



Spatiotemporal Variations of Precipitation and Temperatures Under CORDEX Climate Change Projections: A Case Study of Krishna River Basin, India

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Abstract

The Earth's climate is not static; it changes according to the natural and anthropogenic climate variability. Anthropogenic forcing due to increase of greenhouse gases in the atmosphere has driven changes in climate variables globally. Changes in climatological variables have severe impact on global hydrological cycle affecting the severity and occurrence of natural hazards such as floods and droughts. Estimation of projections under climate signals with statistical and dynamic downscaling models and integration with water resource management models for the impact assessment have gained much attention. The fine-resolution climate change predictions of dynamic regional climate model (RCM) outputs, which include regional parameterization, have been widely applied in the hydrological impact assessment studies. Advancement of the Coordinated Regional Downscaling Experiment (CORDEX) program has enabled the use of RCMs in regional impact assessment which has progressed in recent years. CORDEX model outputs were considered to be valuable in terms of establishing large ensembles of climate projections based on regional climate downscaling all over the world. However, the simulations of RCM outputs have to be evaluated to check the reliability in reproducing the observed climate variability over a region. The present study demonstrates the use of bias-corrected CORDEX model simulation in analyzing the regional-scale climatology at river basin scale, Krishna river basin (KRB), India. The precipitation and temperature simulations from CORDEX models with RCP 4.5 were evaluated for the historical data for the period of 1965 to 2014 with India Meteorological Department (IMD) gridded rainfall and temperature data sets cropped over the basin. The projected increase

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of precipitation under climate signals was predicted to be from 74.4 to 136.7 mm over KRB for the future time period of 2041–2060 compared to the observed periods of 1966–2003. About 1.06 °C to 1.35 °C of increase in temperatures was predicted for the periods of 2021–2040 and 2041–2060, respectively, compared to the observed period of 1966–2014 over KRB. The climate variable projections obtained based on RCM outputs can provide insights toward the variations of water-energy variables and consequent impact on basin yields and losses in river basin management.

Keywords

Bias correction · Dynamic downscaling · Hydrology · Regional circulation model (RCM) · General circulation model (GCM)

8.1 Introduction

The totality of atmosphere, hydrosphere, biosphere, and geosphere and their interactions are referred as climate system (Mcguffie and Henderson-Sellers 1997). The Earth's climate is not static; it changes in response to natural and anthropogenic climate forcing. Climate change refers to climatic conditions over a period of time ranging from months to thousands or millions of years. The standard period is defined as 30 years according to the World Meteorological Organization (WMO). Apart from anthropogenic emission of greenhouse gases, which is considered as external forcing, internal forcing such as volcanic eruption and solar variation determines the dynamics of climate system (IPCC 2007). In this context, increasing temperatures and changes in precipitation patterns have been observed all over the world (Hansen et al. 2010) under anthropogenic climate change. The consequent and immediate impact of climate change is on intensification of global hydrological cycle leading to increase of intensity and frequency of climate hazards such as droughts, floods (Rosenzweig et al. 2010), heat and cold waves, etc. The most significant impact of climate change is anticipated to be on regional water-energy variables of hydrological cycle, thus affecting water supply and demand (Cunderlik and Simonovic 2005). The increasing concern of climate change and its impacts on hydrological variables have motivated several researchers to estimate the projected climatological variables accounting for greenhouse gases in the atmosphere (Ghosh and Mujumdar 2008). In this context, prediction of accurate projections of hydro-climatological variables under climate change is crucial for making adaptive measures and mitigation policies (IPCC 2007). To this end, climate change impact assessment studies have been advanced due to the availability of general circulation models (GCMs) as the most credible tools for investigating the physical processes of the earth surface-atmosphere system. The GCMs can simulate the projections of climatological variables for current as well as for future scenarios accounting for greenhouse gas emission scenarios. These are the numerical models, which analyze the atmosphere on an hourly basis in all three dimensions based on the law of

conservation of energy, mass, momentum, and water vapor and ideal gas law (Mcguffie and Henderson-Sellers 1997). These are complex computer simulations describing the circulation of air and ocean currents and how the energy is transported within a climate system. GCMs are classified as atmospheric general circulation models (AGCM) or oceanic general circulation models (OGCM) for modeling atmospheric and oceanic circulations (Mcguffie and Henderson-Sellers 1997). Most of the climate change impact assessment studies mainly focus on the use of GCM outputs of various climatological variables and their integration with hydrological modeling (Rehana and Mujumdar 2014; Teutschbein et al. 2011; Chen et al. 2011).

The Intergovernmental Panel on Climate Change (IPCC) has been established by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP) to provide scientific, technical, and socioeconomic information for understanding the climate change process. The IPCC provides scientific information to the research community in terms of future possible climate change scenarios for policy- and decision-making (IPCC 2007, 2014). The IPCC has developed long-term emission scenarios based on the radiative forcing and demographic, technical, and socioeconomic information, which are considered a standard reference to be followed for the policymakers, scientists, and other experts. Such emission scenarios enabled the scientific community to carry out climate change analysis, modeling, impact assessment, adaptation, and mitigation studies. Based on the Assessment Report 4 (AR4), IPCC has defined Special Report on Emission Scenarios (SRES) of four storylines as A1, B1, A2, and B2 determined by driving forces such as demographic development, socioeconomic development, and technology change along with CO₂ level changes (IPCC 2007) (<https://www.ipcc.ch/assessment-report/ar4/>). Whereas the IPCC Assessment Report 5 (IPCC 2014) has replaced the SRES of AR4 with Representative Concentration Pathways (RCPs) RCP8.5, RCP6, RCP4.5, and RCP2.6, here, the RCPs refer to time-dependent projections of atmospheric greenhouse gas concentrations (<https://www.skepticalscience.com/rcp.php>), and the numbers 8.5, 6, 4.5, and 2 represent the radiative forcing, expressed as Watts/m². For example, RCP 8.5 is high pathway for which radiative forcing reaches >8.5 Watts/m² by 2100 and continues to rise. The RCP 6 and 4.5 are considered to be stabilization pathways, while for RCP 2 the radiative forcing peaks at approximately 3 Watts/m² before 2100 and then declines. Integration of projected climatological variables under climate change scenarios with water resource decision and management models to study the impact assessment over water quantitative and qualitative availabilities and demands has widely gained much attention in the research community (Ghosh and Mujumdar 2008; Raje and Mujumdar 2010; Rehana and Mujumdar 2014; Mishra et al. 2014).

Assessment of climate change impacts on water resources necessitates accurate projections of various hydroclimate variables, which involves downscaling the projections of climate variables to hydrological variables. It is of growing importance to create accurate projections of hydrometeorological variables by employing climate model outputs with general circulation models (GCMs) and regional circulation models (RCMs) which can then be statistically or dynamically downscaled (Fowler et al. 2007). To obtain the projections of hydrometeorological variables

(precipitation, runoff, temperature, etc.) at regional scales based on large-scale climate simulations (mean sea level pressure, wind speed, humidity, etc.) obtained from GCMs, downscaling models have been advanced (Hewitson and Crane 1992; Wilby et al. 2004; Tripathi et al. 2006; Anandhi et al. 2008; Rehana and Mujumdar 2012). Broadly, the downscaling techniques are classified as dynamic and statistical downscaling models. The statistical downscaling model involves deriving empirical relationships between large-scale climate variable simulations (predictors) obtained from GCMs and regional-scale hydroclimatological variables (predictands) (Wilby et al. 2004). The spatial resolution of statistical downscaling projections depends on the scale of the regional hydrological variables, and also the spatial resolution of GCMs is generally coarse ranging from $2.8^{\circ} \times 2.8^{\circ}$ to $1.1^{\circ} \times 1.1^{\circ}$.

The dynamic downscaling uses a nested higher-resolution regional climate model (RCM) within a coarse resolution GCM. The RCMs work at finer resolution and provides better dynamic downscaling climate change predictions for a particular region (Buontempo et al. 2015) with region-specific parameterization (Singh et al. 2017). The use of RCMs for impact assessment should be based on the evaluation of the climate projections with observed data given the debate on the use of RCM projections directly (Racherla et al. 2012; Feser et al. 2011). Due to the fine-resolution climate model, projections of RCMs, which enable to synthesize the climate change prediction, and hydrological models to study the regional impact assessment studies became widely applicable (Das and Umamahesh 2018). Further, RCMs provide dynamically downscaled GCM outputs at fine resolutions compared to coarser statistical downscaled outputs, which can be directly used in the impact assessment studies (Sun et al. 2006) by testing their performance with current climate (Singh et al. 2017). The recent regional climate model is available through Coordinated Regional Climate Downscaling Experiment (CORDEX), is mainly associated with GCM projections from Coupled Model Intercomparison Project (CMIP5, <http://cmip-pcmdi.llnl.gov/cmip5/>), was downscaled with the RCMs run by various research institutes, and is available for 14 domains covering the entire globe. The present study provides an emphasis to incorporate such CORDEX projections of precipitation and temperatures to study the regional climate change impacts at river basin scales. The Krishna river basin, India, was considered as case study to study the regional climate-induced changes of precipitation and temperatures with various CORDEX model outputs.

8.2 Data and Methods

The Krishna river basin (KRB) is the fifth largest river system of India and occupies an area of 2, 58, 948 km² which is 8% of the total geographical area of the country. Nearly 44% of KRB lies in Karnataka, 26% in Maharashtra, about 15% in Telangana, and another 15% in Andhra Pradesh within the range $73^{\circ}17' - 81^{\circ}9'E$ and $13^{\circ}10' - 19^{\circ}22' N$ (Fig. 8.1). The major tributaries of the river are Ghataprabha, Malaprabha, Tunga-Bhadra, Bhima, Vedavathi, and Musi. The annual average precipitation in the basin is 784 mm, of which approximately 90% occurs during

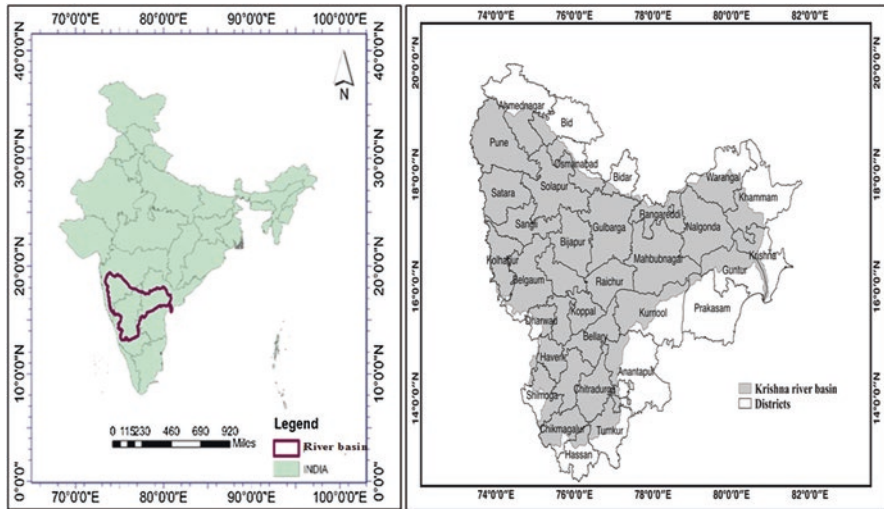


Fig. 8.1 Map for the Krishna river basin (a) Location of the catchment in India (b) Krishna basin and districts map

the southwest monsoon from June to October (<http://india-wris.nrcs.gov.in/wrpinfo/?title=Krishna>). The study used gridded daily precipitation data from the India Meteorological Department (IMD) available for the period of 1901 to 2015 at $0.25^\circ \times 0.25^\circ$ resolution (Rajeevan and Bhat 2009). The gridded daily average temperature data all over India at a resolution of $1^\circ \times 1^\circ$ for the period of 1951–2014 from IMD was cropped to the basin (Srivastava et al. 2009). The temperature was interpolated to $0.25^\circ \times 0.25^\circ$ resolution using the inverse distance weighting method from $1^\circ \times 1^\circ$ resolution. The CORDEX (Coordinated Regional Downscaling Experiment) is mainly associated with GCM projections from Coupled Model Intercomparison Project (CMIP5, <http://cmip-pcmdi.llnl.gov/cmip5/>) and was downscaled with the RCMs run by various research institutes. CORDEX data sets are available for 14 domains covering the entire globe, and the present study selected South-Asian domain of the CORDEX project from Centre for Climate Change Research, Indian Institute of Tropical Meteorology, Pune, India (<http://ccr.tropmet.res.in/home/index.jsp>). Daily precipitation and temperature data simulated by 3 RCMs, driven by various GCMs, were obtained from the CORDEX (www.cordex.org). Three CORDEX experiments: (1) RegCM4(LMDZ), the Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climatic Model version 4 (RegCM4; Giorgi et al. 2012), with deriving GCM as IPSL LMDZ4, from Laboratoire de M'eteorologie Dynamique (France), India; (2) CCLM4(MPI), Consortium for Small-scale Modelling (COSMO) model in Climate Mode version 4.8 (CCLM; Dobler and Ahrens 2008), with deriving GCM as Max Planck Institute for Meteorology, Germany, Earth System Model (MPI-ESM-LR; Giorgetta et al. 2013), from Institute for Atmospheric and Environmental Sciences (IAES), Goethe University, Frankfurt am Main (GUF), Germany; and

(3) REMO2009 (MPI) regional model, with deriving GCM as MPI-ESM-LR (Giorgetta et al. 2013), from Climate Service Center, Hamburg, Germany. The projections for the period of 2006 to 2060 were analyzed under the Representative Concentration Pathway (RCP) 4.5 representing atmospheric radiation at 4.5 W m^{-2} at the end of 2100.

The RCM outputs are generally associated with systematic biases in the simulated projections compared to real observations (Buontempo et al. 2015). The regional climate model simulations are burdened with systematic bias resulting from inadequate physics and bias in GCM simulations used in the boundary conditions affecting the historical and future projections (Ehret 2012). Therefore, the present study adopted quantile-based mapping method developed by Li et al. (2010) with the comparison of cumulative distribution functions (CDFs) of observed and RCM simulated data of precipitation and temperatures for the historical and future scenarios. Here, the CDFs of RCM and IMD gridded data sets of precipitation, and temperatures were compared to correct the bias present in RCM historical and future data sets (Li et al. 2010), where Gamma distribution is used to calculate the CDFs of each time series as follows:

$$X_{m-p.adjst} = F_{o-c}^{-1} \left(F_{m-c} \left(x_{m-p} \right) \right) \quad (8.1)$$

where

$X_{m-p.adjst}$ is the bias-corrected climate variable for current period (RCM-historical)

x_{m-p} = biased RCM variable

F_{m-c} = CDF of RCM Historical data

F_{o-c} = CDF of IMD (Observed) data and F_{o-c}^{-1} is the inverse CDF of IMD data, which gives the observed variable at the corresponding equal CDF level

For bias correction of future RCM data, it is generally assumed that the difference between the model and observed value during the training period also applies to the future period, for a given percentile, which means the adjustment function remains the same. However, the difference or shift between the CDFs for the future and historic periods is also taken into account;

$$X'_{m-p.adjst} = x_{m-p} + F_{o-c}^{-1} \left(F_{m-p} \left(x_{m-p} \right) \right) - F_{m-c}^{-1} \left(F_{m-p} \left(x_{m-p} \right) \right) \quad (8.2)$$

↓
RCM Shift

where

$X'_{m-p.adjst}$ is the bias-corrected climate variable for future period (RCM-future)

x_{m-p} = biased RCM future variable

F_{m-p} = CDF of RCM Future data

F_{o-c} = CDF of IMD (Observed) data

F_{o-c}^{-1} = inverse CDF of IMD data which gives the IMD variable at the corresponding equal CDF level

F_{m-c} = CDF of RCM historical data

F_{m-c}^{-1} = inverse CDF of RCM data which gives the RCM variable at the corresponding equal CDF level

The RCM data sets which are at a resolution of $0.44^\circ \times 0.44^\circ$ were brought to the IMD precipitation data resolution of $0.25^\circ \times 0.25^\circ$ using the inverse distance weighting method after bias correction. The Krishna river basin has shown significant changes after 2003 with spatially averaged precipitation increase of about 28 mm/decade with Pettitt change point detection year as 2003. Therefore, to study the basin-averaged changes of precipitation and temperatures for current and future climate signals, the present study considered two-time intervals of 1966–2003 and 2004–2014. The precipitation and temperatures were analyzed for the time periods of 1966–2003, 2004–2014, 2021–2040, and 2041–2060 with RCP 4.5 over KRB.

8.3 Results and Discussions

The spatial averaged monthly variation of precipitation and temperatures for the period of 1951 to 2014 is shown in Fig. 8.2, with rainfall contributing months as June to October, whereas the dry months as March, April, and May. To examine the spatial variation of precipitation, the annual average precipitations for three time periods of 1951–1972, 1973–1992, and 1993–2014 were studied as shown in Fig. 8.3(a). The average annual precipitation over KRB was estimated at 975 mm, varying between 650 and 1843 mm. The total annual precipitation amount varied from high toward the Western Ghats boundary of the KRB to low toward East of the

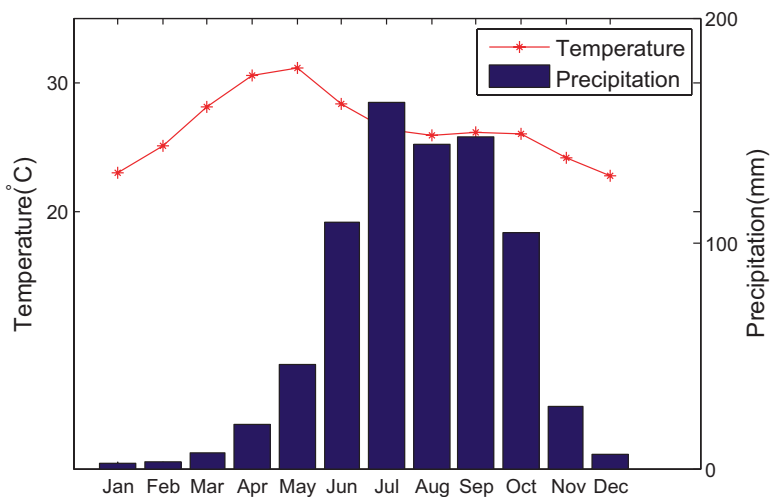


Fig. 8.2 The spatial average monthly average temperature and precipitation over Krishna river basin for 1951–2014

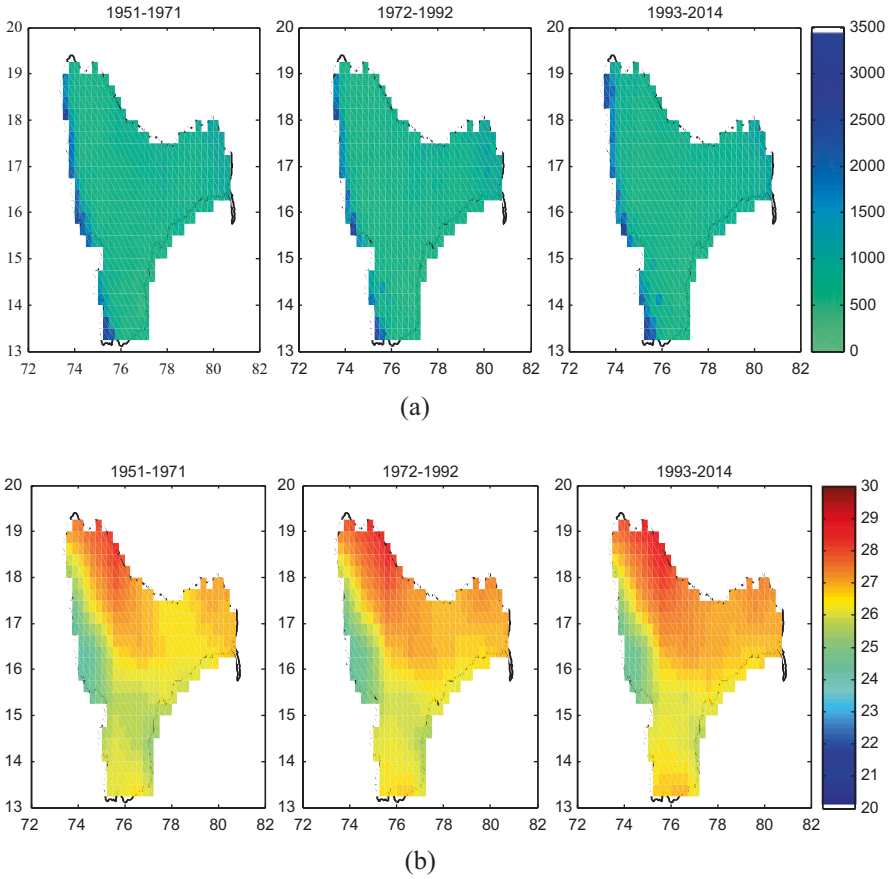
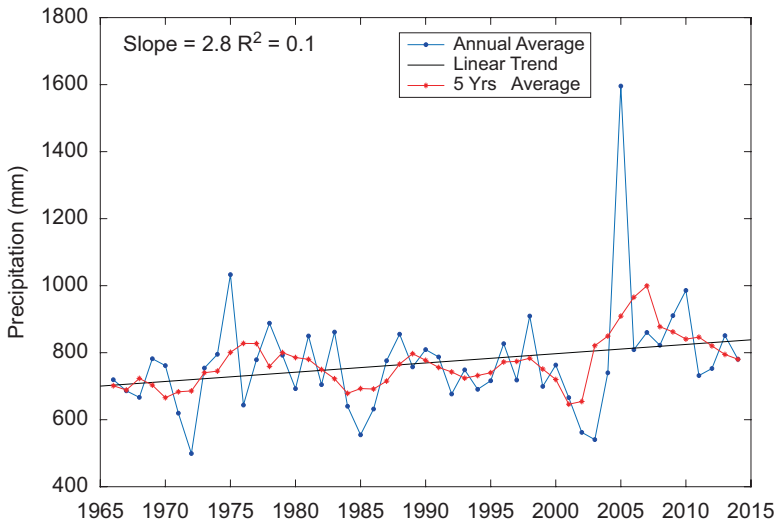


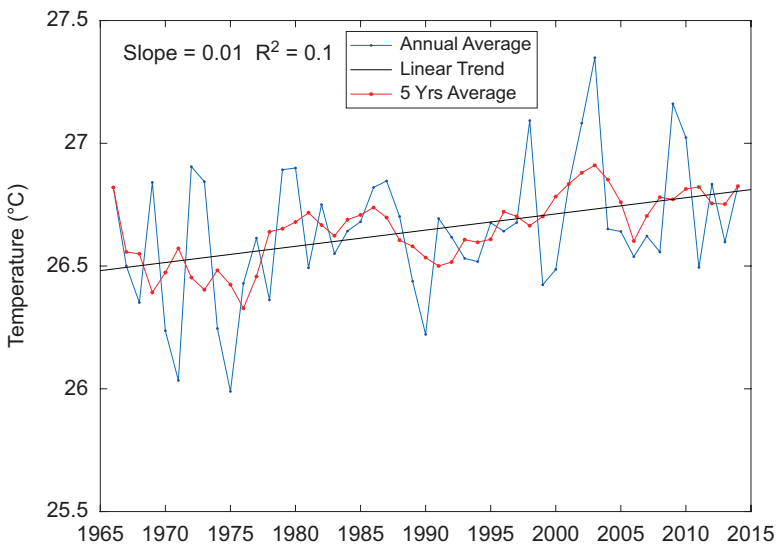
Fig. 8.3 Spatial variation in annual total (a) precipitation in mm (b) temperature in °C for 1951–1971, 1972–1992, and 1993–2014

basin, covering few districts of Telangana. Figure 8.4 (a) shows the temporal trends of basin-averaged precipitation for the period of 1965–2014. The basin-averaged annual average precipitation has shown increasing trends over KRB. The spatially averaged precipitation has shown an increasing trend at a rate of 28 mm/decade (Fig. 8.4(a)). Thus, although there is high spatial variability of precipitation over KRB, the annual average precipitation has shown an increasing trend over the basin. The spatial pattern of average air temperature over the basin is presented in Fig. 8.4(b). Higher average temperatures were observed toward the upper most portion of the basin covering few districts of Maharashtra and Telangana. Figure 8.4(b) shows the temporal trends of basin-averaged temperatures for the period of 1965 to 2014. Correspondingly, temperature has shown an increasing trend of 0.1 °C/decade (Fig. 8.4(b)).

For the assessment of precipitation and temperatures over KRB for the future scenarios, the CORDEX simulations were used. The precipitation and temperature



(a)



(b)

Fig. 8.4 (a) Precipitation and (b) temperature temporal trends in basin-averaged conditions from 1965–2003 to 2004–2014

data extracted from RCM outputs from 1965 to 2060, after bias correction, were used to estimate the precipitation and temperatures over KRB. Basin-averaged precipitation and temperatures were studied for two time periods of 2021–2040 and 2041–2060 along with historical time period of 1965–2003 and 2004–2014 as given in Table 8.1. The study of the compatibility of RCM projections with observed data sets is a prominent step (Singh et al. 2017). Therefore, the study compared the RCM climate projections with the observed data sets for historical period of 1965 to 2014 in reproducing the current climate variability. The bias-corrected monthly precipitation and temperatures from each CORDEX RCM model were well compared with the observed IMD data for the period of 1965–2014 (Fig. 8.5). The RMSE (R-square) values estimated between observed precipitation and each RCM model outputs of COSMO, REMO, and SMHI were estimated at 78.5 (0.2), 70 (0.23), 80

Table 8.1 Spatial average annual precipitation and temperatures for current (1966–2003, 2004–2014) and future period (2021–2040, 2041–2060) for KRB

Hydrological variable	RCM name	Current		Future	
		1966–2003	2004–2014	2021–2040	2041–2060
Average annual precipitation (mm)	Observed	733.12	894.47	–	–
	COSMO	757.91	698.27	762.82	807.52
	REMO	755.36	841.84	864.29	850.7
	SMHI	773.33	834.73	834.73	869.82
Annual temperature (°C)	Observed	26.6	26.7	–	–
	COSMO	26.53	27.05	27.71	28
	REMO	26.54	26.71	27.81	28.09
	SMHI	26.56	27.1	27.74	28.22

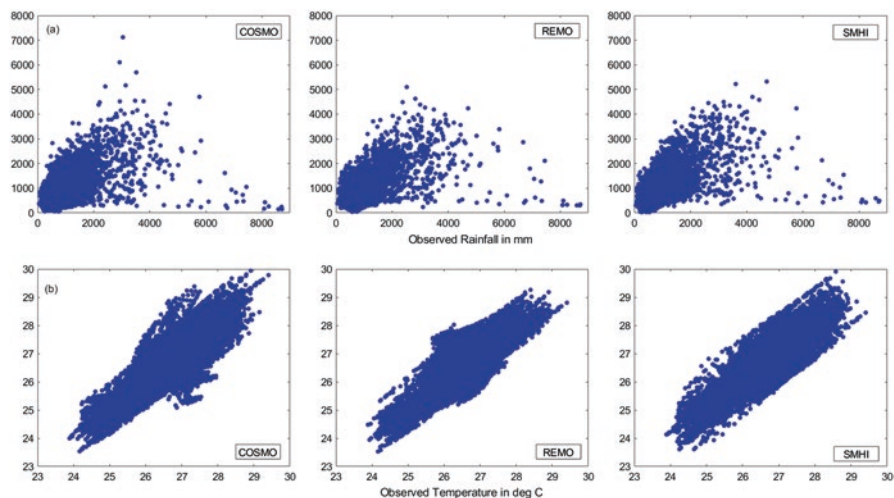


Fig. 8.5 Scatter plots of bias-corrected RCM model outputs of (a) precipitation and (b) temperatures for the period of 1966 to 2014

(0.15), respectively, for the period of 1966 to 2014, whereas the RMSE (R-square) values estimated between observed temperature and each RCM model outputs of COSMO, REMO, and SMHI were estimated at 1.9 (0.6), 1.6 (0.7), and 1.95 (0.52), respectively, for the period of 1966 to 2014. Among the selected three RCMs, the REMO model has shown best performance for simulating precipitation and temperatures over KRB. The precipitation has been predicted to increase under climate change signals with all three RCM models for the future periods of 2021 to 2060 over KRB. The increase in projections of annual average precipitation for the periods of 2021–2040 and 2041–2060 was compared with the observed data periods of 1966–2003 and 2004–2014 over KRB (Table 8.1) (Fig. 8.6(a)). The SMHI model has predicted highest increase of precipitation as varying from 101.6 and 136.7 mm for the future time periods of 2021–2040 and 2041–2060, respectively, compared to the current climate period of 1966–2003 over KRB. While the lowest precipitation projections, varying about 29.7 mm and 74.4 mm of increase for the period of

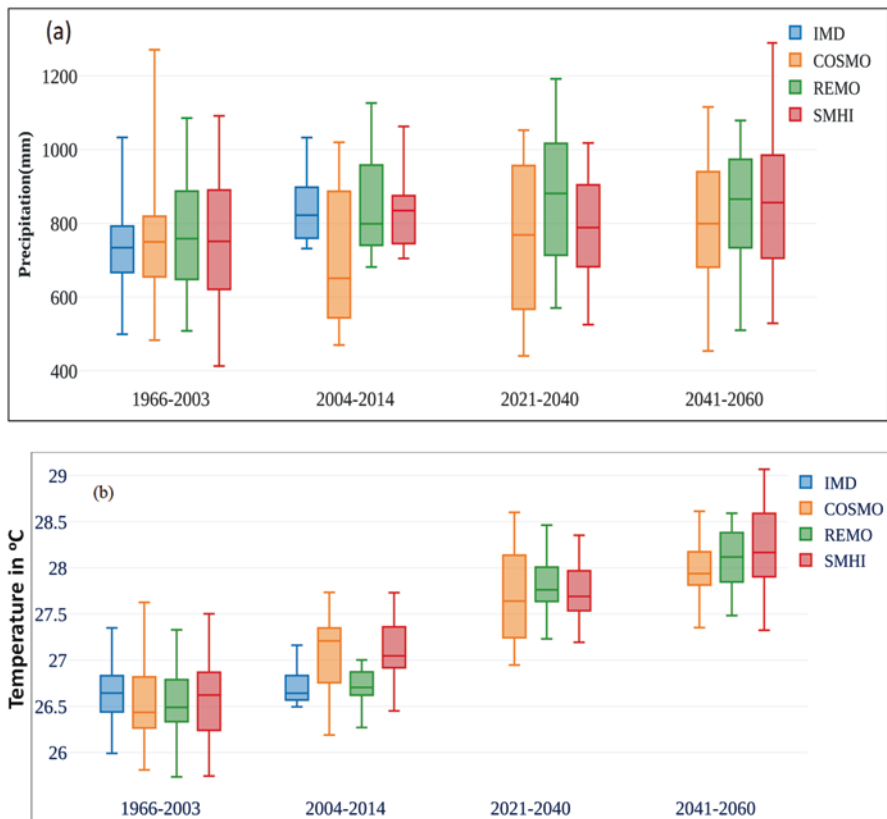


Fig. 8.6 Basin-averaged annual observed and predicted (a) precipitation and (b) temperatures for the period of 1966–2003, 2004–2014, 2021–2040, and 2041–2060 over KRB with various RCM model outputs

2021–2040 and 2041–2060, respectively, compared to observed period of 1966–2003, were noted with COSMO model outputs, moderate precipitation increasing projections were predicted with REMO for the RCP 4.5 for the future time periods of 2021 to 2060. Overall, the projected increase of precipitation under climate signals was predicted to be from 74.4 to 136.7 mm over KRB for the future time period of 2041–2060 compared to the observed periods of 1966–2003. About 1.06 °C–1.35 °C of increase in temperatures was predicted for the periods of 2021–2040 and 2041–2060, respectively, compared to the observed period of 1966–2014 over KRB (Fig. 8.6 (b)) (Table 8.1).

8.4 Conclusions

With consideration of fine resolution and simple in extraction, the RCM outputs can be used in the hydrological impact assessment studies under climate variability. Comparable to complex statistical downscaling models, which requires advanced computational expertise, the RCM projections can be used for brief analysis of spatiotemporal variability of climate variables at river basin scales. Such basic analysis of river basins can provide insights toward the variations of water-energy variables and consequent impact on basin yields and losses in terms of evapotranspiration, etc. The fine-resolution projections of precipitation and temperatures will provide a basis to study the streamflow variabilities with integration with distributed hydrological models. However, given the limitations toward the reliability of RCM outputs with observed climate variables and the use of bias correction method adopted, the CORDEX model projections have to be applied for impact assessment studies with proper evaluation. The bias-corrected projections should be evaluated for extreme precipitation and temperature indices at catchment scales to study the reliability of RCMs for modeling the extreme climate variables (Singh et al. 2017). Further, with the uncertainty involved in the projections of each RCM model and with each RCPs, uncertainty evaluation must be performed for climate variables and associated hydrological model. Given the variations over the climate variable projections from various climate models, RCPs and various water management models accumulate climate and model uncertainty in the impact assessment (Kay et al. 2009; Wu et al. 2015). Implementation of multimodal weighted mean variables to study the possible range of uncertainty bounds accumulating from various stages of decision-making and cascading of uncertainties (Rehana and Mujumdar 2014) can be potential future research problem. Further, the application of RCM model outputs for the hydrological impact assessment has to be validated by comparing the historical spatiotemporal variability of simulations of hydrological events. Thus, the simulations of hydrological, drought, irrigation, and water quality associated with RCM outputs must be validated with historical occurrence of events in terms of frequency, durations, and intensities along with spatial extents of the events. The use of RCM outputs for the assessment of hydrological studies at catchment scales will emphasize on the adaptive measures to be applied for the sustainable water resource management.

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