (k/q)$. There are q - 1 of the q-quantiles, one for each integer k satisfying $0 < k < q$.

Some q-quantiles have specific names. The 2-quantile is called the median. The 3-quantiles are called tertiles, or terciles (T). The 4-quantiles are called quartiles (Q). The 5-quantiles are called quintiles (QU). The 6-quantiles are called sextiles (S). The 10-quantiles are called deciles (D). The 12-quantiles are called duo-deciles (Dd). The 20-quantiles are called vigintiles (V). The 100-quantiles are called percentiles (P). The 1000-quantiles are called permilles (Pr). More generally, one can consider the quantile function for any distribution. This function is defined for real variables between zero and one and is mathematically the inverse of the cumulative distribution function.

2) Weibull distribution function based bias correction method

The Weibull distribution is a continuous probability distribution. It is named after Waloddi Weibull.

The probability density function (PDF) of a Weibull random variable *x* is

$$f(x;\lambda,k)=\begin{cases}\frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1}e^{-(x/\lambda)^k} & x\geq 0,\\ 0 & x<0,\end{cases}$$

where $k > 0$ is the shape parameter and $\lambda > 0$ is the scale parameter of the distribution. Its complementary cumulative distribution function is a stretched exponential function. The Weibull distribution is related to a number of other probability distributions.

(i) Distribution function

The cumulative distribution function for the Weibull distribution is

$F(x;k,\lambda)=1-e^{-(x/\lambda)^k}$; for $x \geq 0$, and $F(x; k; \lambda) = 0$ for $x < 0$.

The quantile (inverse cumulative distribution) function for the Weibull distribution is

$Q(p;k,\lambda)=\lambda(-ln(1-p))^{1/k}$; for $0 \leq p < 1$.

We can also write the Weibull function in the form

$$f(T)=\frac{\beta}{\eta}\left(\frac{T-\gamma}{\eta}\right)^{\beta-1}e^{-\left(\frac{T-\gamma}{\eta}\right)^{\beta}}$$

$$f(T)\geq 0,\ \ T\geq 0\ \text{ or }\ \gamma,\ \ \beta>0,\ \ \eta>0,\ \ -\infty<\gamma<\infty$$

where β is the shape parameter, also known as the Weibull slope, η is the scale parameter, and γ is the location parameter.

Frequently, the location parameter is not used, and the value for this parameter can be set to zero. When such is the case, the PDF equation reduces to that of the two-parameter Weibull distribution. A form of the Weibull distribution is known as the one-parameter Weibull distribution. This distribution, in fact, takes the same form as the two-parameter Weibull PDF, the only difference being that the value of β is assumed to be known beforehand. This assumption means that only the scale parameter needs be estimated, allowing for analysis of small data sets. This study uses the one-parameter Weibull distribution.

3) Multiple linear regression model

Generally, many models are available to estimate the effects of climate change on agriculture, and a simple and widely used approach is a multiple linear regression model. We have focused on rice yield, which is linked only to the year-to-year variability of climate variables, to plant growth from observed precipitation, and to temperature, neglecting other influences, as a simple approximation. The yield projection is performed by use of the simple multiple linear regression approach for all-India yield estimate and the effect of weather (rainfall and temperature) on rice yield, with the coefficients obtained using observed data (Yield and AISMR from area averaged CRU data).

We specified the following simple regression data model:

$$Y_{it} = \beta X_{it} + Z_i + u_{it}$$

where

Y_{it} = rice yield for the agro climatic zone i in season year t

β = vector of coefficients

X_{it} = set of climate variables, such as rainfall and temperature, for zone i at time t

Z_i = y- intercept for the input variables (rainfall and temperature)

u_{it} = error term (this term is neglected for simplicity)

i = cross-sectional unit (i.e., all-India averaged yield)

t = year

4. RESEARCH RESULTS

4.1 Percentile-based bias correction method results

In this section, we show the results of the percentile-based bias correction method.

1) Bias correction of temperature for the historical run

Long records of observed temperature are available on the continental areas of the South Asian summer monsoon region. The temperature in the observations (CRU data) for the past 100 years has been used for bias correction in the baseline simulation of CMIP5 model outputs.

(i) Spatial pattern of observed and simulated temperature

The large-scale South Asian monsoon temperature patterns in the summer (JJAS), as simulated by the 12 coupled models are shown in Figure 1. For the purpose of comparison, the long-term means of seasonal temperature have been computed based on the CRU temperature (T) data set (1901-2000) and compared with (historical) control simulations of 12 different models from the CMIP5 run for the period 1901-2000.

Most models simulate the observed temperature climatology for the JJAS season (Fig. 1). Most models simulate higher seasonal mean temperature over the Indian land mass. A few models show a higher temperature over India, namely, ACCESS, CNRM, CSIRO, GISS, and HadGEM2-ES. The rest of the models simulate close to observed seasonal mean temperature patterns. The monthly simulated temperature is corrected to match the monthly observed temperature for each grid point for a window of 100 years. After applying bias correction, most of the models show very close to observed temperature (Fig. 2) for the JJAS season.

Most model simulations in Fig. 1 compare well with the observation of temperature, although there is a modest dispersion between the observation and different CMIP5 GCMs; the bias corrected data generally corresponds well with the observed seasonal climatology (Fig. 2).

(ii) Spatial temperature difference

In this section, the difference between observation and model-simulated temperature is shown to illustrate the bias in the models by regridding the model data sets to the grid dimension of the observation (1 degree × 1 degree). The average JJAS temperature over the period 1901-2000 has been calculated for each grid separately, and the difference in average JJAS temperature between the observed and the uncorrected simulated temperature and bias corrected simulated temperature data is shown in Fig. 3 and Fig. 4, respectively.

A positive (negative) difference means that in the model simulation for the specific region, the temperature is higher (lower). As can be seen from Fig. 3, the difference between the uncorrected simulated temperature and the observation varies roughly above −4° and +4° C in many areas. After bias correction, the difference between the corrected simulated temperature and the observation varies roughly between −4° and +4° C (Fig. 4). Therefore, differences between the corrected data and the observation have decreased significantly.

2) Bias correction of precipitation for the historical run

Long records of observed precipitation are available on the continental areas of the South Asian summer monsoon region. The precipitation in the observations (CRU data) for the past 100 years has been used for bias correction in the baseline simulation of CMIP5 model outputs.

(i) Spatial pattern of observed and simulated precipitation

The large-scale South Asian monsoon precipitation patterns in the summer (JJAS) as simulated by the 12 coupled models are shown in Fig. 5. For the purpose of comparison, the long-term means of seasonal precipitation have been computed based on the CRU precipitation (P) data set (1901-2000) and compared with (historical) control simulations of 12 different models from the CMIP5 run for the period 1901-2000. The simulated rainfall patterns are also compared with the observed precipitation of the Global Precipitation Climatology Project (GPCP) (Adler et al. 2003) for the period 1979-2000 (figure not shown).

Although most models simulate the general maximum precipitation over the west coasts of India and the Bay of Bengal, some of them miss the rainfall maximum in the equatorial Indian Ocean (Fig. 5). Apart from this problem, in the Indian monsoon context, the observed maximum rainfall during the monsoon season along the west coast of India and the north Bay of Bengal and adjoining northeast India is only realistically simulated in a few models, ACCESS, CNRM, HadGEM2-ES, and MIROC5, and to some extent in Can-ESM, GFDL-ESM2M, GISS, MPI-ESM, and NOR-ESM (Fig. 5). This poor quality of simulation may possibly be linked to the coarse resolution of the models, as the heavy rainfall over these regions is generally in association with the steep orography. The monthly simulated precipitation is corrected to match the monthly observed precipitation for each grid point for a window of 100 years. After applying bias correction for each grid, most of the models show very close to observed precipitation (Fig. 6) for the JJAS season.

Most model simulations in Fig. 5 compare well with the observation of precipitation. Although there is a modest dispersion between the observation and different CMIP5

GCMs, the bias corrected data generally corresponds well with the observed seasonal climatology (Fig. 6).

(ii) Spatial precipitation difference

In this section, the difference between observation and model-simulated precipitation are shown to illustrate the bias in the models by regridding the model data sets to the grid dimension of the observation (1 degree × 1 degree). The average JJAS precipitation over the period 1901-2000 has been calculated for each grid separately, and the difference in average JJAS precipitation between the observed and the uncorrected simulated precipitation and bias corrected simulated precipitation data are shown in Fig. 7 and Fig. 8, respectively.

A positive (negative) difference means that the model simulation is wetter (drier) than the observed precipitation value for those specific regions. In Fig. 7, the difference between the uncorrected simulated precipitation and the observation varies roughly above −4 and +4 mm d−1 in many areas. After bias correction, the difference between the corrected simulated precipitation and the observation varies roughly between −2 and +2 mm d−1 (Fig. 8). Therefore, differences between the corrected data and the observation have decreased significantly.

4.2 Time series of percentile-based quantile-mapping bias correction

The percentile-based quantile-mapping bias correction method has shown that the bias in the simulated temperature and precipitation is reduced considerably (Figs. 4 and 8) compared with the uncorrected data set (Figs. 3 and 7). The time series of the quantile bias corrected data are then plotted for an area averaged over the Indian monsoon region bounded by latitudes between 5N and 35N and longitudes between 65E and 95E.

1) Calculating trend for RCP4.5 and RCP8.5 scenarios and reconstructing the projections

To correct the CMIP5 model-simulated precipitation and temperature data for the Indian region, we regridded the CMIP5 model data on a 1-degree × 1-degree grid to match the observed CRU temperature and precipitation data sets. The CRU data set is a global land data set available from 1901-2000. The values in the oceanic regions are masked out using ocean mask in the CMIP5 models. Then the percentile-based bias correction method is applied to the CMIP5 models at each grid point in the historical data set. To correct the model bias in the future time slice, that is, from 2001 to 2100, the year-to-year increase in temperature and precipitation is calculated using the fitted linear trends from the 2001-2100 periods for both RCP4.5 and RCP8.5 scenarios at each grid point. These trend values at each grid point are added to the bias corrected results, to reconstruct the temperature (Figs. 9 and 10) and precipitation (Figs. 11 and 12) projection for the twenty-first century period (2001-2100).

2) Bias correction of temperature and precipitation for the historical period

To see the convergence among the models, a simple comparison is made by plotting the area averaged over the Indian monsoon region bounded by latitudes between 5N and 35N and longitudes between 65E and 95E. One can notice projections of temperature from figures for RCP4.5 (Fig. 9) and RCP8.5 (Fig. 10) scenarios. In the uncorrected data at the start of 1901, the temperature simulation for RCP4.5 ranges between 23.5° and 30° C, but after bias correction, the simulated temperature converges between 25.5° and 27.5° C among 12 different CMIP5 models (Fig. 9). Similar convergence among the models in the RCP8.5 is also evident (Fig. 10).

In the uncorrected data at the start of 1901, the precipitation simulation for RCP4.5 ranges between 550 and 1050 mm, but after bias correction, the simulated precipitation converges between 800 and 1000 among 12 different CMIP5 models (Fig. 11). Similar convergence among the models in the RCP8.5 is also evident (Fig. 12). The convergence among the models for precipitation is weaker than for the temperature because of large dispersions in the model-simulated precipitation in

RCP4.5 and RCP8.5, but after bias correction, the models are reasonably close to the observed mean.

3) Bias correction of temperature and precipitation for the RCP4.5 and RPC8.5 projections

The bias corrected temperature and precipitation for two scenarios (RCP4.5 and RCP8.5) are shown in Figs. 9 to 12. The uncorrected projected data for the temperature in the RCP4.5 scenario show a large range of dispersion at the end of the twenty-first century between 25° and 31° C, but after bias correction, the simulated temperature converges between 27° and 29° C among 12 different CMIP5 models (Fig. 9) by the end of the twenty-first century. Similar convergence among the models in the RCP8.5 is also evident (Fig. 10). Whereas the uncorrected temperature ranges between 26° and 34.5° C, after correction, the temperature converges between 29° and 33° among 12 different CMIP5 models (Fig. 10) by the end of the twenty-first century.

The uncorrected projected data for the precipitation in the RCP4.5 scenario shows a large range of dispersion at the end of the twenty-first century between 650 and 1150 mm, but after bias correction the simulated precipitation converges between 850 and 1100 among 12 different CMIP5 models (Fig. 11) by the end of twenty-first century. Similar convergence among the models in the RCP8.5 is also evident (Fig. 12). Whereas the uncorrected precipitation ranges between 700 and 1200 mm, after correction the precipitation converges between 900 and 1150 mm among 12 different CMIP5 models (Fig. 12) by the end of the twenty-first century.

4.3 Weibull distribution function (CDF) based bias correction method results

In this section, we show the results of the Weibull distribution function based bias correction method for the historical period (1901-2000).

1) Bias correction of temperature and precipitation for the historical run

(i) Spatial pattern of observed and simulated temperature

The monthly simulated temperature is corrected to match the monthly observed temperature for each grid point for a window of 100 years. After applying the Weibull distribution function based bias correction method for temperature, most of the models show very close to observed temperature (Fig. 13) for the JJAS season. The Weibull distribution function based bias correction method is similar to the percentile-based method, but only differs in treatment. The differences in the methodology of the two methods are shown in Sections 3.1.1 and 3.1.2.

Most model simulations in Fig. 13 compare well with the observations of temperature. Although there is a modest dispersion between the observation and different CMIP5 GCMs, the Weibull distribution function based bias corrected data generally correspond well with the observed seasonal climatology.

(ii) Spatial temperature difference

A positive (negative) difference means that model simulation is higher (lower) than the observed temperature value for those specific regions. After bias correction, the difference between the corrected simulated temperature and the observation varies roughly between −2° and +2° C (Fig. 14), which is similar to the results obtained using the percentile-based method (Fig. 4). The differences between the bias corrected data and observation have not decreased significantly with use of the Weibull distribution function based bias correction method but produces a result similar to the percentile-based method. The pattern correlation obtained by both methods also shows a similar result (Table 2).

(iii) Spatial pattern of observed and simulated precipitation

The monthly simulated precipitation is corrected to match the monthly observed precipitation for each grid point for a window of 100 years. After applying the Weibull distribution function based bias correction method for precipitation, most of the models show very close to observed precipitation (Fig. 15) for the JJAS season. The Weibull distribution function based bias correction method is similar to the percentile-based method, but only differs in treatment.

(iv) Spatial precipitation difference

A positive (negative) difference means that model simulation is wetter (drier) than the observed precipitation value for those specific regions. After bias correction, the difference between the corrected simulated precipitation and the observation varies roughly between −2 and +2 mm d−1 (Fig. 16), which is similar to the results obtained using the percentile-based method (Fig. 8). The differences between the bias corrected data and observation have not decreased significantly with use of the Weibull distribution function based bias correction method but produces a result similar to the percentile- based method. The pattern correlation obtained by both methods also shows a similar result (Table 2).

2) Time series and CDF plot of temperature and precipitation

The results of the Weibull distribution function based bias correction method area averaged over the Indian latitudes and longitudes are shown in Figs. 17 to 20. The area average over the Indian monsoon region is done over the latitudes between 5N and 35N and the longitudes between 65E and 95E.

The time series plot for temperature of 12 CMIP5 models is shown in Fig. 17. The uncorrected model data are shown by red line, the observed data (CRU-T) by blue line, and the bias corrected data by green line. The CDF plot for each model is shown in Fig. 18. The CDF distribution varies from 0 to 1. The uncorrected model data are shown by red dots, the observed data (CRU-T) by blue dots, and the bias corrected data by green dots.

The time series plot for precipitation of 12 CMIP5 models is shown in Fig. 19. The uncorrected model data are shown by red line, the observed data (CRU-P) by blue line, and the bias corrected data by green line. The CDF plot for each model is shown in Fig. 20. The CDF distribution varies from 0 to 1. The uncorrected model data are shown by red dots, the observed data (CRU-P) by blue dots, and the bias corrected data by green dots.

After bias correction, the model-simulated mean corresponds well with the observations in each individual model (Figs. 17 and 19). The bias correction brings the model-simulated CDF close to the observed CDF (Figs. 18 and 20). As we have shown in the previous sections, the percentile-based quantile matching method produces similar results compared with the CDF-based methodology, evidenced by spatial pattern differences of temperature and precipitation (Fig. 4 and Fig. 14 for temperature; Fig. 8 and Fig. 16 for precipitation), respectively. The pattern correlation table also revealed the similarity in the results obtained from the two methods (Table 2). Neither method is superior, but both methods suggest their usefulness for climate application analysis.

4.4 Climate change impacts and projection of total food grain production over South Asia

The impact of climate change on food grain yield over South Asia is shown as an example of climate application of this study. This way of projecting the yield changes by use of different climate model simulations is unique in that it uses the regression coefficients (using climate variables T and P), calculated from observations, to prepare baseline yield data and compare with different available future scenarios. In the Section 4.4.4, we have presented the regression model of the relation between climate variables and (total food grain) crop yields. These estimated regression coefficients are used to simulate the effects of climate change on total food grain yield.

1) Rainfall signal in Indian food grain yield

Kharif crops are directly affected by day-to-day variations in summer monsoon rainfall (Preethi and Revadekar 2012; Revadekar and Preethi 2012). Thus, the quantum of rainfall in the summer monsoon season is also very important for kharif crops. Kharif is the main crop-growing season in India, which coincides with the summer monsoon season. During the summer monsoon season, the country receives plenty of rainfall, which is critical for the kharif crops, which account for more than 50% of the foodgrain production in the country (Krishna Kumar et al. 2004).

Year-to-year fluctuations in summer monsoon rainfall over India have a strong impact on the variability of aggregate kharif foodgrain production (Parthasarathy et al. 1992; Gadgil 1996; Webster et al. 1998). Years with deficient and excess monsoon rainfall are associated with low and high production of food grain, respectively. However, the negative impact of deficit rainfall is larger than the positive impact of good rainfall (Gadgil and Rupa Kumar 2006).

The fact is that reduction of rainfall causes adverse effect on the food grain yield. Therefore, a detailed analysis has been carried out in this section to see the relation between seasonal indices of precipitation and kharif foodgrain yield in India.

2) Variation in food grain production in India

Although the food grain production may have achieved the highest possible yield, the decrease in area under cultivation during the kharif season is a worrisome trend. Much of the increase is likely the result of the development of crop varieties, use of fertilizers, expanded use of high-yield varieties, and changes in crop patterns and agricultural practices, as mentioned by Krishna Kumar et al. (2004). Therefore, the time series of kharif yield is linearly de-trended to obtain its year-to-year natural variability (Fig. 21). The figure indicates that inter-annual variability of summer monsoon rainfall may be the primary factor that affects the yield in India. Substantial decrease in yield is associated with drought years, and the increase in yield is associated with normal and excess years. Fig 21 clearly shows that negative impacts of deficit rainfall are larger than the positive impacts of good rainfall on food grain yield in India. Gadgil and Rupa Kumar (2006) also noted similar features.

The thermal stress resulting from future climate change in tropical regions could lead to marked reductions in crop yields. At regional scales, the effects of climate change could be more adversely felt, particularly in India, which shares only 2% of the world's geographical area but supports 18% of the world's population. For a temperature rise of 2.0° to 3.5° C, Kumar and Parikh (1998) have estimated that even after accounting for adaptation, the loss in farm-level net revenue would range between 9% and 25%. The positive effect of CO_2 enrichment on photosynthetic productivity is usually cancelled out when temperature rises. This outcome may also lead to water stress and, hence, decreased yields. In India, a 15%-20% decrease in yield has been projected to result from a 3° C rise in temperature (Aggarwal and Sinha 1993).

3) All-India yield indices versus observed precipitation and temperature

To obtain a representative value for the country as a whole, an all-India time series of indices of precipitation are constructed by area-averaging the indices at all land-point grids. All values of monthly and seasonal all-India indices of precipitation are obtained by considering a 45-year period from 1966 to 2010.

The variability of rainfall does correlate better with JJAS crop yields (Fig. 21a) than the variability of temperature correlates with the summer monsoon season (JJAS) crop yields (Fig. 21b). The correlation between crop yields and JJAS rainfall variability is very high (0.71**). Although the correlation between crop yields and JJAS temperature variability is very low (-0.03), the mean temperature plays a key role in the total food grain yield. Therefore, changes in the mean temperature over a long period could affect the total food grain yield.

4) Application of bias corrected data to yield projection

The bias corrected data set can be used for various applications of impact assessment studies of climate. The result of impact on future agricultural food grain production in India is analyzed here.

The model projected total food grain yield changes in India is calculated by use of the observed yield and climate variables, such as temperature (T) and precipitation

(P), with a multiple linear regression model. The observed yield and climate variables are presented in Table 3 for the period 1966 to 2010. The mean total food grain yield for a 45-year period stands out as 1107.35 kg/ha, the mean precipitation for a 45-year period is 831.7 mm, and the mean temperature for a 45-year period is 26.29° C. The result of the regression model is shown in Tables 4 and 5. Using both P and T variables for prediction cannot be justified (Table 4), because the mean T correlation with the yield is very low (-0.03). It is advisable to use only the P variable for yield projection (Table 5), but because we cannot completely neglect the role of temperature in the crop yield, I have shown both cases.

5) Regression results for CMIP5 models

The estimated regression coefficients, using the observed yield and the climate variables, including both rainfall and temperature (Table 4), are used for creating the baseline total food grain yield changes in India from different CMIP5 models.

The same coefficients are used for both uncorrected precipitation (P) and temperature (T) and bias corrected precipitation (P) and temperature (T) for RCP4.5 (Fig. 22) and RCP 8.5 (Fig. 23) as shown in the respective figures. The bias corrected projections converge among models in the yield projections, whereas uncorrected yield projections are dispersed.

The model results indicate that the total food grain yield is going to increase. The increase in the total food grain yield is approximately 90 kg/ ha in the RCP4.5 scenario (Fig. 22) from 2001 until the end of 2100 (1280-1190 kg/ha). The increase in the total food grain yield is approximately 180 kg/ ha in the RCP8.5 scenario (Fig. 23) from 2001 until the end of 2100 (1370-1190 kg/ha).

The estimated regression coefficients, using the observed yield and the climate variable, including only rainfall and not temperature (Table. 5), are used to create the baseline total food grain yield changes in India from different CMIP5 models. In general practice, the regression equation also contains temperature, but because temperature correlation is very low, the variable can be neglected.

The same coefficients are used for both uncorrected precipitation (P) and bias corrected precipitation (P) for RCP4.5 (Fig. 24) and RCP8.5 (Fig. 25), as shown in the respective figures. The bias corrected projections converge among models in the yield projections, whereas uncorrected yield projections are dispersed.

The model results indicate that the total food grain yield is going to increase. The increase in the total food grain yield is approximately 50 kg/ ha in the RCP4.5 scenario (Fig. 24) from 2001 until the end of 2100 (1210-1160 kg/ha). The increase in the total food grain yield is approximately 90 kg/ ha in the RCP8.5 scenario (Fig. 25) from 2001 until the end of 2100 (1250-1160 kg/ha).

These estimates are only scenarios. Many scenarios could be generated using different climate and non-climatic variable impacts on the future food grain yield. As we can see only a marginal increase of 50 kg/ha in the RCP4.5 scenario and 90kg/ha in the RCP8.5 scenario, the caveats of this application study are as follows:

1) It uses only one or two climate variables for yield predictions.

2) It is desirable to use more climate variables, such as precipitation (P), temperature (T), evapo-transpiration (ET), soil moisture (Q), and non-climatic variables.

3) Because the data are available as all-India averaged indices, the yield prediction has limited reliability using the regression approach.

4) This method can produce better results if we consider smaller areas, such as a zonal, basin scale study or a district level study.

5) If district level crop yields and high-resolution climate variables such as precipitation (P), temperature (T), evapo-transpiration (ET), and soil moisture (Q) data sets are available, then better results can be achieved.

6) Land use for crops may significantly change or decrease by the end of 2100; this change may have an impact on food grain yield, which imposes certain uncertainties in the estimate.

The combination of bias corrected spatial downscaling of climate data and regression model can be more suitable for agricultural applications other than hydrological applications.

5. CONCLUSIONS

The quantile-mapping bias correction technique has shown good improvement in temperature and precipitation fields of CMIP5 models, in acceptance with observations in the baseline simulation.

The bias corrected data set can be applied to application studies. One of the examples in this study has shown some improvements in terms of agricultural yield projection scenario (convergence among different CMIP5 models). The bias corrected data sets and their use for agricultural yield projection for all India from different GCM data sets (namely 12 models) for two scenarios (RCP4.5 and RCP8.5) are presented in detail in this study.

Some limitations and advantages of the bias corrected downscaling technique are the following:

1) One of the important assumptions of the bias correction study is the stationarity of the model bias, but the bias in the data is non-stationary. Solving the problem of non-stationarity of the bias in the data is very challenging and difficult.

2) Bias correction does not alter the climate signal or change the projected climate, but it brings the model mean very close to the observations, which is desirable for many application studies.

3) Certain variables are affected significantly because of bias correction and introduce inconsistency among the climate variables, because each climate variable is bias corrected independently.

4) Unlike the dynamical downscaling, this method does not preserve the relations among different climate variables in a dynamical sense.

5) Though dynamical downscaling is desirable for climate application studies, it is very expensive in terms of cost and computational time. Bias corrected downscaling is inexpensive and very quick for achieving the desired high resolutions for climate application studies.

The quantile matching method cannot be applied to a multimodel ensemble (MME) mean. It can be applied only to individual models because the model-simulated distribution varies from model to model. If we make an MME mean before bias correction, it may produce a different result because the distribution of each model is not retained. It is advisable to apply bias correction (quantile matching) to an individual model before making an MME. The MME-mean values after bias correction in this study are shown to produce better results than each individual model.

The future agricultural scenario simulated using the regression approach also has many limitations:

1) The regression approach considers only climate variables, and no non-climate variables are considered in the analysis, which limits the reliability of the results.

2) Simulating a single index for the all-India food grain yield is a challenge, so caution should be exercised in interpreting the future food availability with this result.

3) Recent studies have shown that the decrease in the ground water availability over the Indo-Gangetic plains poses a great threat to sustainable agricultural production.

4) Overexploitation of groundwater in many parts of India has led to salinity and unsuitability for agriculture.

5) Although the total food grain yield showed a slight increase (because of the use of high-yield varieties of grains and technology) in recent decades, the yields have not kept pace with the population growth.

6) The agricultural land (cropping area) is decreasing for the kharif season, and this development is a worrisome trend.

We notice only a marginal increase of 50 kg/ha in the RCP4.5 scenario and 90 kg/ha in the RCP8.5 scenario. Previous studies have shown thermal stress resulting from future climate change in tropical regions could lead to marked reduction in crop yields.

TABLES

Table 1 Description of 12 coupled climate model simulations used in the study, including historical, RCP4.5, and RCP8.5 scenario runs.

No	Model	Institution	Country	Resolution	Components of the models		
				(latxlonxmonth)	Atm. model	Ocean.	Land mo.
1	ACCESS1-0	CSIRO	Australia	145x192x3072	AGCM v1.0	NOAA/ GFDL MOM4p1	-
2	BCC-CSM1.1	BCC	China	64x127x3072	BCC_AGCM2.1	MOM4_ L40	BCC_AVIM1.0
3	CanESM2	CCCma	Canada	64x128x3072	CanAM4	CanOM4 and CMOC1.2	CLASS2.7 and CTEM1
4	CNRM-CM5	CNRM, CERFACS	France	128x256x3072	ARPEGE Climat (v5.2.1)	NEMO3.3. v10.6.6p	SURFEX (v5.1)
5	CSIRO-Mk3.6	CSIRO	Australia	96x192x3072	AGCM v7.3.8	GFDL MOM2.2	-
6	GFDL-ESM2M	NOAA GFDL	USA	90x144x3072	AM2	MOM4	LM3
7	GISS- E2- R	NASA/GISS	USA	90x144x3072	GISS-E2	-	-
8	HadGEM2-ES	MOHC	UK	145x192x3072	HadGAM2	HadGOM2	MOSES2 and TRIFFID
9	INM-CM4	INM	Russia	120x180x3072	INM-CM4	-	-
10	MIROC5	AORI	Japan	128x256x3072	MIROC-AGCM6	COCO4.5	MATSIRO
11	MPI-ESM-P	MPI-M	Germany	96x192x3072	ECHAM6	MPIOM	JSBACH
12	NorESM1	NCC	Norway	96x144x3072	CAM-Oslo	MICOM	CLM

Table 2 Description of 12 coupled climate model performances for pattern correlation coefficient from percentile-based method and Weibull distribution method.

S.NO	Models	Temperature (T)			Precipitation (P)		
		Raw data - Pattern correlation with observation	Bias corrected data (Precentile-based method)	Bias corrected data (Weibull-based method)	Raw data - Pattern correlation with observation	Bias corrected data (Precentile-based method)	Bias corrected data (Weibull-based method)
1	ACCESS1-0	0.98	0.99	0.99	0.87	0.99	0.98
2	BCC-CSM1.1	0.95	0.99	0.99	0.72	0.95	0.95
3	CanESM2	0.94	0.99	0.99	0.86	0.98	0.98
4	CNRM-CM5	0.95	0.99	0.99	0.86	0.99	0.99
5	CSIRO-Mk3.6	0.96	0.99	0.99	0.75	0.97	0.96
6	GFDL-ESM2M	0.96	0.99	0.99	0.82	0.99	0.97
7	GISS- E2- R	0.96	0.99	0.99	0.71	0.97	0.96
8	HadGEM2-ES	0.97	0.99	0.99	0.82	0.99	0.99
9	INM-CM4	0.97	0.99	0.99	0.81	0.98	0.98

S.NO	Models	Temperature (T)			Precipitation (P)		
		Raw data - Pattern correlation with observation	Bias corrected data (Precentile-based method)	Bias corrected data (Weibull-based method)	Raw data - Pattern correlation with observation	Bias corrected data (Precentile-based method)	Bias corrected data (Weibull-based method)
10	MIROC5	0.96	0.99	0.99	0.86	0.99	0.99
11	MPI-ESM-P	0.95	0.99	0.99	0.80	0.99	0.97
12	NorESM1	0.97	0.99	0.99	0.75	0.99	0.99

Table 3 Observed all-India yield, precipitation, and temperature index data

Year	Yld (Kg/Ha)	P (mm)	T (°C)
1966	625	739.9	26.86
1967	746	859.9	21.87
1968	741	754.5	24.18
1969	758	831	29.32
1970	837	939.7	21.61
…	…	…	…
2010	1644	935	26.81

Table 4 Regression coefficients calculated from the multiple linear regression model using observed data (both P and T)

Observed All-India Data		(Mean of 45 years of data)
Agricultural yield Yld (kg/ha)	Precipitation P (mm)	Temperature T (° C)
1107.35	831.72	26.29
Regression coefficients calculated from observed yield data		
Intercept (Constant- Unit less)	(kg/ha)/(mm) × P (Slope-1)	(kg/ha)/(° C)*T (Slope-2)
8.16	0.811	16.14

Table 5 Regression coefficients calculated from the linear regression model using observed data (using only precipitation).

Observed All-India Data	
Agricultural yield Yld (kg/ha)	Precipitation P (mm)
1107.35	831.72
Regression coefficients calculated from observed yield data	
Intercept (Constant- Unit less)	(kg/ha)/(mm) × P (Slope)
599.39	0.6107

FIGURES

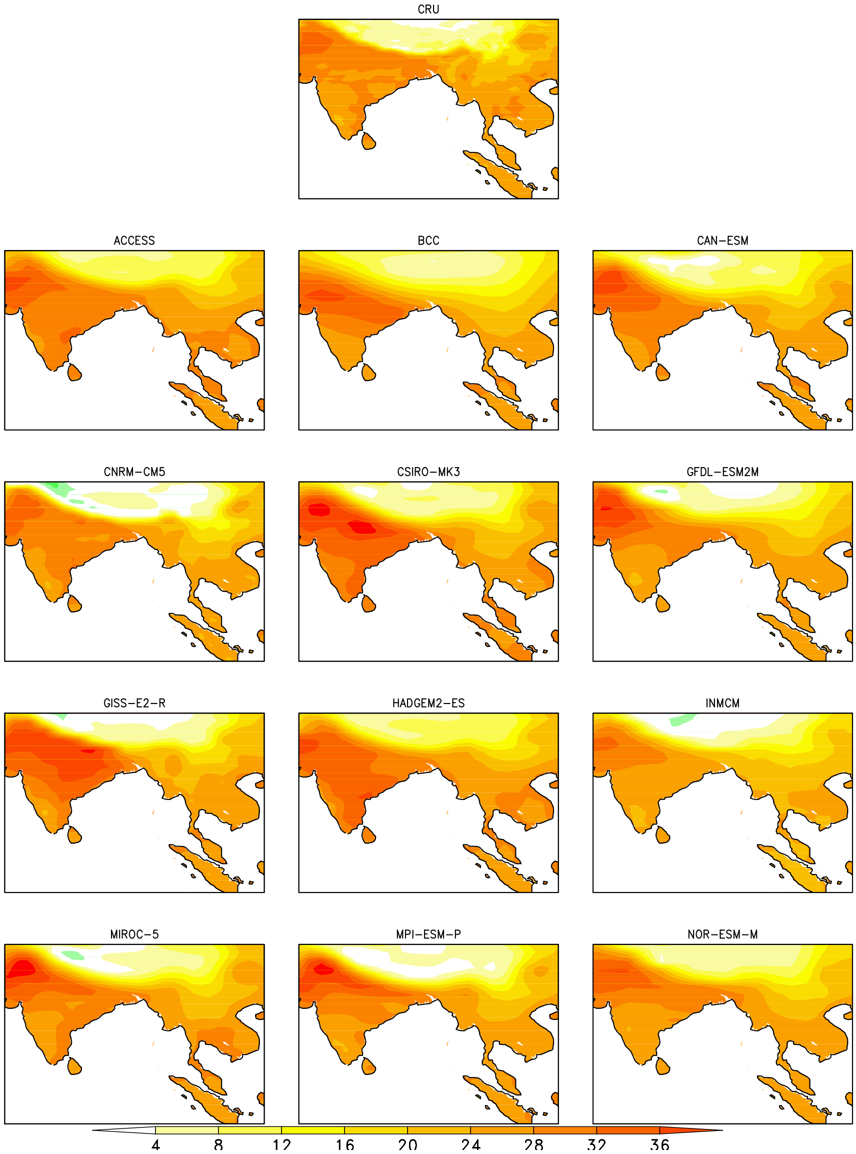


Figure 1 Mean JJAS observed CRU temperature over the South Asian monsoon region followed by 12 models of simulated temperature in the historical run. [Unit: °C]

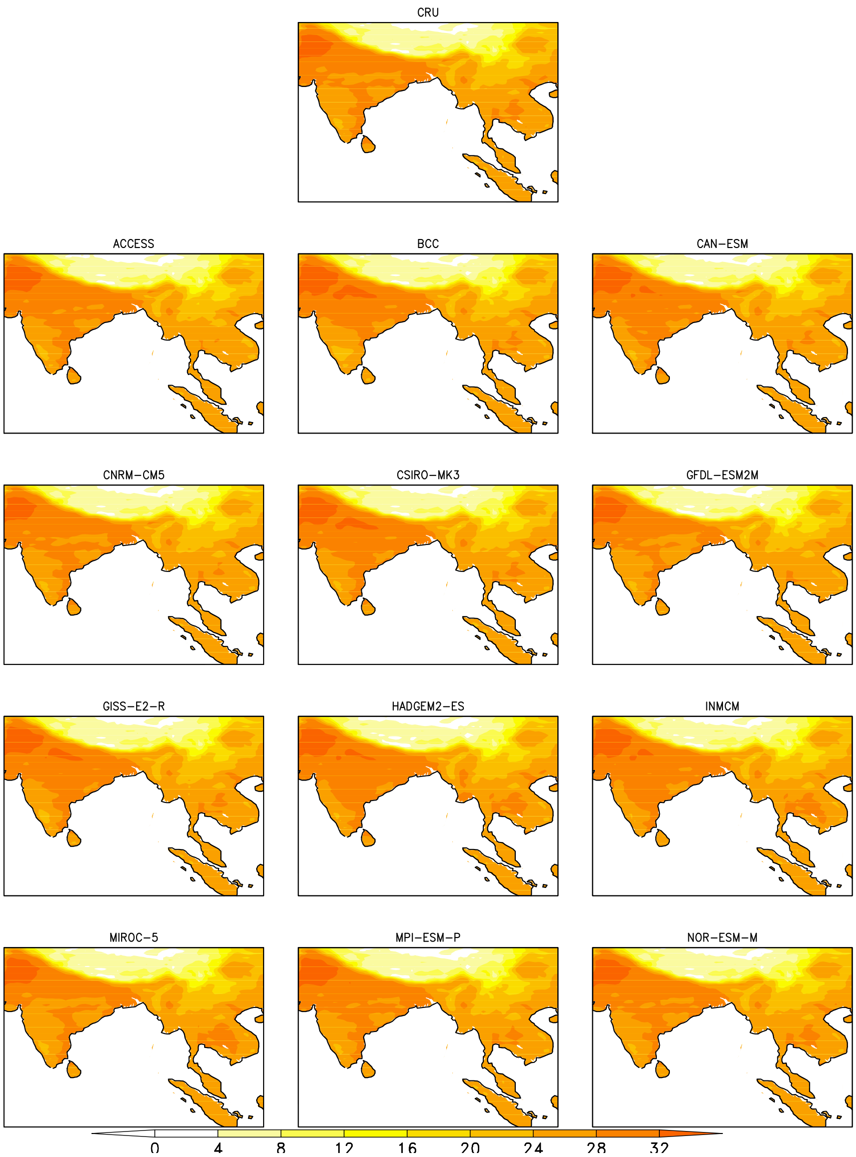


Figure 2 Mean JJAS observed CRU temperature over the South Asian monsoon region followed by 12 bias corrected model outputs in the historical run with respect to CRU temperature. [Unit: °C]

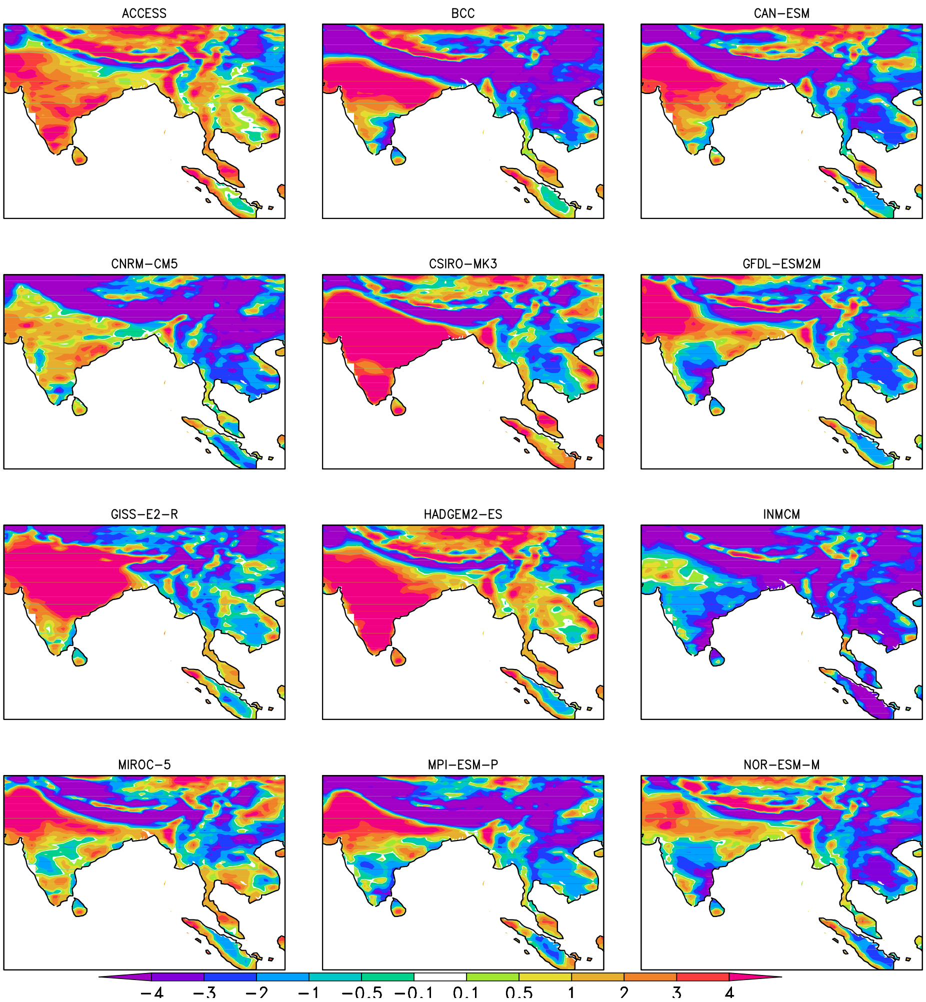


Figure 3 Difference in mean JJAS temperature over the South Asian monsoon region in 12 uncorrected model outputs in the historical run with respect to CRU temperature (i.e, raw CMIP5 temp. - observation). [Unit: °C]

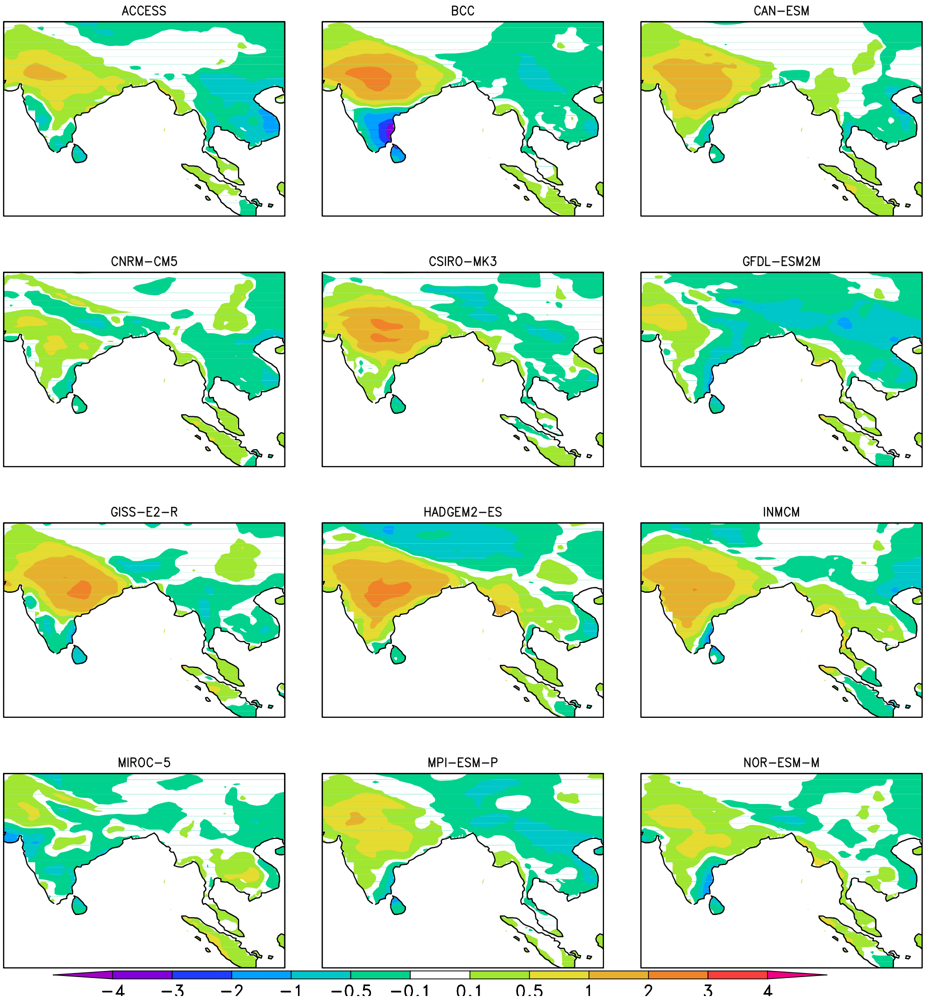


Figure 4 Difference in mean JJAS temperature over the South Asian monsoon region in 12 bias corrected model outputs in the historical run with respect to CRU temperature. (i.e, bias corrected CMIP5 temp. - observation). [Unit: °C]

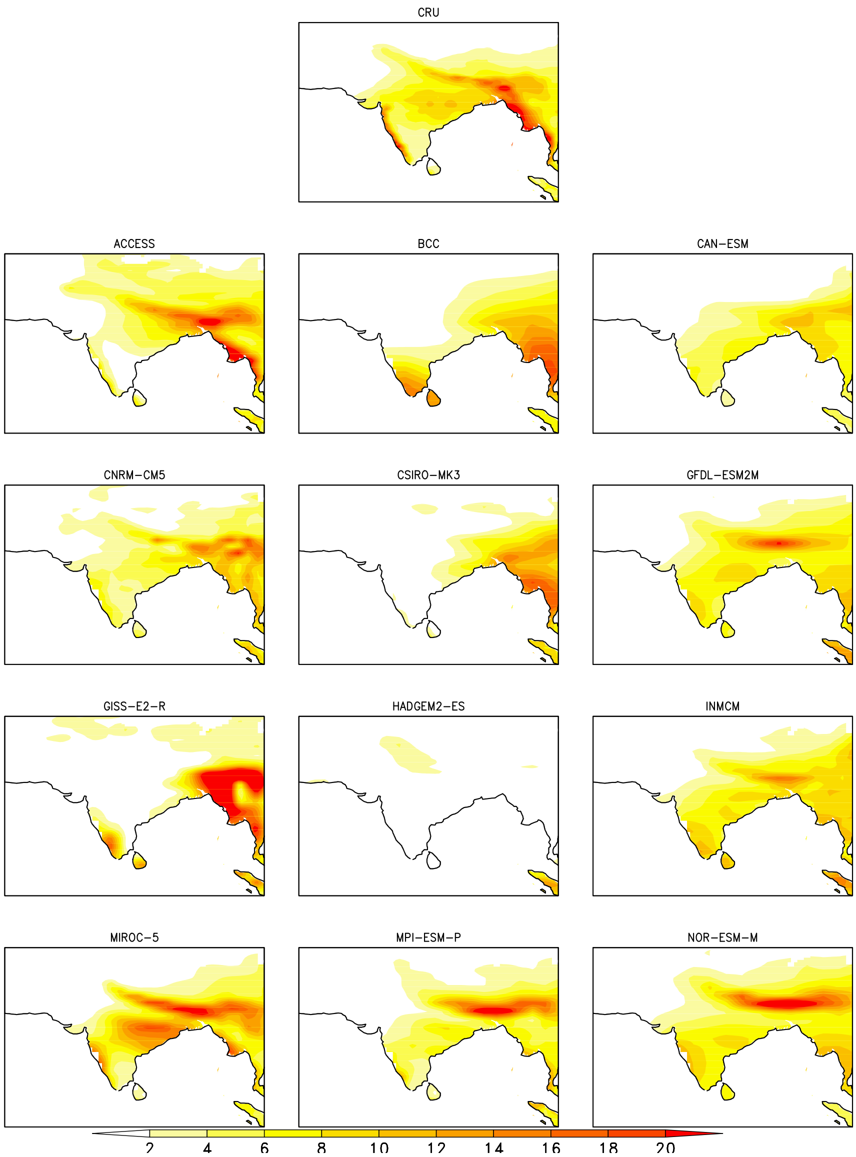


Figure 5 Mean JJAS observed GPCP precipitation over the South Asian monsoon region followed by 12 models of simulated precipitation in the historical run. [Unit: mm/day]

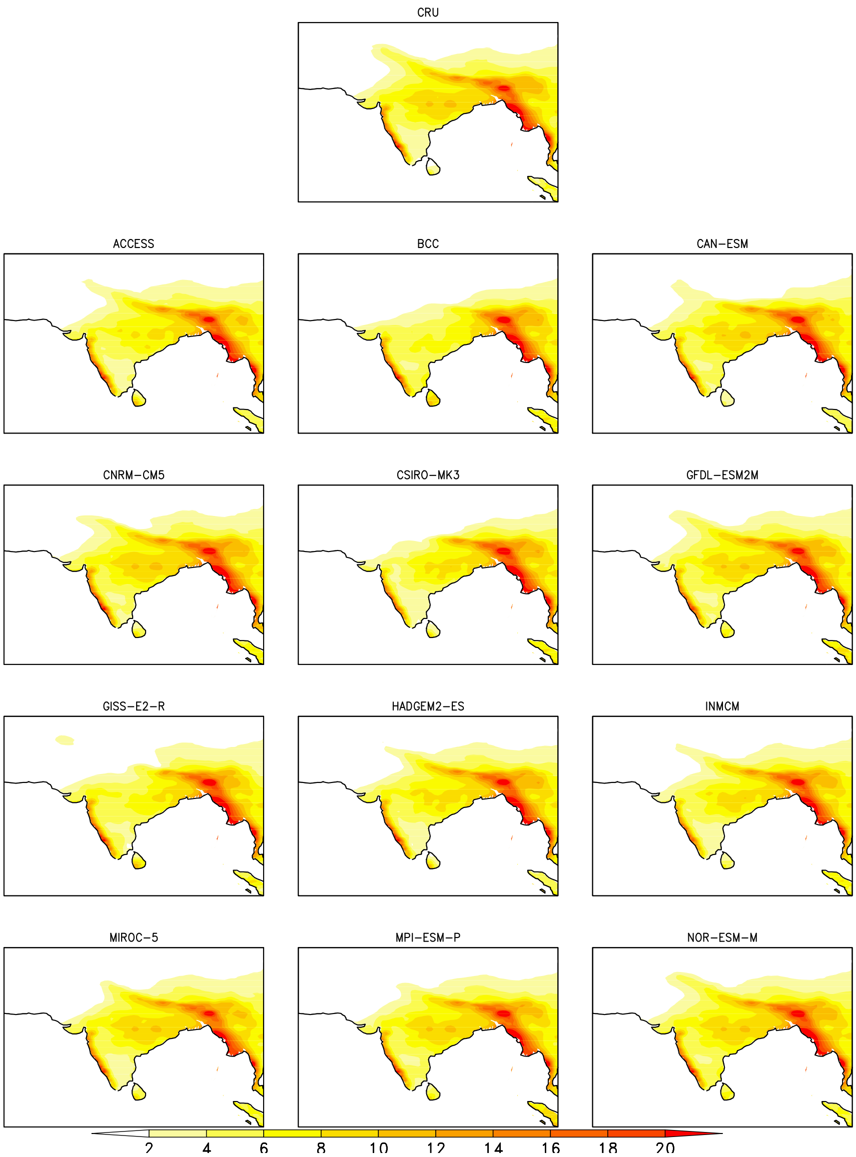


Figure 6 Mean JJAS observed CRU precipitation over the South Asian monsoon region followed by 12 bias corrected model outputs in the historical run with respect to CRU precipitation. [Unit: mm/day]

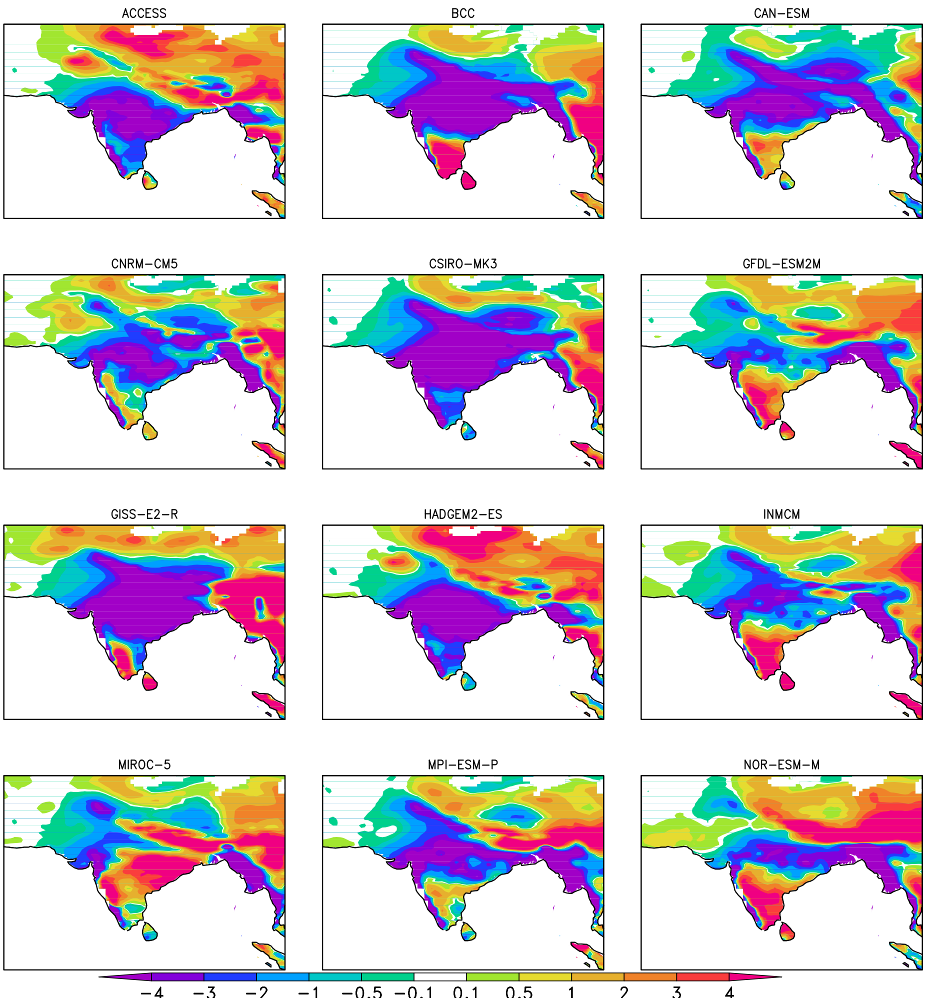


Figure 7 Difference in mean JJAS precipitation over the South Asian monsoon region in 12 uncorrected model outputs in the historical run with respect to CRU precipitation (i.e, raw CMIP5 precip. - observation). [Unit: mm/day]

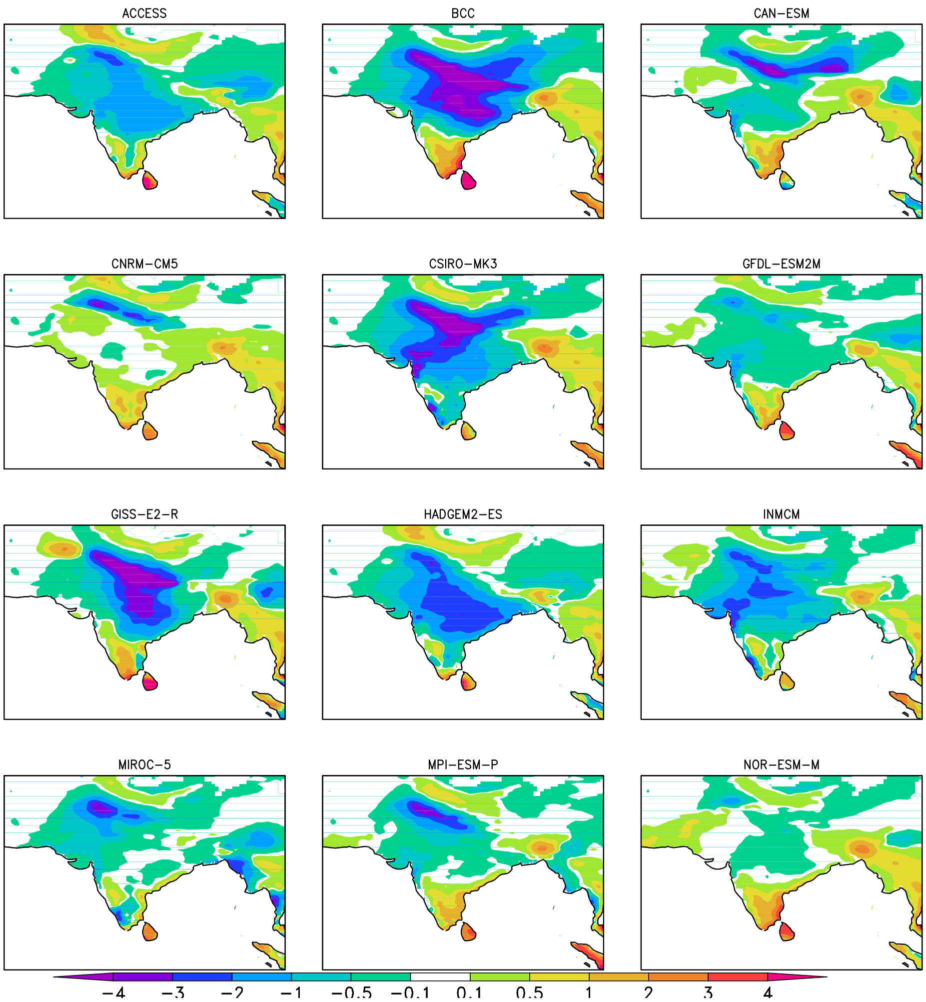


Figure 8 Difference in mean JJAS precipitation over the South Asian monsoon region in 12 bias corrected model outputs in the historical run with respect to CRU precipitation (i.e, bias corrected CMIP5 precip. - observation). [Unit: mm/day]

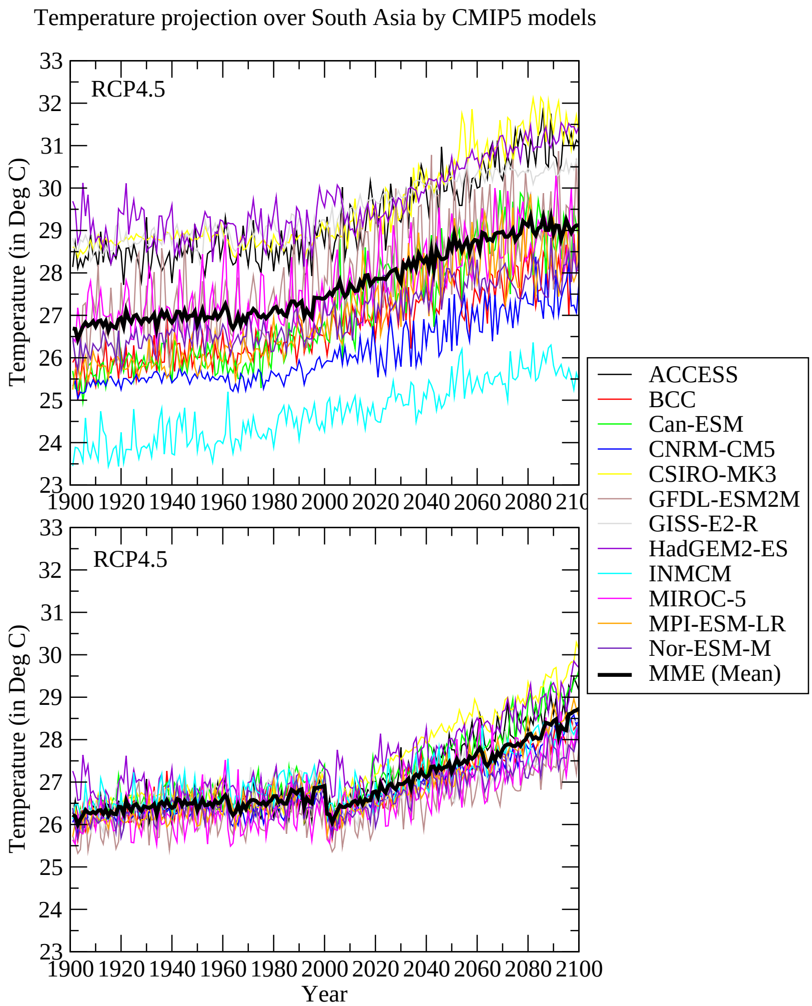


Figure 9 (Top panel) Temperature projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario. (Bottom panel) Bias corrected temperature projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario. [Unit: °C]

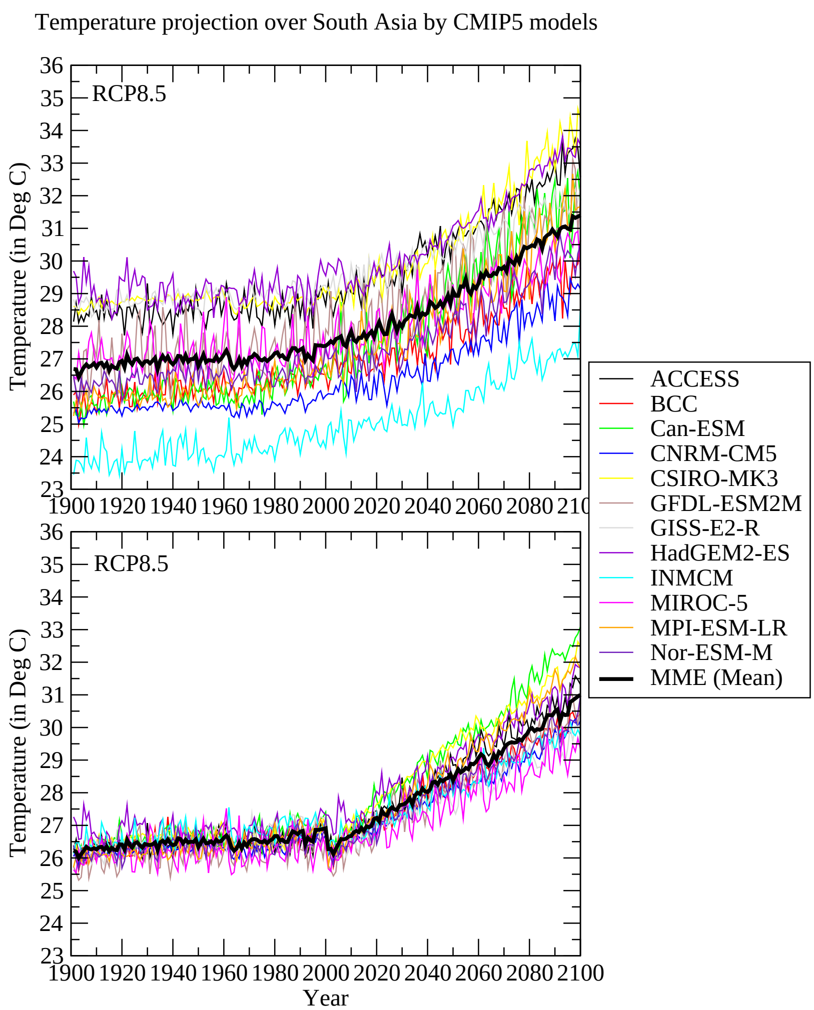


Figure 10 (Top panel) Temperature projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario. (Bottom panel) Bias corrected temperature projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario. [Unit: °C]

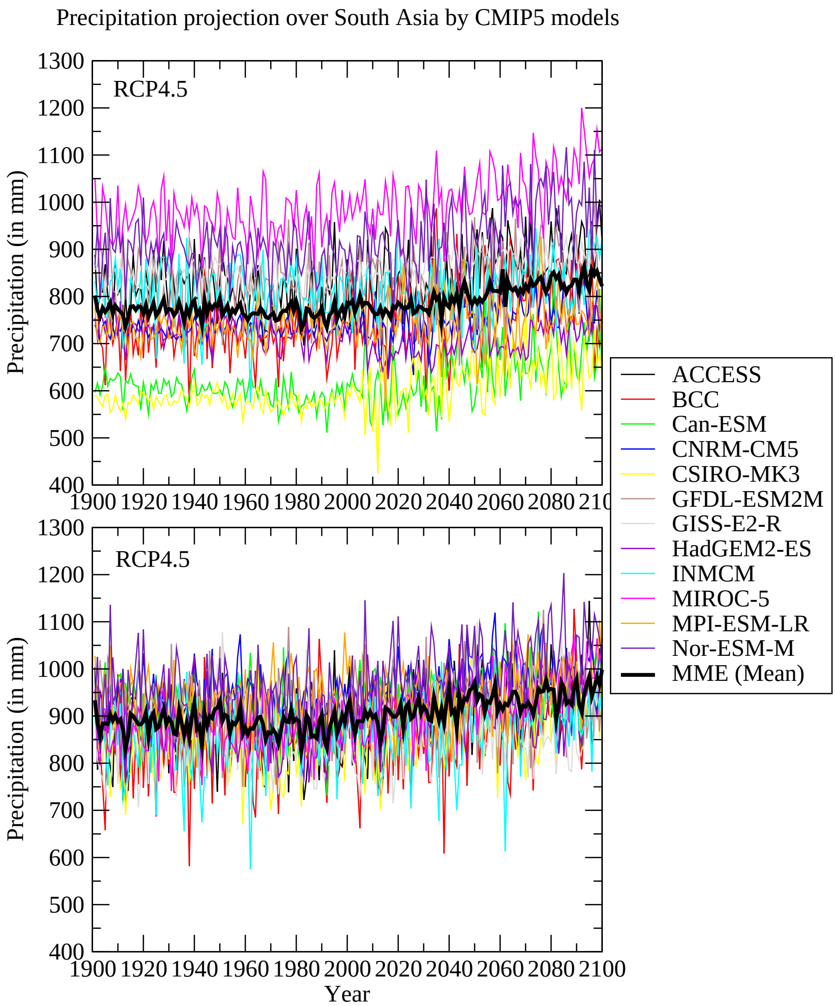


Figure 11 (Top panel) Precipitation projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario. (Bottom panel) Bias corrected precipitation projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario. [Unit: mm]

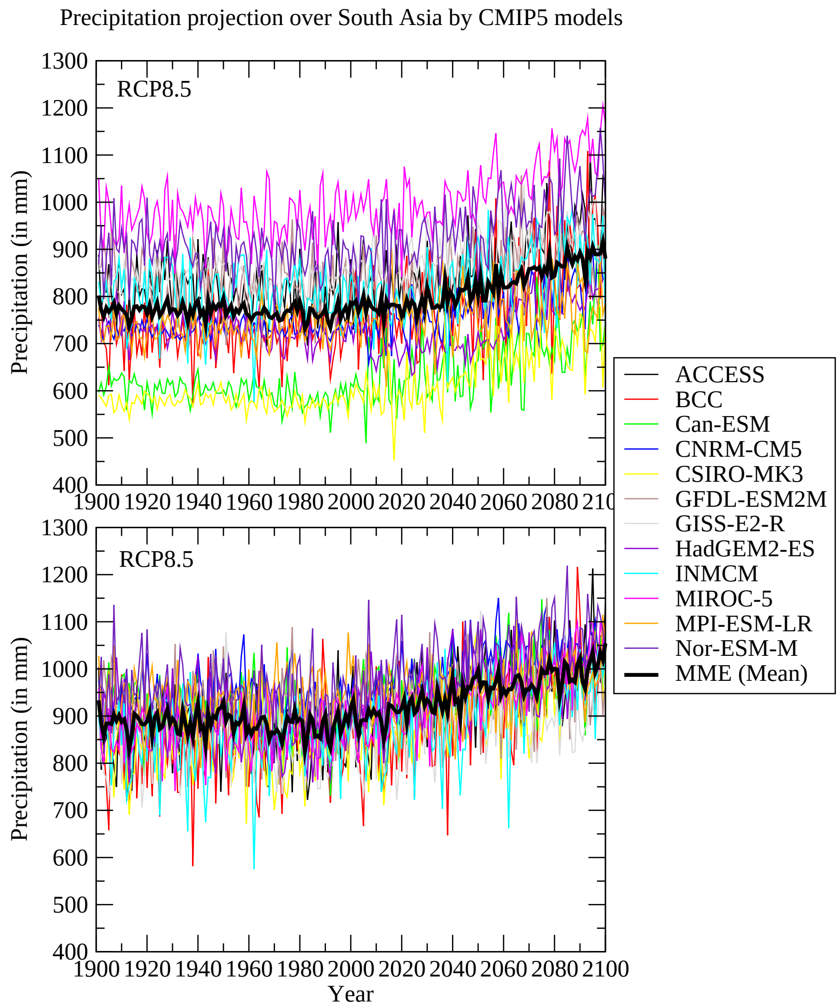


Figure 12 (Top panel) Precipitation projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario. (Bottom panel) Bias corrected precipitation projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario. [Unit: mm]

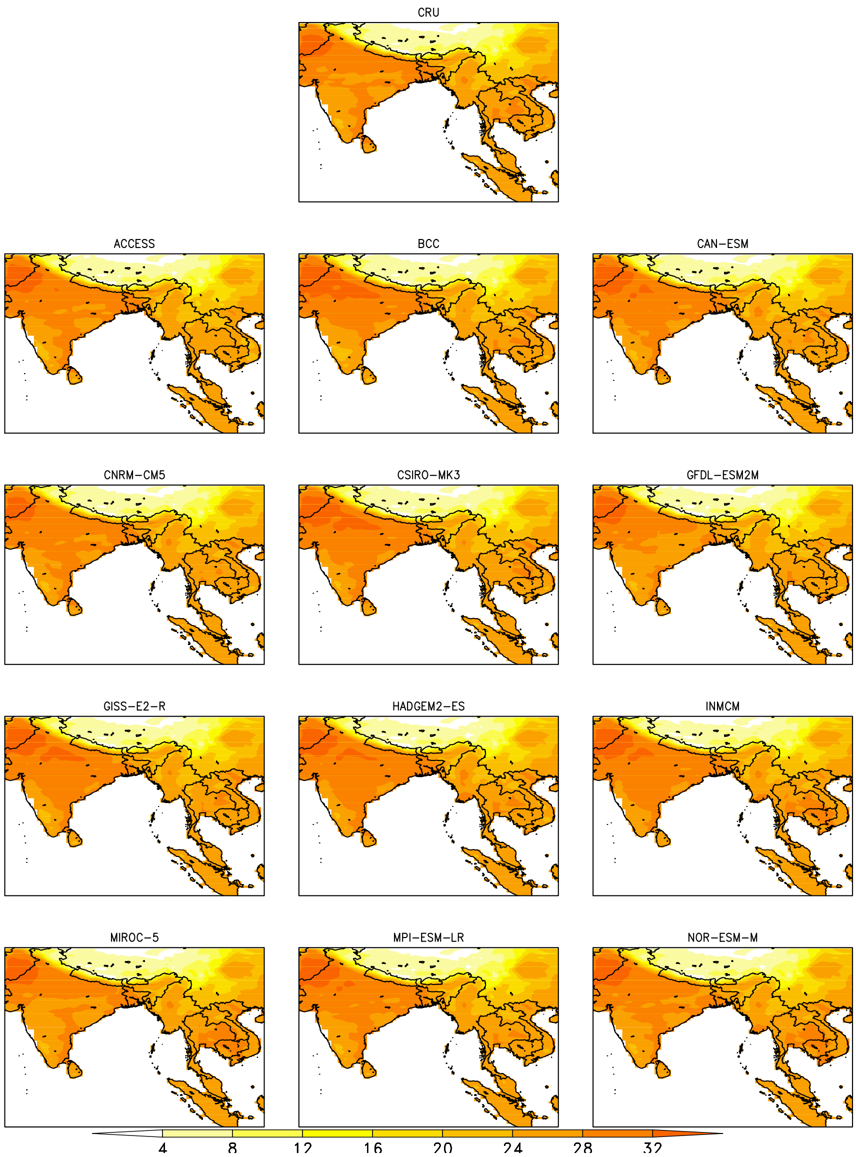


Figure 13 Mean JJAS observed CRU temperature over the South Asian monsoon region followed by 12 bias corrected model outputs in the historical run with respect to CRU temperature using CDF (Weibull distribution function) based bias correction method. [Unit: °C]

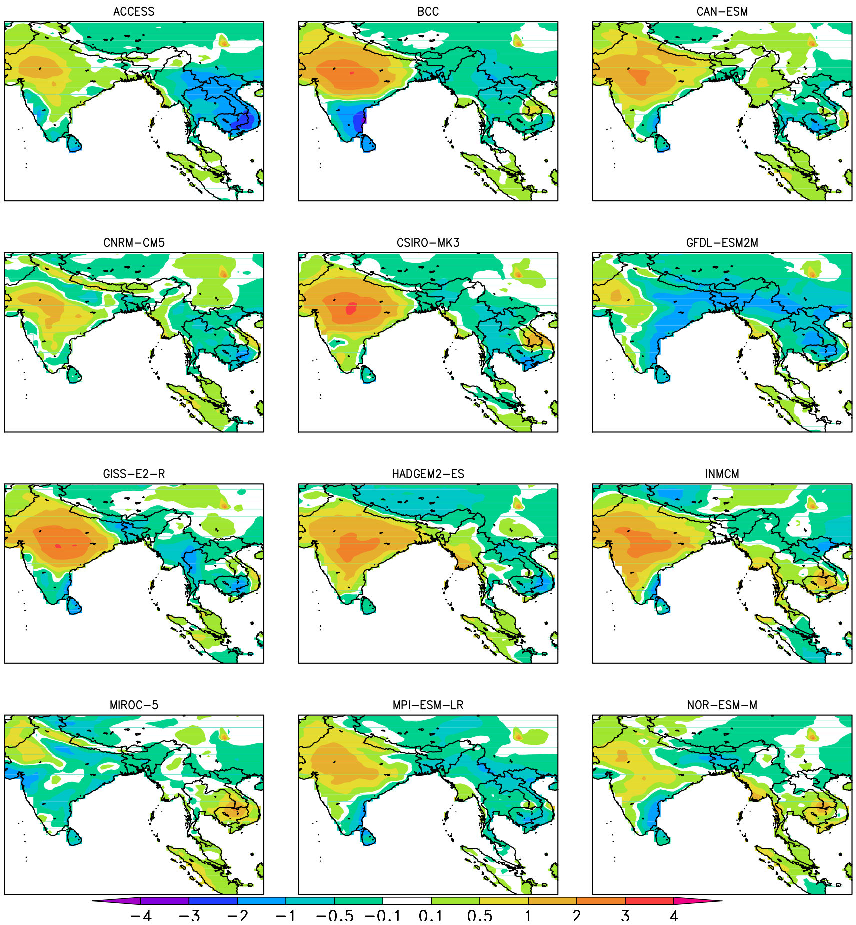


Figure 14 Difference in mean JJAS temperature over the South Asian monsoon region in 12 bias corrected model outputs in the historical run with respect to CRU temperature (i.e., bias corrected CMIP5 Temp. - observation) using CDF (Weibull distribution function) based bias correction method. [Unit: °C]

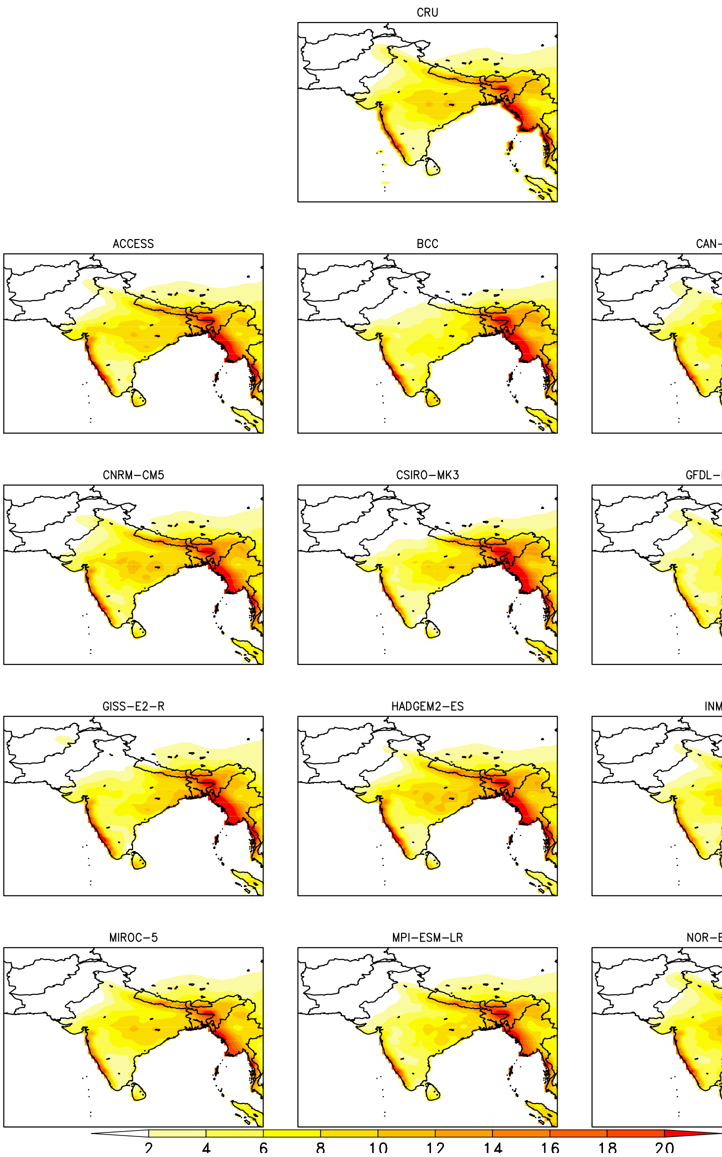


Figure 15 Mean JJAS observed CRU precipitation over the South Asian monsoon region followed by 12 bias corrected model outputs in the historical run with respect to CRU precipitation using CDF (Weibull distribution function) based bias correction method. [Unit: mm/day]

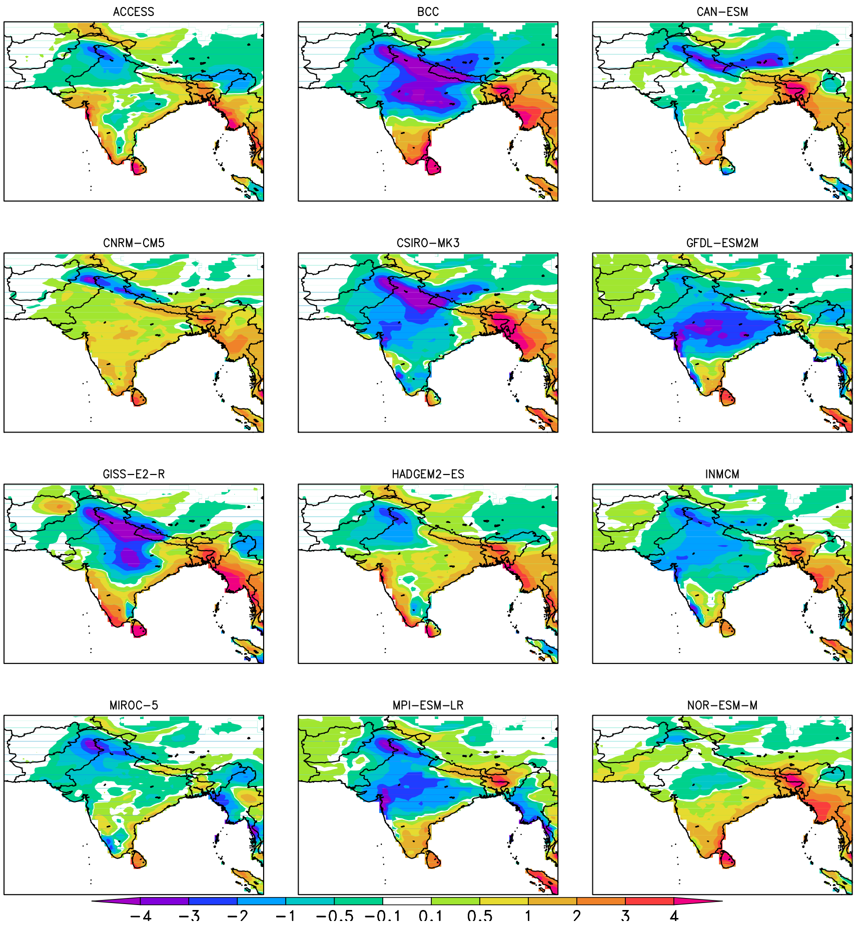


Figure 16 Difference in mean JJAS precipitation over the South Asian monsoon region in 12 bias corrected model outputs in the historical run with respect to CRU precipitation (i.e., bias corrected CMIP5 precip. - observation) using CDF (Weibull distribution function) based bias correction method. [Unit: mm/day]

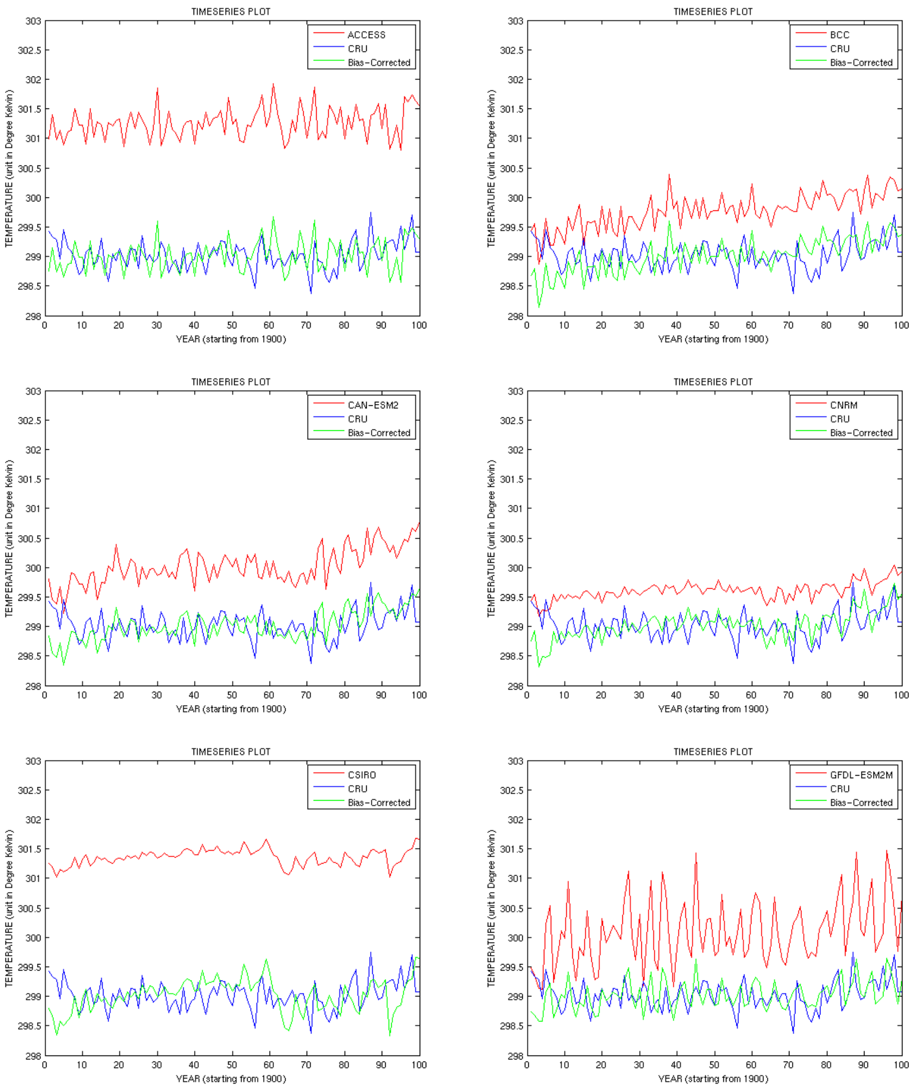
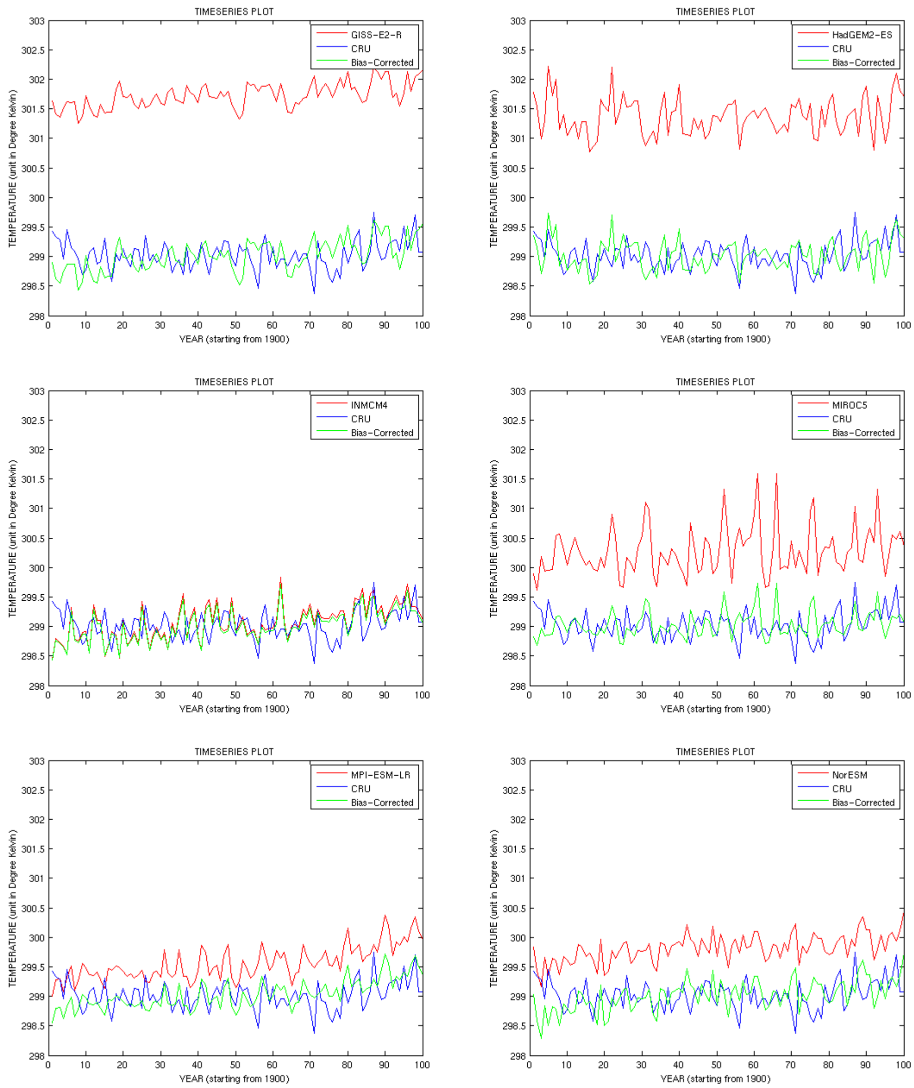


Figure 17 Time series of bias corrected temperature over the South Asian monsoon region from 12 models in the historical run scenario using CDF (Weibull distribution function) based bias correction method. [Unit: °K]



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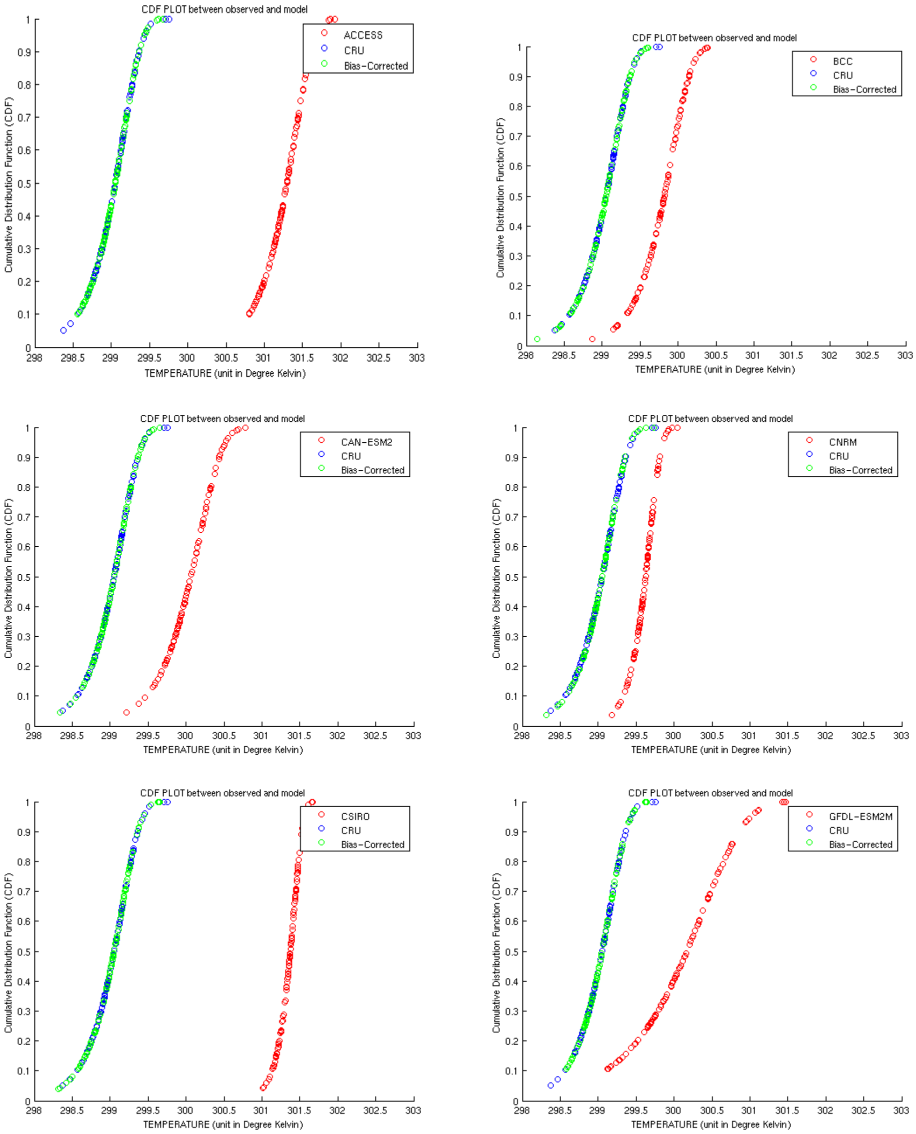
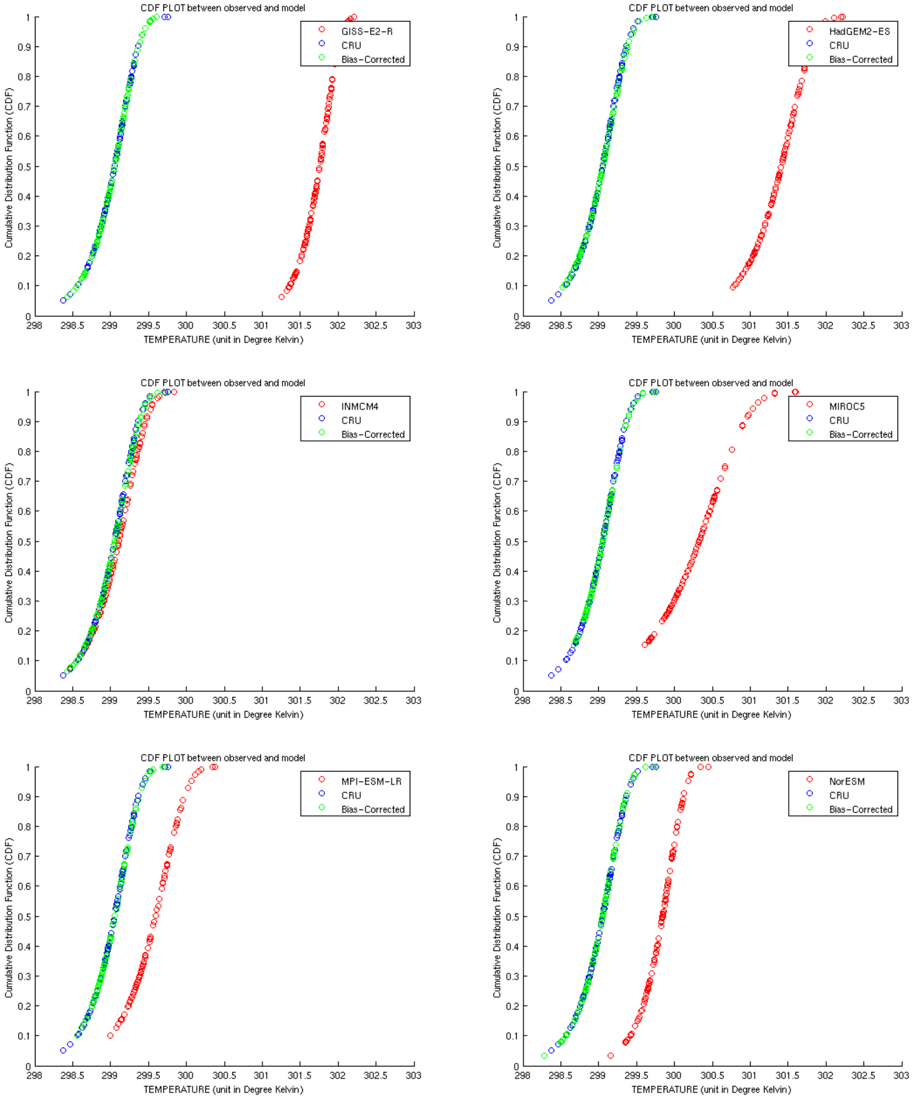


Figure 18 CDF of the models using CDF (Weibull distribution function) based bias correction method. [Unit: °K]



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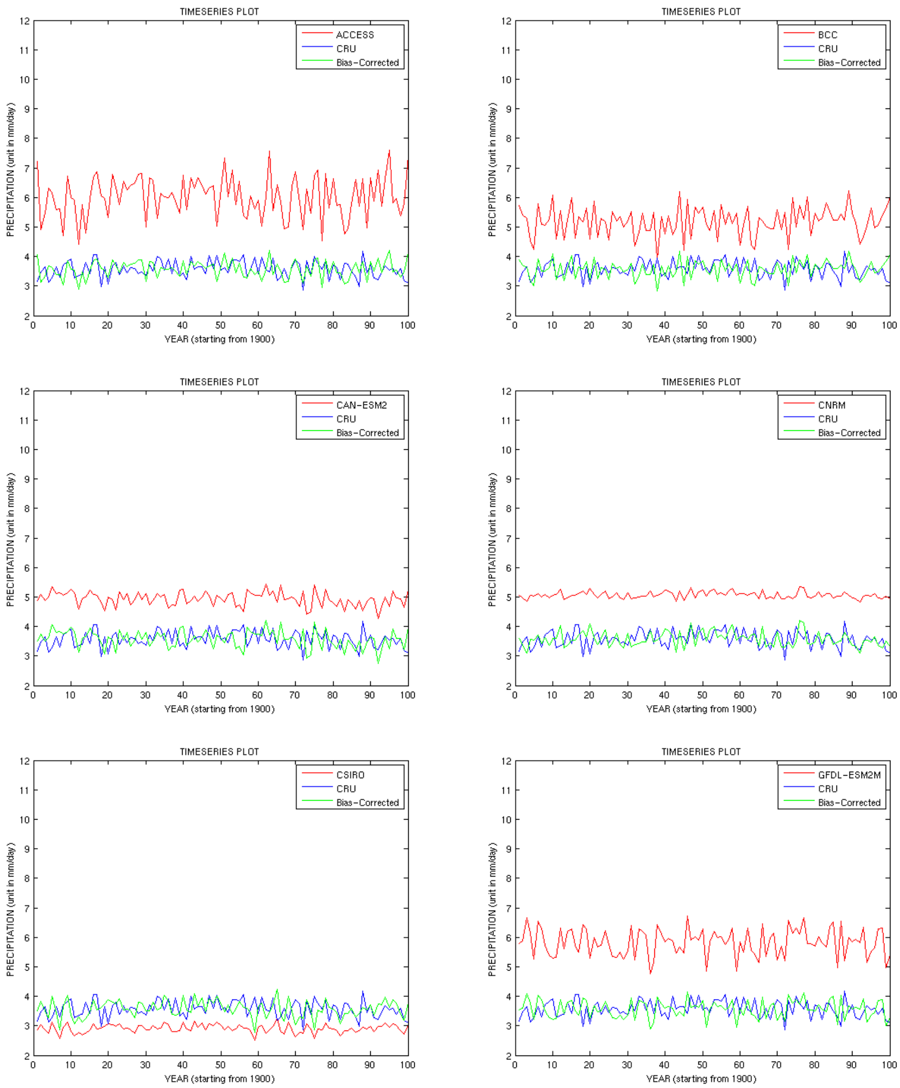
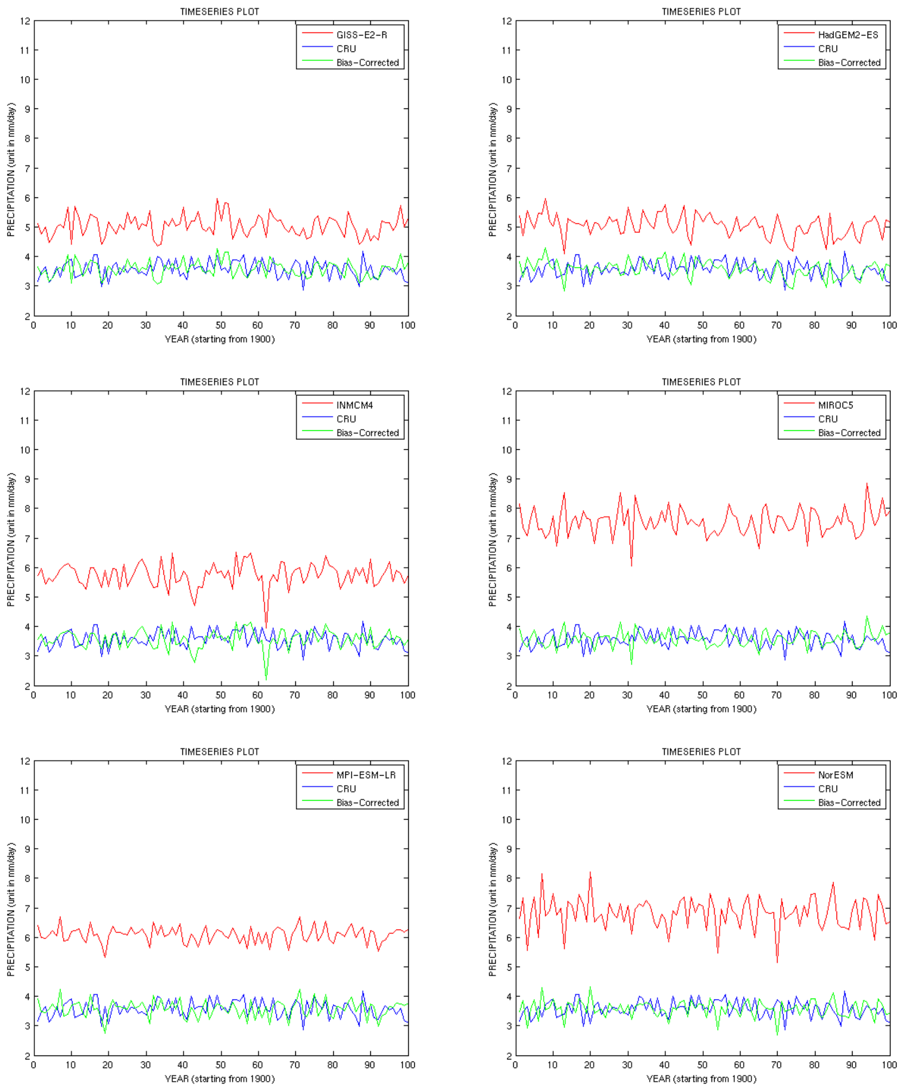


Figure 19 Time series of bias corrected precipitation over the South Asian monsoon region from 12 models in the historical run scenario using CDF (Weibull distribution function) based bias correction method. [Unit: mm/day]



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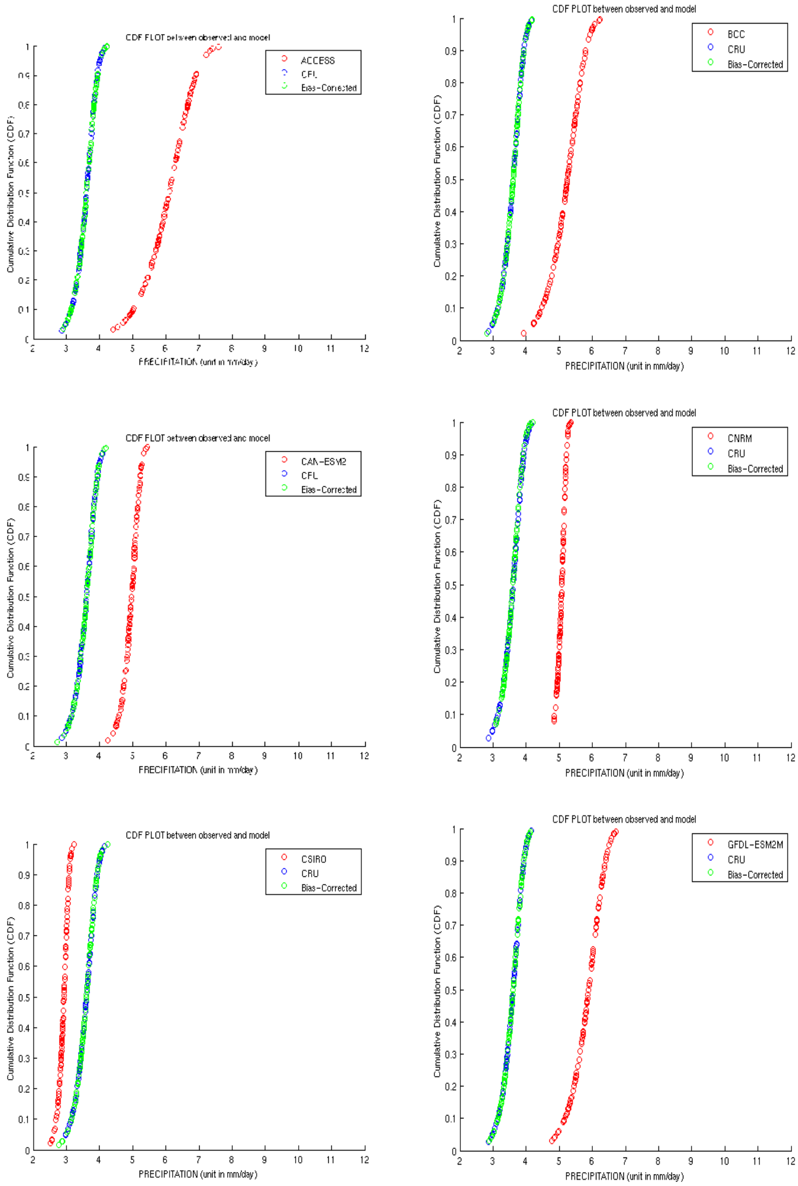

Figure 20 CDF of the models using CDF (Weibull distribution function) based bias correction method. [Unit: mm/day]

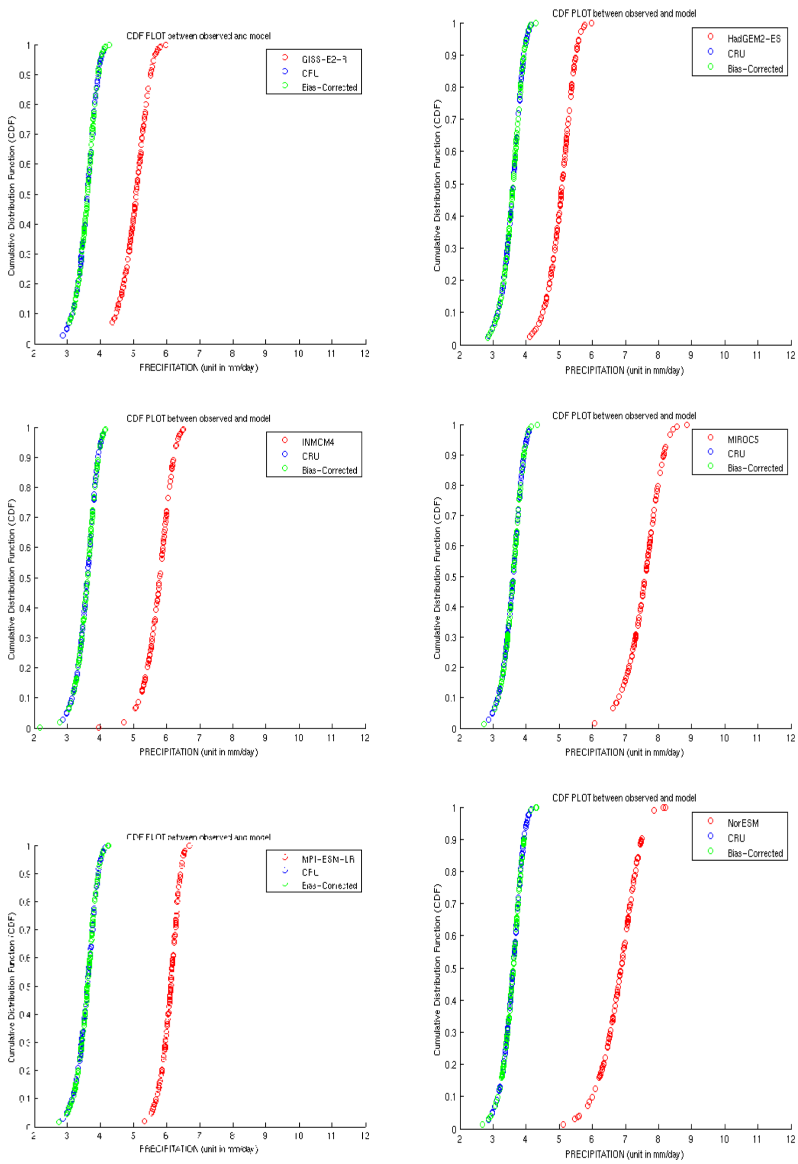

Figure 20 Continued.

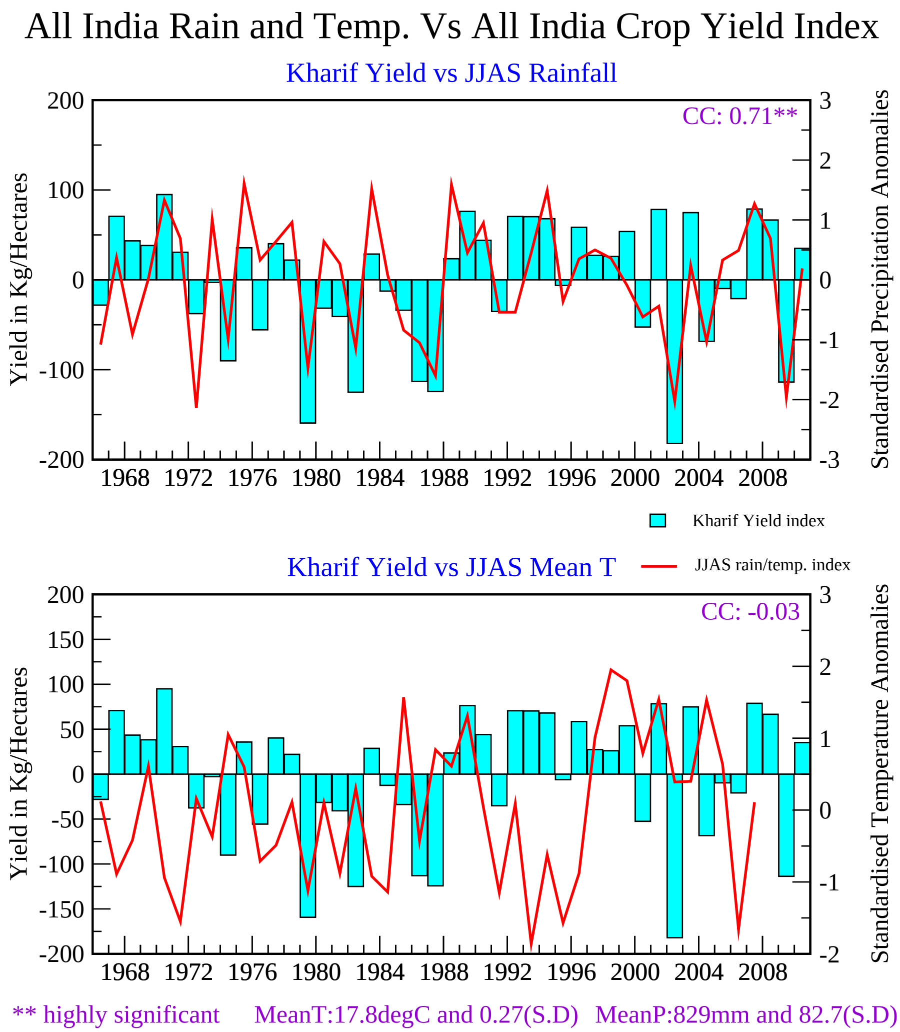

Figure 21 (a) All-India rainfall index vs. all-India crop yield index. (b) All-India temperature index vs. all-India crop yield index. [Unit for temperature: °C. Unit for precipitation: mm. Unit for agricultural yield: kg/ha].

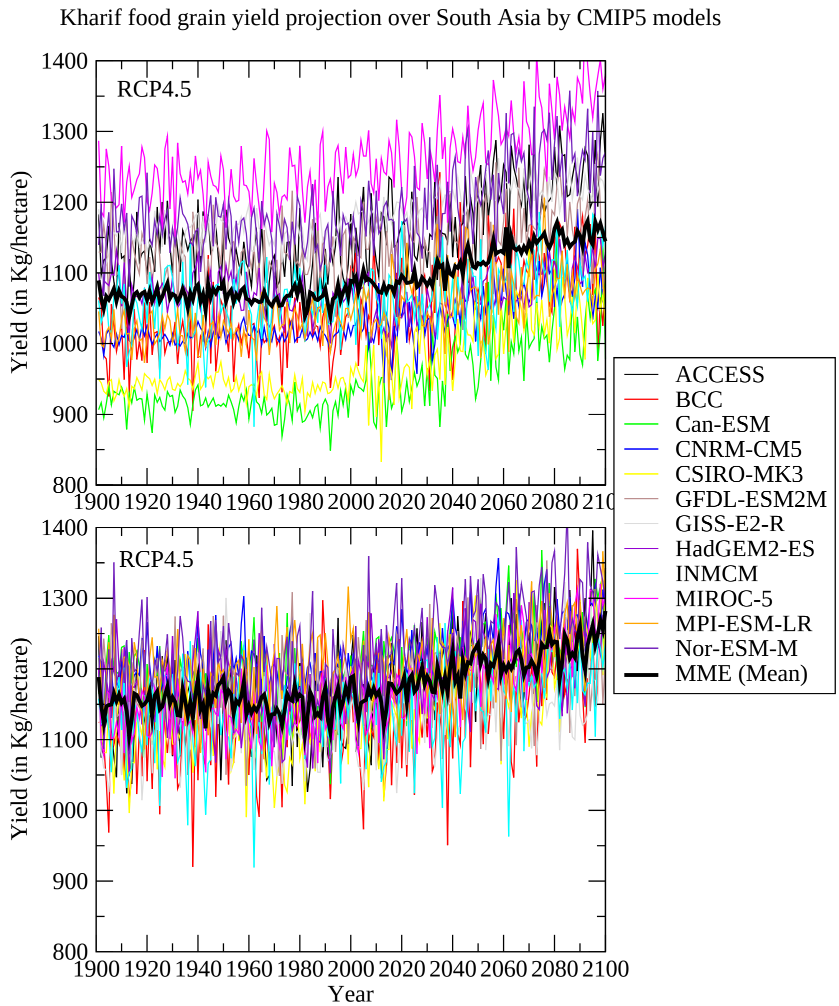

Figure 22 Food grain yield projection using both temperature and precipitation. (Top panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario for raw data (not bias corrected). (Bottom panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario for reconstructed data (bias corrected). [Unit: kg/ha]

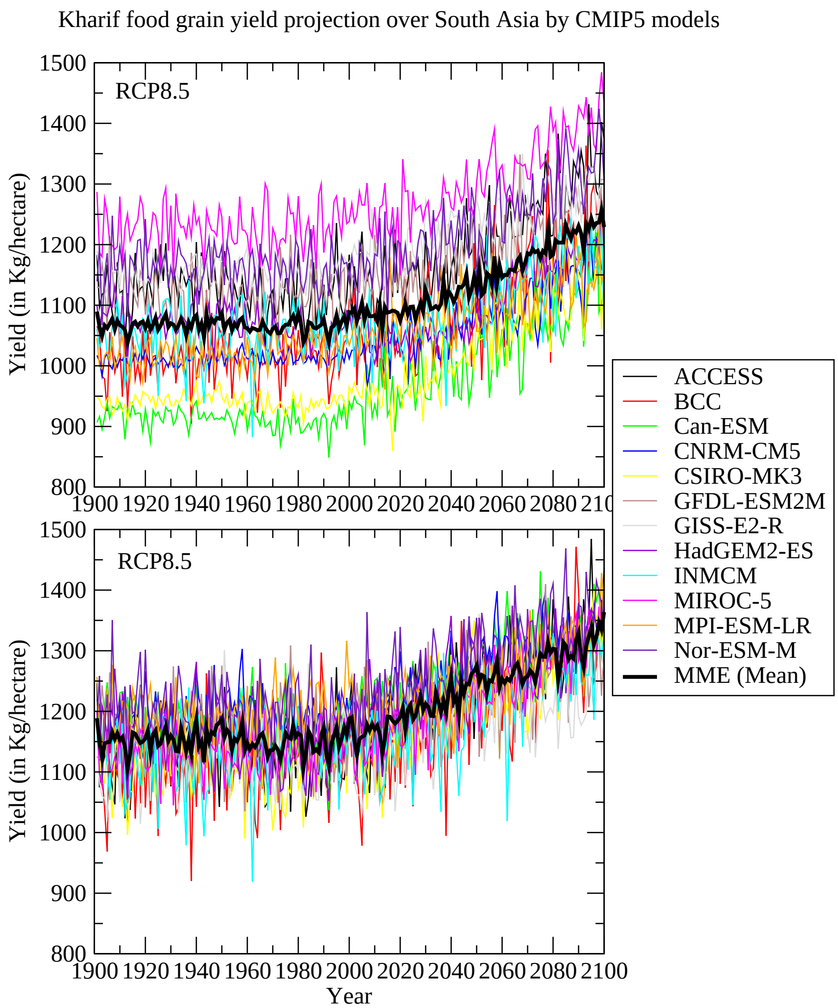

Figure 23 Food grain yield projection using both temperature and precipitation. (Top panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario for raw data (not bias corrected). (Bottom panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario for reconstructed data (bias corrected). [Unit: kg/ha]

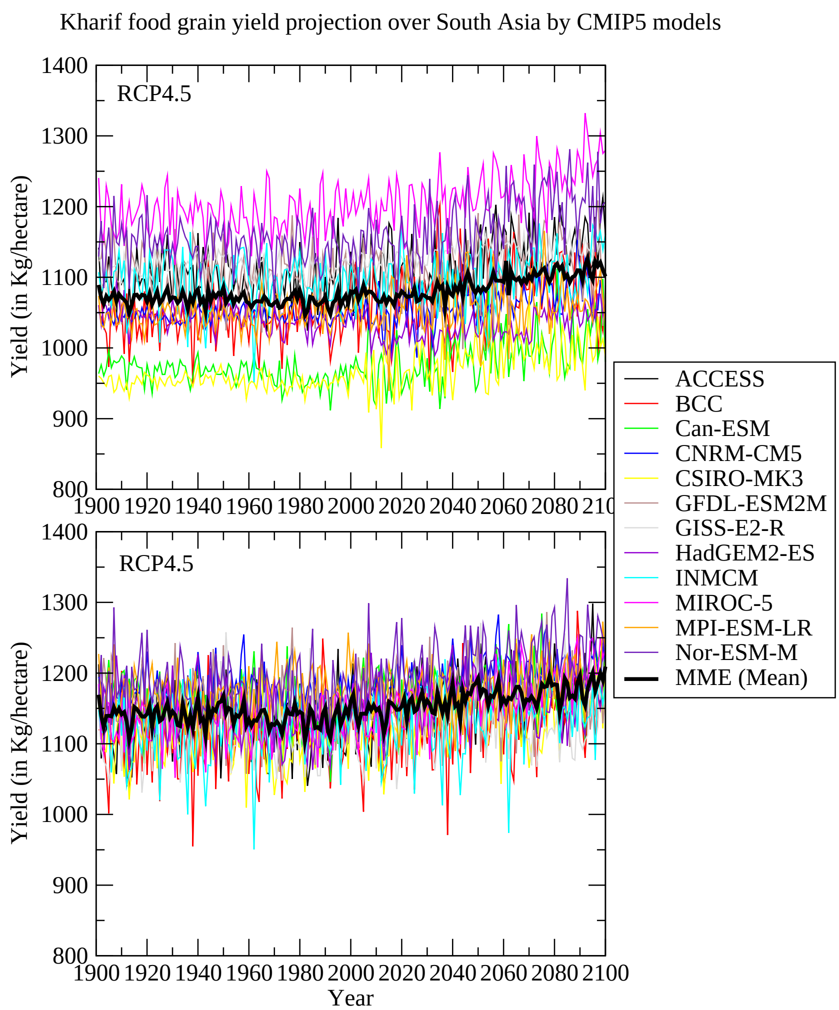

Figure 24 Food grain yield projection using only precipitation. (Top panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario for raw data (not bias corrected). (Bottom panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP4.5 scenario for reconstructed data (bias corrected). [Unit: kg/ha]

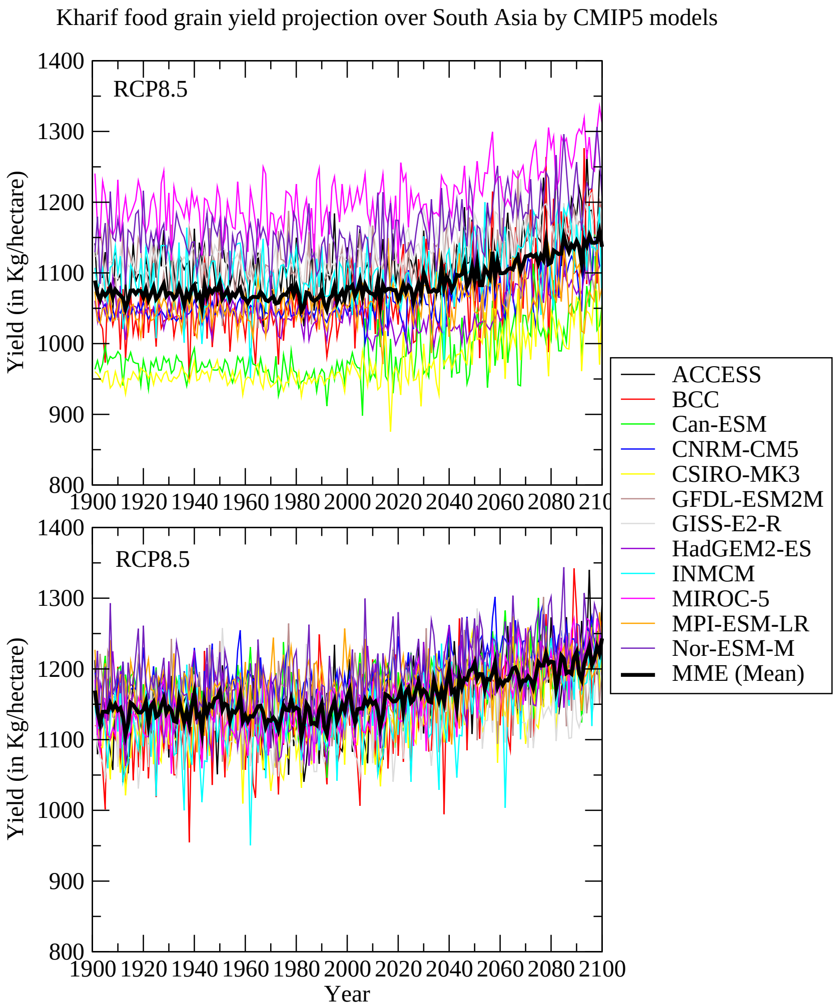

Figure 25 Food grain yield projection using only precipitation. (Top panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario for raw data (not bias corrected). (Bottom panel) Food grain yield projection over the South Asian monsoon region from 12 models in the RCP8.5 scenario for reconstructed data (bias corrected). [Unit: kg/ha]

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APEC Climate Center

12, Centum 7-ro, Haeundae-gu, Busan 612-020, Republic of Korea
Tel: +82-51-745-3900 Fax: +82-51-745-3949
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