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Assessment of CORDEX-SA experiments in representing precipitation climatology of summer monsoon over India

A. Choudhary¹, A. P. Dimri¹ & P. Maharana²

Abstract The present work assesses the performance of 11 regional climate simulations in representing the precipitation patterns of summer monsoon over India for the period 1970–2005. These simulations have been carried out under Coordinated Regional Climate Downscaling Experiment–South Asia (CORDEX-SA) project. The regional climate models (RCMs) have been inter-compared as well as evaluated against the observation to identify the common weaknesses and differences between them. For this, a number of statistical analysis has been carried out to compare the model precipitation field with the corresponding observation. Model uncertainty has been also evaluated through bias studies and analysis of the spread in the ensemble mean (hereafter, ensemble). The models which perform better than the rest are identified and studied to look for any improvement in the ensemble performance. These better performing experiments (best RCM experiments) are further assessed over the monsoon core region (MCR) of India. This has been done to understand how well the models perform in a spatially homogeneous zone of precipitation which is considered to be a representative region of Indian summer monsoon characteristics. Finally, an additional analysis has been done to quantify the skill of models based on two different metrics—performance and

convergence including a combination of the two. The experiment with regional model RegCM4 forced with the global model GFDL-ESM2M shows the highest combined mean skill in capturing the seasonal mean precipitation. In general, a significant dry bias is found over a larger part of India in all the experiments which seems most pronounced over the central Indian region. Ensemble on an average tends to outperform many of the individual experiments with bias of smaller magnitude and an improved spatial correlation compared with the observation. Experiments which perform better over India improve the results but only slightly in terms of agreement among experiments and bias.

1 Introduction

Studies over the last decade based on observations and climate models have indicated towards the consequential risk the climate change poses to the present day state of Indian summer monsoon (hereafter, ISM) (Hu et al. 2000; Cubasch et al. 2001; May 2002; Fan et al. 2012). In the last few decades, this has been observed in the form of changes in precipitation variability and increased frequency of precipitation extremes like floods and droughts (Goswami et al. 2006; Rajeevan et al. 2008; Guhathakurta et al. 2011; Singh et al. 2014). Such kind of developments will have serious socio-economic impacts on the life of people as the livelihood and economies of the major part of the Indian population are still based upon the monsoon-dependent systems especially agriculture. There is a growing need for impact studies and devising effective adaptation strategies to deal with this issue for which projected climate information or data is required for making future climate predictions. Global climate models (hereafter, GCMs) provide such data but the resolution is too coarse to be applied for regional scale impact studies where there is a need for finer level spatial

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data. Also for India where the precipitation is subjected to a high degree of spatial variation, GCM data would not be suitable for such studies because the fine-scale processes are not adequately represented in GCM physics. Therefore, regional climate models (hereafter, RCMs) are required which dynamically downscale GCM output to scales that can be employed directly by the end users (Sun et al. 2006). Like any other model, RCMs cannot perfectly simulate the climate and they have errors in form of biases against real observations. It is important to evaluate the models—to understand the shortcomings and quantify the magnitude of errors which could then be corrected or accounted for while using it as a tool for impact studies. Also, each RCM has its own internal model physics (parameterization schemes)—they use different methods to discretize the equations and to reproduce effects at sub-grid scale (Déqué et al. 2007). This gives rise to uncertainty in the simulations and simultaneously makes it necessary to study these discrepancies. Lucas-Picher et al. (2011) and Kumar et al. (2013) in their study over India found the amount of precipitation and its distribution at regional scale differ substantially between a set of RCMs forced with same lateral boundary conditions. Mishra et al. (2014) also reported 18–60% uncertainty in precipitation and 1–3 °C in temperature in a similar set of RCMs which is the focus of present study. The uncertainty in projections of climate may arise from other sources also like internal variability and scenario uncertainty (Hawkins and Sutton, 2009).

Over the past few years, the use of RCMs to study the regional climate has seen marked increase across the globe (Alley et al. 2007). For Indian region, also a number of efforts have been made at individual levels to study the climatic regime of India based on RCM simulations (Jacob and Podzun 1997; Ji and Vernekar 1997; Ratnam and Kumar 2005; Bhaskaran et al. 1996; Dobler and Ahrens 2010; Lucas-Pitcher et al. 2011; Dimri 2012; Mathison et al., 2013; Dash et al. 2006, 2013; Maharana and Dimri 2014; Maharana and Dimri 2016). These studies have been mainly carried out either over specific regions or using one or few RCMs driven by a single GCM or reanalysis. However, Kumar et al. (2013) for the first time studied a set of high-resolution multi-model projections of climate change over India in which eight simulations from three RCMs were forced with reanalysis and two GCMs. This is still a small number, considering a greater importance in terms of reliability of a larger ensemble. This underlines the need of a common framework under which multi-individual or multi-institutional modeling efforts are made in coordination to provide an ensemble of RCM outputs based on multiple RCMs. In this regard, the World Climate Research Programme's project, Coordinated Regional Climate Downscaling Experiment (hereafter, CORDEX), is a coordinated effort of a number of modeling centers across the globe in order to generate an ensemble of high-resolution

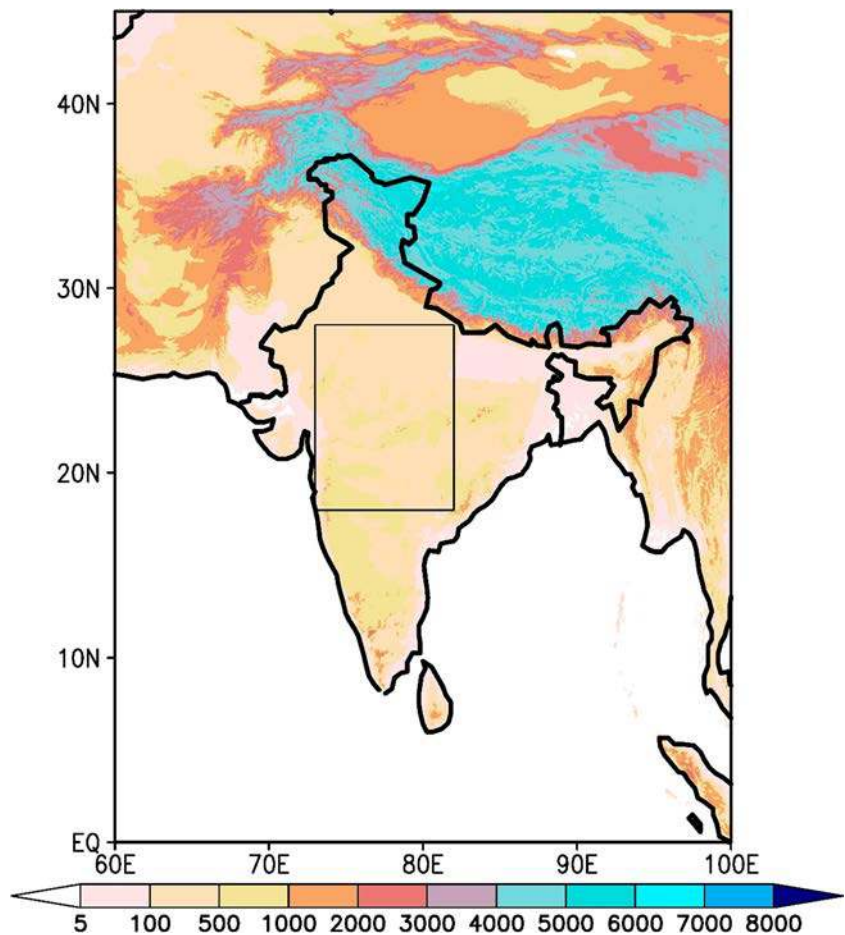
past, present, and future regional climate projections for different regions or domains across the world (Giorgi et al. 2009; Jones et al. 2011; Lake et al. 2017). CORDEX-South Asia (hereafter, CORDEX-SA) a part of a larger global effort CORDEX comprises of regional climate information for the South Asia region from RCM runs that are obtained by downscaling the Atmosphere-Ocean coupled General Circulation Model (AOGCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al. 2012). Previous studies done by Mishra et al. (2014) and Ali et al. (2014) based on CORDEX-SA experiments have focused mainly on evaluating the RCMs in simulating extremes of precipitation over India. Simultaneously and equally important is the need to evaluate the ensembles' ability in representing with certainty the long-term mean precipitation of a season so as to take into account the overall state of the changing field during entire period of that season. Ghimire et al. (2015), Choudhary and Dimri (2017), and Nengker et al. (2017) carried out such a work in studying the ability of CORDEX-SA RCMs in representing the seasonal mean precipitation and temperature pattern over Himalayan region. However, the present study has been carried out with a focus on evaluating the performance of a set of 11 regional climate simulations (or experiments) under CORDEX-SA in representing the patterns of seasonal mean summer monsoon (June–September hereafter, JJAS) precipitation over India (see Fig. 1 for description of study region) for the time period 1970–2005 which represents the present climate. The study is organized as follows: in section 2, the study area, dataset used, and the working methodology are briefly described. In section 3, the results and discussions are presented, beginning with the evaluation of mean annual cycle of precipitation and summer monsoon climatology over all India region, the added value of RCMs, the associated frequency distribution followed by an analysis of the spread among the experiments. The better performing experiments or models (Best RCM experiments) are identified and further analyzed over monsoon core region (hereafter MCR) of India. In the final subsection of results and discussion, the analysis on model skill and ensemble weighting are presented which are carried out as an additional part of the study. Finally, in section 4, key results are summarized and conclusions are presented regarding the main shortcomings, strengths, and uncertainties in the CORDEX-SA experiments.

2 CORDEX-SA experiment, data, and methodology

2.1 Study area

The study focuses on India which is a part of the larger CORDEX-SA domain. It lies between 8°4' and 37°6' north latitude and 68°7' and 97°25' east longitude. The region is

Fig. 1 Study region considered over Indian political boundary (hereafter called “India”) and Indian monsoon core region (hereafter called “MCR”—box) with topography (in meters)



defined as per the official political boundary of country (see Fig. 1). The peninsular part of India is bounded by the Indian Ocean on the south of the Deccan plateau region, the Arabian Sea on the southwest with mountain range of Western Ghats running along the coastline, and the Bay of Bengal on the southeast which is flanked by Eastern Ghats mountain range. Himalayan mountain ranges and Tibetan plateau bounds the northern plains of country. The climate of India is primarily characterized by a tropical wet to subtropical hot and wet season with dry semi-arid to arid climate over northwest part of India. The country as a whole receives 70 to 90% of its total annual precipitation during the summer monsoon season (Pant and Rupa Kumar 1997) which is considered as months from June–September. India comprises of a complex topography with diverse precipitation regimes and spatial pattern owing to the local effects of interaction of these varying terrain and land-surface heterogeneities with large-scale climate forcings (Gadgil 1978; Sud and Smith 1985; Webster 1987; Goswami et al. 2010).

2.1.1 Indian monsoon core region

The ISM is heterogeneously distributed over the Indian region with high spatial variability. The spatially averaged study of

monsoon characteristics over India may not give a certain and exact picture of the performance of models in simulating those characteristics. The model performance also varies spatially. So a core region of ISM (hereafter, MCR) is considered in this study as the area spanning 73–82° E and 18–28° N (Fig. 1, box), based on a study by Mandke et al. (2007) over which the mean and standard deviation of precipitation are found to be homogeneous or spatially uniform. This region shows coherence in space with respect to intraseasonal variation and shows high mean seasonal precipitation. So, it is considered to be a homogeneously representative region of typical ISM characteristics. Singh et al. (2014) also considered the same area as the core region of monsoon in her study on changes in extremes of precipitation during the South Asian summer monsoon.

2.2 CORDEX-SA experiments and data

In this study, a total of 11 experiments which consists of 11 combinations arising out of 4 RCMs driven with 9 GCMs (see Table 1) are selected to study their performance in simulating summer monsoon (JJAS) precipitation over India. The data is available on CORDEX-SA database maintained by Centre for Climate Change Research, Indian Institute of Tropical

Table 1 CORDEX-SA experiment details (Source: CORDEX South Asia Database, CCCR, IITM <http://cccr.tropmet.res.in/cordex/files/downloads.jsp>)

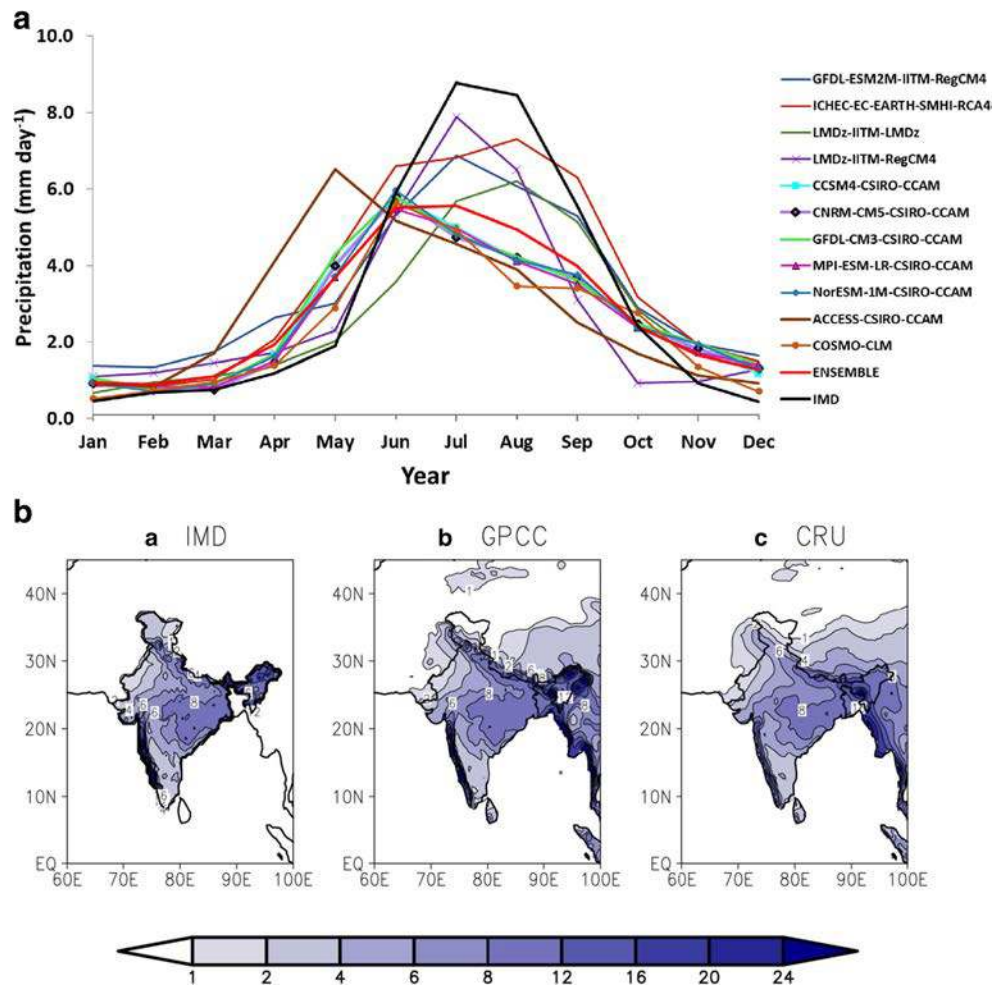
S. no.	Experiment name	RCM description	Driving GCM	Contributing institute
1	LMDz-IITM-RegCM4	The Abdus Salam International Centre for Theoretical Physics (ICTP) Regional Climatic Model version 4 (RegCM4; Giorgi et al., 2012)	IPSL LMDz4	Centre for Climate Change Research (CCCR), Indian Institute of Tropical Meteorology (IITM), India
2	LMDz-IITM-LMDz	Institut Pierre-Simon Laplace (IPSL) Laboratoire de Me'teorologie Dynamique Zoomed version 4 (LMDz4) atmospheric general circulation model (Sabin et al., 2013)	IPSL Coupled Model version 5 (IPSL-CM5-LR; Dufresne et al. 2013)	CCCR, IITM, India
3	GFDL-ESM2M-IITM-RegCM4	ICTP RegCM4	Geophysical Fluid Dynamics Laboratory, USA, Earth System Model (GFDL-ESM2M-LR; Dunne et al. 2012)	CCCR, IITM
4	ICHEC-EC-EARTH-SMHI-RCA4	Rosby Centre regional atmospheric model version 4 (RCA4; Samuelsson et al., 2011)	Irish Centre for High-End Computing (ICHEC), European Consortium ESM (EC-EARTH; Hazeleger et al. 2012)	Rosby Centre, Swedish Meteorological and Hydrological Institute (SMHI), Sweden
5	NorESM1-M-CSIRO-CCAM	Commonwealth Scientific and Industrial Research Organisation (CSIRO), Conformal-Cubi Atmospheric Model (CCAM; McGregor and Dix, 2001)	NorESM1-M	CSIRO Marine and Atmospheric Research, Melbourne, Australia
6	MPI-ESM-LR-CSIRO-CCAM		MPI-ESM-LR	
7	GFDL-CM3-CSIRO-CCAM		GFDL-CM3	
8	CNRM-CM5-CSIRO-CCAM		CNRM-CM5	
9	CCSM4-CSIRO-CCAM		CCSM4	
10	ACCESS-CSIRO-CCAM		ACCESS	
11	COSMO-CLM	Consortium for Small-scale Modeling (COSMO) model in CLimate Mode version 4.8 (CCLM; Dobler and Ahrens, 2008)	Max Planck Institute for Meteorology, Germany, Earth System Model (MPI-ESM-LR; Giorgetta et al. 2013)	Institute for Atmospheric and Environmental Sciences (IAES), Goethe University, Frankfurt am Main (GUF), Germany

Meteorology (IITM), Pune, India which is the coordinating institution of this project. It is to be noted that experiment LMDz-IITM-LMDz at S. No. 2 (see Table no. 1) is not an RCM in true sense rather a zoomed version of GCM IPSL-CM5-LR. The period chosen for study is 1970–2005 to represent the present climate. This period is chosen as it was the common data span available in the dataset of all the 11 experiments. The RCM experiments' data are available at $\sim 0.44^\circ$ grid resolution and over South Asia domain. Since this analysis is limited to and focused on studying precipitation over India, only so the data used here is masked to have data over only Indian land points (hereafter, India).

To evaluate the model results in representing the precipitation over India, the India Meteorological Department (hereafter, IMD) gridded precipitation dataset (Rajeevan and Bhatte 2009) which is available at 0.5° spatial and daily resolution from 1971 to 2005 is used as observational reference throughout the study. For the initial comparison of climatology though two more gauge-based gridded observational datasets namely Global Precipitation Climatology Center (GPCC) (version 6, available

for 1901–2006; Schneider et al. 2011) and Climatic Research Unit (CRU) (version 3.0, available for 1902–2006; Mitchell and Jones 2005) both of which are available at 0.5° spatial and monthly temporal resolution have been used. This is done for a prior assessment of uncertainty within the observations before choosing the IMD as a reference for further model evaluation. In Fig. 2b, it can be seen that all the three observations agree quite well in capturing the spatial pattern of ISM precipitation. The western coast and central part of India and foothills of Himalayas are shown as high precipitation regions in all the three datasets. Similarly, the northwestern part of India (due to the parallel orientation of Aravalli mountain range to southwesterly monsoon jet) and southeastern coast of India (which falls in the rain shadow region of Western Ghats) are seen as low precipitation receiving regions in all the three observations. There is a strong agreement between the three. So, further in the study, only IMD (Fig. 2b(a)) dataset is used for model evaluation to keep the analysis simple. IMD data set is prepared using quality controlled precipitation data from more than 6000 rain-gauge stations over India and is validated against another gridded data

Fig. 2 **a** Mean annual cycle of precipitation (mm day^{-1}) over India for the period 1970–2005 from the 11 CORDEX-SA experiments, their ensemble, and IMD. The 11 CORDEX-SA experiments are described in Table 1. **b** JJAS precipitation climatology (mm day^{-1}) for the period 1970–2005 in three different observations **b(a)** IMD, **b(b)** GPCC, and **b(c)** CRU (In case of IMD, the observation are over India only)



set—Asian Precipitation—Highly Resolved Observational Data Integration Towards Evaluation of the Water Resources (APHRODITE) (Yatagai et al. 2005; Rajeevan and Bhat, 2009). Earlier also in many studies, this dataset was used to study the observed dynamics of Indian monsoon and as a reference to evaluate model simulations (Das et al. 2012; Pattnayak et al. 2013; Pattnayak et al. 2016; Kumar et al. 2013; Das et al. 2014; Maharana and Dimri 2014).

For the evaluation of model simulated southwesterly low-level jet (850 hPa wind fields), NCEP-NCAR Reanalysis 1 data (hereafter, NCEP) (Kalnay et al. 1996) is used as a reference.

2.3 Methodology

2.3.1 Criteria for performance evaluation

To evaluate the performance of the ensemble of the CORDEX-SA experiments, two general criteria are adopted: firstly, comparison with IMD—how well the models and their ensemble compared with the IMD are able to capture or represent the climatology of JJAS precipitation. And secondly,

the evaluation of the uncertainty or spread in the simulations so as to account for degree of agreement among various experiments in simulating precipitation. First of all, the mean annual cycle is studied to see how well the annual distribution of precipitation are represented by the experiments especially the peak during the JJAS season. For climatology assessment, the spatial distribution of long-term mean (1971–2005) of JJAS precipitation (seasonal average; mm day^{-1}) is analyzed by looking at the bias between the model (or experiments; will be used interchangeably hereafter) and IMD to see whether the models are overestimating or underestimating the actual precipitation. Further, the performance of RCM is also compared with that of its parent GCM to see the added value of downscaling. The uncertainty or degree of agreement among the simulations is seen here in the form of spread between the experiments and its distribution in space. The spread among the experiments is also studied with respect to IMD through ranked histogram which is discussed later in this paper. Furthermore, for a robust assessment of the ability of models in capturing the climatological pattern of precipitation over India spatial correlation of model simulated precipitation with that of

IMD in terms of Pearson correlation coefficient (Hall 2015) is also calculated and shown in the Taylor diagram (Taylor 2001).

2.3.2 Identification of best RCM experiments

In order to identify better performing CORDEX-SA experiments with respect to the simulation of climatology, we adopt a method from Menon et al. (2013). We compare the long-term (1970–2005) seasonal mean precipitation area averaged over India of experiments with that of observed precipitation (IMD). The climatological mean precipitation of IMD is 6.62 mm day^{-1} , with a standard deviation of 0.75 mm day^{-1} . The experiments that fall within ± 2 standard deviations (horizontal dashed lines) from IMD are considered here as better performing experiments and we call it as Best RCM experiments. The experiments that fall within ± 1 standard deviation (horizontal dashed lines) from IMD have also been shown to further narrow down on the better performing experiments.

For the monsoon core region, we apply the same procedure for best model selection wherein the climatological mean precipitation of IMD is 6.79 mm day^{-1} , with a standard deviation of 1.09 mm day^{-1} . The experiments that fall within ± 2 standard deviations (horizontal dashed lines) from IMD are considered here as better performing experiments over MCR.

3 Results and discussion

3.1 All India monsoon

Figure 2a shows the mean seasonal cycle of precipitation of the 11 CORDEX-SA experiments, their ensemble, and IMD averaged over India and for the study period (1970–2005). The IMD distribution is best represented by LMDz-IITM-RegCM4 with the precipitation peaking during July in the monsoon season and then declining. Though it shows an underestimation of precipitation in the monsoon season but the shape is well reproduced in comparison with other experiments which show either a large underestimation of precipitation during this season or a shift in the peaking month or both. We can notice that an almost similar cycle of precipitation is seen in all the GCMs downscaled using CCAM RCM (except for ACCESS) with a large difference towards drier side. On the other hand, the CCAM simulation forced with ACCESS particularly stands out of the rest of the ensemble members during the monsoon season. In general, there is no close similarity between the experiments or individually with the IMD in distribution.

For the first hand comparison of the spatial distribution of model simulated precipitation and their ensemble with that of IMD, the seasonal mean climatology was compared (Fig. S1). For a better evaluation, the climatological

bias is calculated as model climatology minus IMD climatology. Figure 3 shows the JJAS mean precipitation bias (mm day^{-1}) of 11 CORDEX-SA experiments (a–k) and their ensemble (l) with respect to IMD (Fig. 2b(a)) over India. In all the experiments, the models are able to capture the key features of the spatial distribution of mean precipitation of ISM reasonably well with varying degree and signs of biases. Almost all the experiments show realistically high precipitation along the west coast of India where the Western Ghats mountain range lies, hilly region of northeast India and along the foothills of Western Himalayan mountainous region because of the orographic interaction with the southwest humid monsoon winds (Fig. S1). On the other hand, the northwestern part particularly Rajasthan rightly shows less precipitation as seen in the IMD also. This is because of the well-known reason of the parallel orientation of the Aravalli mountain stretch with the southwest monsoon winds. The southwestern part of India which lies in the leeward side of Western Ghats receives less precipitation because of the rain-shadow effect and this phenomenon is also well-represented by almost all the experiments and their ensemble. The overall pattern of mean precipitation distribution may be getting represented but biases also exist which vary in their sign and magnitude spatially for individual experiments as well as across the set of experiments. Feng and Fu (2006) in their study on inter-comparison of 10 RCMs for precipitation over Asia also found that the RCMs are able to capture the basic spatial pattern of precipitation distribution but there are distinctions in location and intensity in them. Interestingly, over the regions of high precipitation (due to orography), i.e., along the western coast, foothills of western Himalaya and northeast region of India, the value is overestimated in most of the experiments with a large (+ve) bias of up to 10 mm day^{-1} as seen in one of the experiments LMDz-IITM-LMDz (Fig. 3b) along the western coast. In other RCM-based studies also (Jacob and Podzun 1997; Ji and Vernekar 1997; Bhaskaran et al. 1996; Ratnam and Kumar 2005; Dash et al. 2006; Nguyen and McGregor 2009; Dobler and Ahrens 2010; Mathison et al. 2013; Dimri, 2012; Moors et al. 2012; Kumar et al. 2013) almost all reported a general overestimation of orographic precipitation over these regions. These errors are possibly associated with the parameterization of convection in the model. The unrealistic simulations in the experiments may not be only due to RCM shortcomings but also due to some contribution made by the error in large-scale forcings from their parent GCMs. For, e.g., Menon et al. (2013) in his study on GCMs found that IPSL-CM5A-LR which has been used in the CORDEX-SA experiment LMDz-IITM-LMDz (Fig. 3b) poorly simulates the Indian monsoon. Over northwest India around the state of Rajasthan

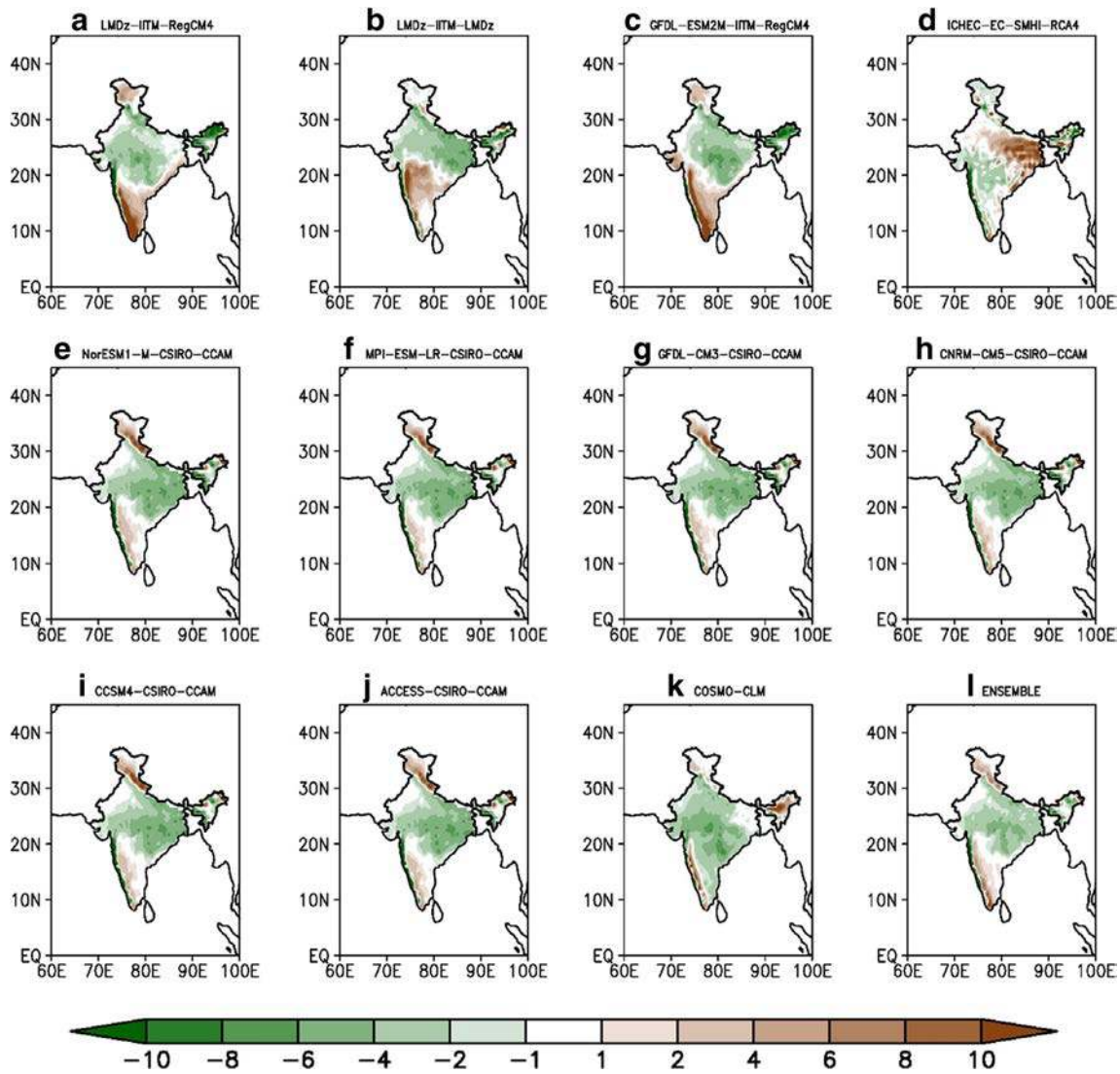


Fig. 3 JJAS precipitation bias (mm day^{-1}) for the period 1970–2005 of 11 CORDEX-SA experiments (a–k) and their ensemble (l) with respect to IMD over India

and the southwestern India which receive generally less average precipitation, almost all the experiments and their ensemble show a good resemblance with the observed climatology which can be seen in the low values of bias within $\pm 1 \text{ mm day}^{-1}$ except for COSMO-CLM (Fig. 3k) where the bias is slightly higher towards the negative side. In fact, this particular experiment shows a negative (dry) bias for almost whole India but simultaneously with a strong overestimation at west coasts and northeast region. A slight underestimation is also seen at the foothills of Himalaya in the northern India. Similar findings for COSMO-CLM were reported by Dobler and Ahrens (2010) who also found an underestimation of convection (based on outgoing long-wave radiation data) over large parts of India. This indicates towards shortcomings in the model physics related with possibly convection or cumulus parameterization. In another work by Rockel and

Geyer (2008) who ran the COSMO-CLM model for the South Asian region found a similar result. They suggested that the overestimation of precipitation over Western Ghats and the warm adjoining oceans removes most of the moisture from atmosphere resulting in a dry bias over interior areas like central India. In fact, for central Indian region, most of the experiments except RCA4 regional model forced with EC-EARTH global model (Fig. 3d) are generating not enough precipitation as seen in the IMD. The above reason mentioned for COSMO-CLM could be contributed for these experiments' underestimation also though such studies are not available to substantiate our views. Regarding the RCA4 model's overestimation, it could be linked to Willen (2008) who in her work on an earlier version of RCA (3.0) found the cloud fraction is getting overestimated compared to IMD resulting in a higher precipitation. Especially over the mountainous

regions, accurately representing velocities in complex terrain is known to be difficult in numerical models which may contribute to an unrealistic forcing of the grid scale precipitation scheme (Samuelsson et al. 2011). In other experiments, Fig. 3a, c where RegCM4 model has been forced with two different GCMs, the results are quite similar in that both show an overestimation of precipitation of up to 10 mm day⁻¹ over peninsular India when compared with IMD. An underestimation of up to 6 mm day⁻¹ is seen over the plains of Central India such as Madhya Pradesh and Chhattisgarh region and parts of northeast India. Pattanayak et al. (2013) and Dash et al. (2013) made a similar inference for earlier version of RegCM–RegCM3. Maharana and Dimri (2014) who reported similar findings for RegCM4 based on precipitation and outgoing long-wave radiation explained the reason for this phenomenon that a higher precipitation at Western Ghats results in an excessive loss of moisture from atmosphere and a positive bias of temperature over Bay of Bengal results in reduced moisture above the sea. Thus the disturbances coming into central India from Bay of Bengal do not have enough moisture content causing reduced precipitation. Mishra et al. (2014) in their work on four CORDEX-SA experiments as named in Fig. 3b–d, k also found in general, an underestimation of mean annual maximum precipitation in the central parts of India. Another remarkable observation is that the six experiments (Fig. 3e–j) which uses CCAM regional model show almost no difference in their results as we can see in their contour structures and corresponding values even though

they have been forced with six different GCMs. This may suggest that this regional model is insensitive to the large scale forcings (GCMs) in simulation of mean state of atmosphere. Whether it is a serious shortcoming of CCAM model, we can say only after we inter-compare their GCMs. An important achievement of these six CCAM simulations is that they all capture the low precipitation in southwestern part almost in resemblance with the IMD which ultimately improves the ensemble performance over this region. Nguyen & McGregor (2009) found similar performance of CCAM over southwestern parts of India. Though interestingly, a dry bias is seen at the western coastal line unlike other experiments but the precipitation gradually picks up in the upper reaches of Western Ghats as wet bias is seen there.

A paired Student's *t* test for difference between the JJAS mean precipitation values of experiments (including ensemble) and that of IMD (Table 2) is further carried out to understand the overall bias over India and its significance. We do this for all-India grid points considering it as our sample where the null hypothesis would be that there is no difference between the two means, i.e., of experiment and of IMD. Alternative hypothesis would be that there is a significant difference or bias (dry or wet depending upon the sign). In general, a significant dry bias (at 5% level) is seen in almost all simulations except Rossby Centre RCM (RCA4) where a non-significant positive bias (0.22 mm day⁻¹) is found. Samuelsson et al. (2011) who used an earlier version of RCA (RCA3) linked the wet biases to the use of the resolved scale vertical velocity in the convective trigger mechanism of

Table 2 Difference between JJAS mean precipitation (mm day⁻¹) between each CORDEX-SA experiment and IMD over India (Paired difference spatial *t* test (between pair of grid points))

S. no.	Model comparison (Model–IMD)	Paired differences			<i>t</i>	<i>P</i> value
		Mean bias	Std. deviation	Std. error mean		
1	GFDL-ESM2M –IITM-RegCM4 - IMD	– .88	5.86	.17	– 4.89	.000
2	ICHEC –EC –EARTH-SMHI-RCA4 - IMD	.22	4.67	.13	1.35	.176
3	LMDz-IITM-LMDz - IMD	– 1.46	4.69	.13	– 10.28	.000
4	LMDz-IITM-RegCM4 - IMD	– 1.00	4.61	.13	– 5.22	.000
5	CCSM4-CSIRO-CCAM - IMD	– 2.05	6.34	.18	– 15.44	.000
6	CNRM-CM5-CSIRO-CCAM - IMD	– 2.05	5.03	.14	– 15.47	.000
7	GFDL-CM3 –CSIRO-CCAM - IMD	– 2.06	6.74	.19	– 15.78	.000
8	MPI-ESM-LR –CSIRO-CCAM - IMD	– 2.17	4.63	.13	– 16.53	.000
9	NorESM1-M –CSIRO-CCAM - IMD	– 1.99	4.69	.13	– 15.01	.000
10	ACCESS-CSIRO-CCAM - IMD	– 2.06	3.57	.10	– 15.57	.000
11	COSMO-CLM - IMD	– 2.12	4.69	.13	– 21.01	.000
12	ENSEMBLE (11 experiments) - IMD	– 1.60	3.94	.11	– 14.37	.000

Kain–Fritsch convection scheme in the model, which may be associated with excessive convective triggering particularly over mountainous regions during the summer season. The smallest bias is seen for the experiment GFDL-ESM2M-IITM-RegCM4 ($-0.88 \text{ mm day}^{-1}$) while largest bias is seen for MPI-ESM-LR forced CCAM experiment ($-2.17 \text{ mm day}^{-1}$). The ensemble shows a negative bias of $-1.60 \text{ mm day}^{-1}$.

It is important to assess the added value of downscaling of GCM by RCM as simply increasing the resolution may not result in an improved or more realistic simulation of observed climate (e.g., Jacob et al. 2007; Rauscher et al. 2010). Fine-scale simulations may show no added value or could even show worsening of the results due to errors in the lateral forcing of the RCMs (Warner et al. 1997), issues with the domain size (Vannitsem and Chomé

2005; Leduc and Laprise 2009), imperfections in the parameterization physics of the RCMs (Jiao and Caya 2006), or a combination of these factors (e.g., Castro et al. 2005). Lack of improvement with downscaling to finer resolution is also found in other studies carried out in the recent past (e.g., Pope and Stratton 2002; Mass et al. 2002; Dobler and Ahrens 2010; Haslinger et al. 2013). Moreover, the performance of model at finer resolution could be dependent on seasonality and physiography as the climatic regime is dictated by these factors and so is the precipitation variability (Iorio et al. 2004; Rauscher et al. 2010; Chan et al. 2013). Di Luca et al. (2012) described added value of a RCM as the relative improvement in the finer RCM simulation with respect to its coarser driving fields or forcing. In the present work, added value of each CORDEX-SA experiment is defined

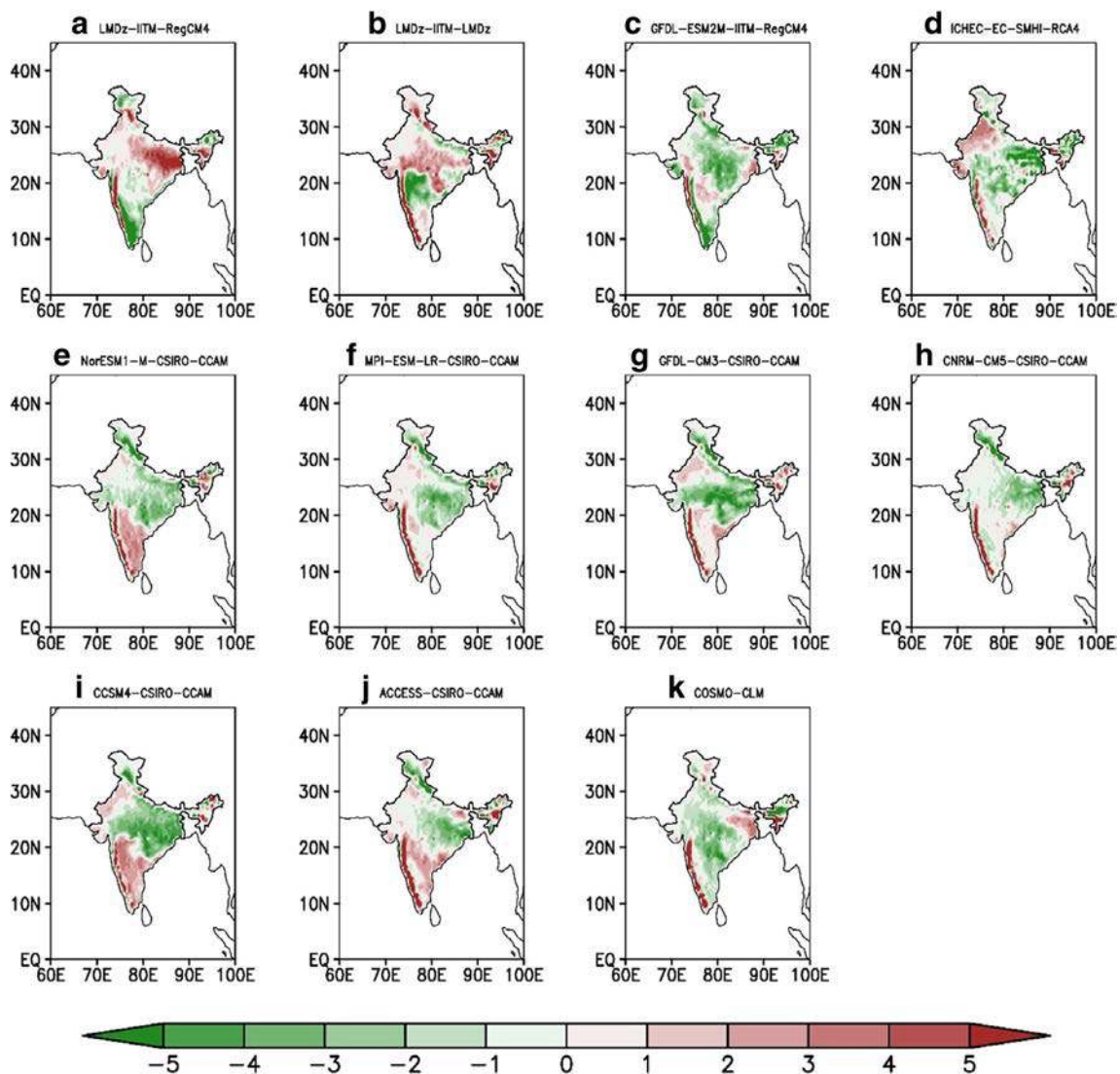
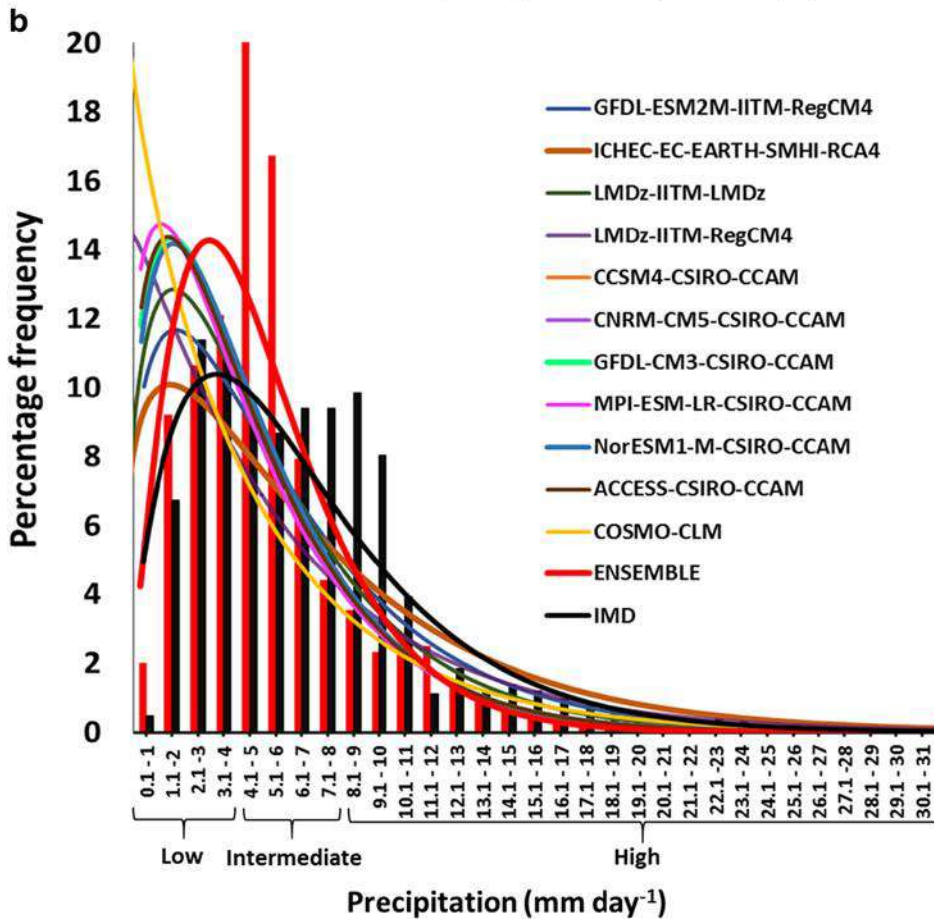
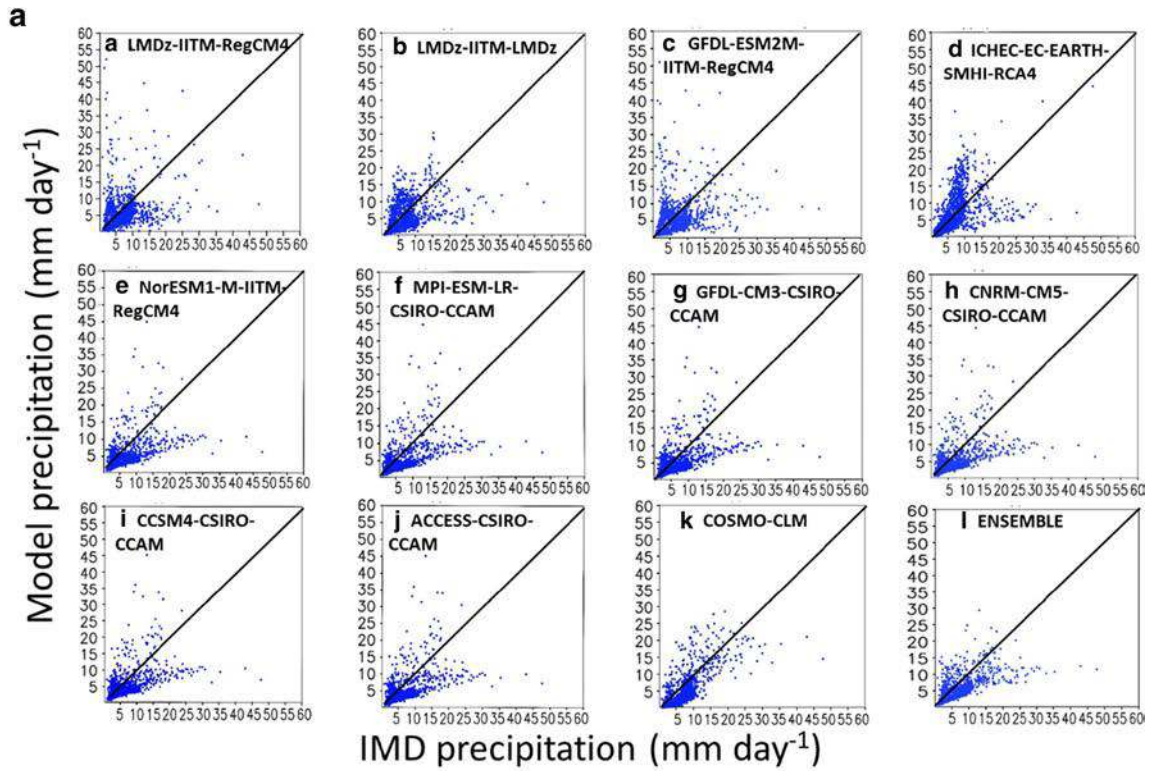


Fig. 4 Added value for JJAS mean precipitation (mm day^{-1}) of 11 CORDEX-SA RCM experiments (a–k) over their parent GCMs as absolute bias in GCM simulation minus absolute bias in RCM simulation

(with respect to IMD observation). See Table 1 for name of RCM and corresponding parent GCM for different experiments



◀ **Fig. 5** **a** Scatter plot of averaged (1970–2005) JJAS mean precipitation (mm day^{-1}) over India from 11 CORDEX-SA experiments (aa-ak) and their ensemble (a(l)) versus that of IMD. **b** Probability distribution of the JJAS mean precipitation (mm day^{-1}) as gamma function (in line) of 11 CORDEX-SA experiments, their ensemble, and that of the IMD (see Table 3 for corresponding parameters of distribution). Also shown here (in bar) for only ensemble and IMD is the percentage of precipitation data falling within a particular class interval. The range has been classified into low, intermediate, and high based upon respectively $+1\sigma$, $+2\sigma$, and $+3\sigma$ of the lowest value from IMD

as the difference of absolute bias in RCM simulation from that in its parent or forcing GCM simulation, that is,

$$\text{Added value} = \text{absolute bias in RCM simulation} \\ - \text{absolute bias in GCM simulation}$$

where the bias in both RCM and GCM is calculated from the IMD observation.

The same method was used by Karmacharya et al. (2016) for calculating added value of a high-resolution regional climate simulation of ISM. This method is selected because of the simplicity of computation and direct relation of added value with the reduction in amount of bias. In Fig. 4, it can be seen that along Western Ghats (western coastline of India) almost all the experiments show an improvement or added value in terms of reduction of precipitation bias by at least 5 mm day^{-1} . The corresponding parent GCMs of these experiments show in general a dry bias along the Western Ghats (see Fig. S2). The RCMs on the other hand due to the presence of orographic interaction with the low-level jet in its fine-scale environment tends to have an increased moisture supply over this region. This is apparent as a reduction in precipitation bias after downscaling when compared to parent GCM and hence could be seen as an added value although the bias in RCMs is towards positive side (see Fig. 3). Further, for some of the experiments where CCAM RCM is involved, it is also observed that the added value extends well up to the leeward side of Western Ghats (Fig. 4e, g, i, j) as the wet bias in the corresponding GCMs (Fig. S2 d, f, h and i) seems to be reduced after downscaling (Fig. 3e, g, i, j). However, over central Indian region, CCAM RCM irrespective of different GCM forcings shows a degradation after downscaling due to a large dry bias in the RCM results which is described earlier in the section on bias assessment of models. Therefore, it can be concluded that over central Indian region various GCMs seem to perform better than their downscaled counterpart from CCAM RCM. We find similar results after downscaling of GCMs IPSL-CM5-LR and GFDL-ESM2M by RegCM4 (Fig. 3a, c) where the effect of the driving GCM seems to be minor. Of the other experiments, zoomed version of GCM IPSL-CM5-LR i.e. LMDz-IITM-LMDz (Fig. 4b) and its downscaled result from RCM RegCM4 produces added value over the central and eastern Indian region respectively mainly

because of poor performance of the parent GCM IPSL-CM5-LR in form a consistent large dry bias over these regions. Overall, the results present a clear benefit (or added value in the sense of smaller absolute biases) by the use of higher resolution RCM simulation at least over specific regions. Nonetheless, it can also be concluded that the added value of RCM can vary spatially over a geographically heterogeneous region like India with the possibility of both improvement and worsening of results.

Figure 5a presents the scatter plot to assess resemblances or associations in the spatially distributed (grid point) mean JJAS precipitation values of CORDEX-SA experiments with that of IMD. It is found that precipitation generally lies between 0 to 15 mm/day. More the data points/blue dots are closer to the diagonal line, more the simulation match closely with the IMD. As can be seen from the figure for most of the experiments and the ensemble, there are slightly more dots towards the IMD side of the diagonal line indicating that experiments show in general smaller amount of precipitation than the IMD—a dry bias of model which was seen in the climatology analysis earlier. Though this is not the case for ICHEC-EC-EARTH-SMHI-RCA4 where there is higher precipitation than the IMD. For GFDL-ESM2M-IITM-RegCM4, more number of dots is closer to the diagonal line than in case of any other experiment which suggests a good capture of precipitation distribution by this experiment.

To assess the performance of experiments in simulating the entire range of spatially distributed values of precipitation over India their probability distribution with respect to spatially distributed JJAS mean values have been studied in comparison with that of IMD (Fig. 5b). For determining the frequency distribution of CORDEX-SA experiments and IMD, the value of JJAS mean precipitation intensity at each grid point (a single value as time average over the study period) is taken and the gamma distribution parameters are calculated (Table 3 and Fig. 5b) for the entire range of values. Figure 5b also shows the frequency distribution of ensemble and IMD as histogram. As suggested by location parameter and “ σ ” the ensemble shows smaller mean precipitation as well as spatial variability than the IMD. Though the gamma distribution shapes of individual distributions differ in shape from the IMD but the ensemble improves upon them as its shape shows best resemblance with IMD which is indicated by its shape parameter, “ α ” (2.664) (Table 3) being closest to that of IMD (2.087) compared with experiments. In general, for the experiments as well as ensemble most of the precipitation is concentrated within lower to intermediate range and frequency is overestimated when compared with IMD. However, IMD shows a larger distribution in high range of precipitation. The scale parameter, “ β ” of ensemble being smaller than that of IMD which makes the shape of earlier getting squeezed quantifies this fact. This is also indicative of the widespread dry bias shown by experiments.

Table 3 Corresponding to Fig. 5 (gamma distribution), the parameters of spatial distribution of mean JJAS precipitation over India where “ x ” is the no. of grid points in the study area; “ σ ” is the standard deviation over area and “ μ ,” “ α ,” and “ β ” are respectively, the location, shape, and scale parameters of the gamma distribution

S. no.	Distribution parameters Model/observation	x	μ	σ	α	β
1	GFDL-ESM2M-IITM-RegCM4	1249	6.214	5.031	1.526	4.073
2	ICHEC-EC-EARTH-SMHI-RCA4	1249	7.320	6.291	1.354	5.406
3	LMDz-IITM-LMDz	1249	5.633	4.493	1.572	3.583
4	LMDz-IITM-RegCM4	1249	6.099	5.959	1.048	5.822
5	CCSM4-CSIRO-CCAM	1249	5.046	3.995	1.595	3.163
6	CNRM-CM5-CSIRO-CCAM	1249	5.042	3.976	1.608	3.135
7	GFDL-CM3-CSIRO-CCAM	1249	5.038	3.938	1.637	3.078
8	MPI-ESM-LR-CSIRO-CCAM	1249	4.929	4.068	1.468	3.357
9	NorESM1-M-CSIRO-CCAM	1249	5.104	3.946	1.673	3.051
10	ACCESS-CSIRO-CCAM	1249	5.036	4.017	1.572	3.204
11	COSMO-CLM	1249	4.972	5.108	0.947	5.249
12	ENSEMBLE	1249	5.495	3.367	2.664	2.063
13	IMD	1249	7.132	4.936	2.087	3.417

Figure 6 presents yearly variability of monsoonal mean precipitation for IMD and each of the experiment along with their ensemble. The variability has been measured in terms of standard deviation in the 36 years’ values (for

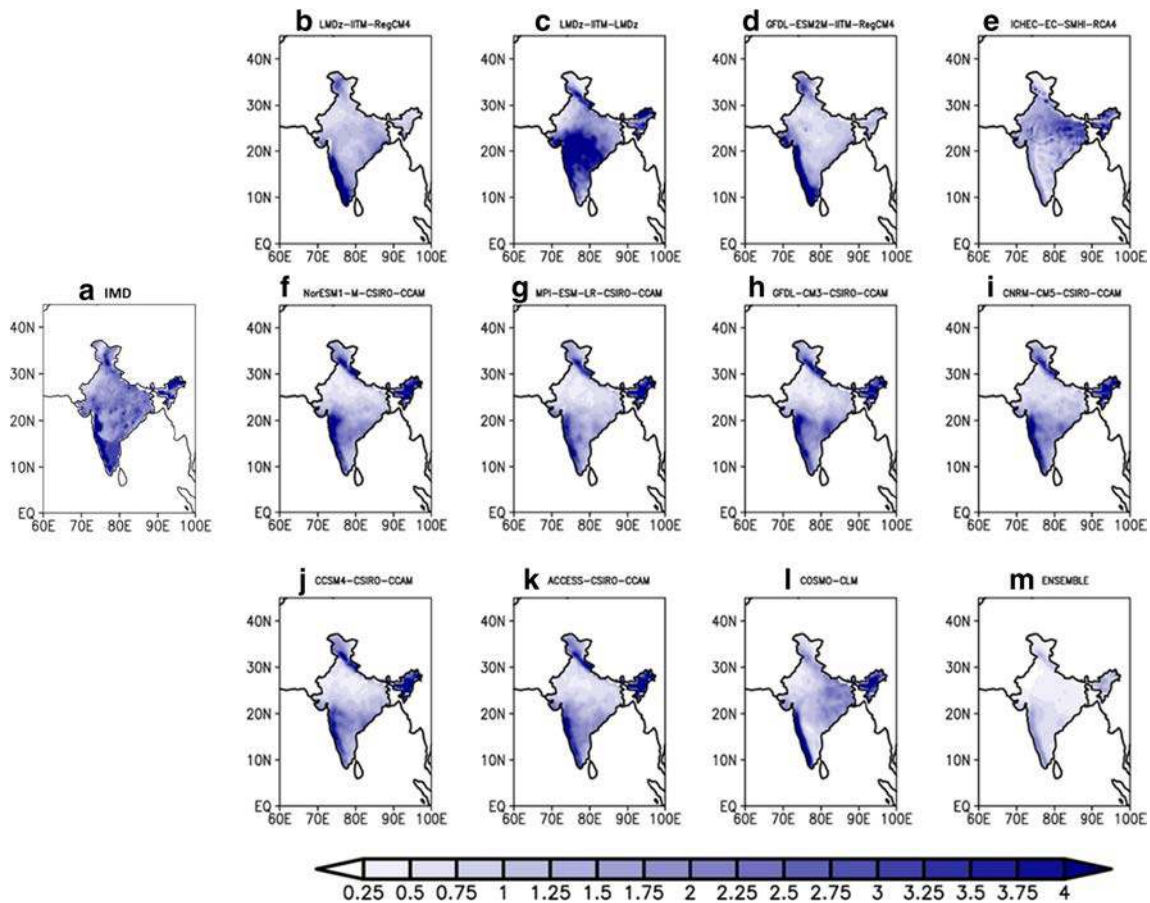


Fig. 6 Variability (as standard deviation in mm day^{-1}) in yearly JJAS mean precipitation over the period 1970–2005 as simulated by 11 CORDEX-SA experiments (b–l) and their ensemble (m) over India. Also shown in a is the same for IMD

IMD only 35 years) of JJAS mean precipitation at each grid point in the study area. The regions where the experiments and IMD (Fig. 6a) show high variability are also the regions of high precipitation. All the experiments correctly show high variability of precipitation of up to 4 mm day^{-1} along the western coast of India which the IMD also presents. On the other hand, in the central parts of India, most of the experiments showing smaller precipitation (in comparison with IMD) also show smaller variability in comparison with IMD. On the other hand, LMDz-IITM-LMDz (Fig. 6c) shows high variability in the same region. The ensemble due to the cancelation of fluctuations shows very small variability throughout the study region.

To identify the level of agreement or confidence in the present set of simulations the spread in the experiments is examined. In Fig. 7a, the spatial distribution of ensemble spread is represented as the standard deviation of the 11 experimental 36-year JJAS mean values at each grid point we can see that the spread is not same everywhere which means

the uncertainty in the experiments has a spatial variation also. As seen in the climatological analysis also, there are regions like over parts of Rajasthan where most of the models are in complete agreement in capturing the magnitude and regional grid to grid variation of precipitation and the spread in millimeter per day is almost zero everywhere across that space. Remarkably, the areas with large inter-experiment spread are also the areas with the large ensemble bias. Over the regions of high precipitation—the west coast and the northeast parts of India—experiments are showing higher uncertainty ($> 4 \text{ mm day}^{-1}$) than the regions of low precipitation like southwestern and Rajasthan region where there is a better agreement among experiments. Summarizing the findings, it can be said that the spread between experiments in capturing the precipitation varies on spatial scales and the spread or the uncertainty is itself in general large.

Figure 7b shows that on the basis of metric (explained in methodology) that we have used here five experiments comes out to be the good performing experiments among this lot and

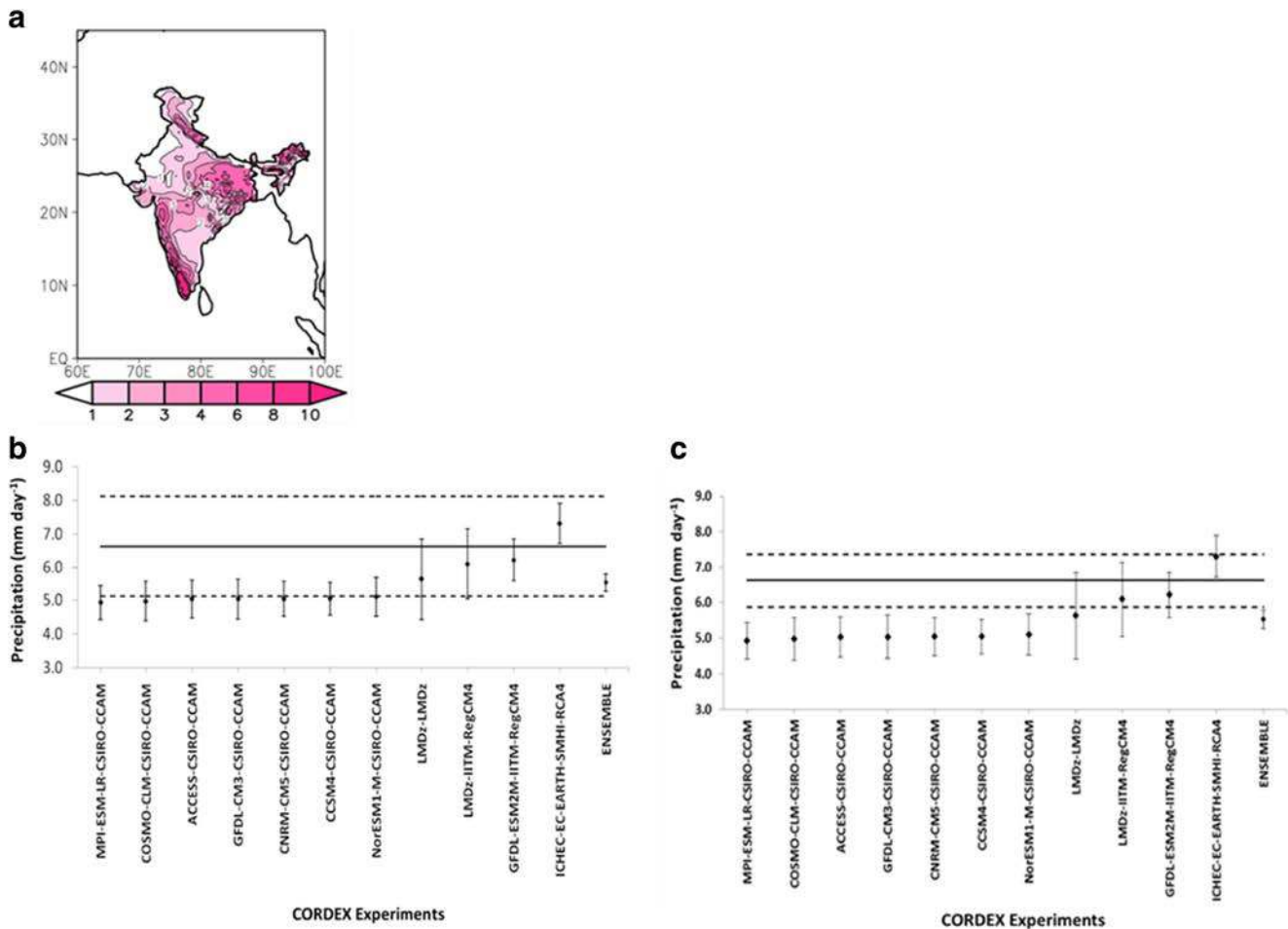


Fig. 7 **a** Spatial distribution of ensemble spread among the 11 CORDEX-SA experiments during JJAS (mean) precipitation (mm day⁻¹) for the period 1970–2005 over India. **b** JJAS precipitation climatology (black markers) for the period 1970–2005 over India from 11 CORDEX-SA experiments and their ensemble. The black horizontal

line represents the precipitation climatology of IMD and the upper/lower dashed lines depict ± 2 standard deviation from the mean. Black markers with error bars represent mean and ± 1 standard deviation of the 11 CORDEX-SA experiments and their ensemble. **c** Same as **b** but upper/lower dashed lines depicting ± 1 standard deviation from the mean

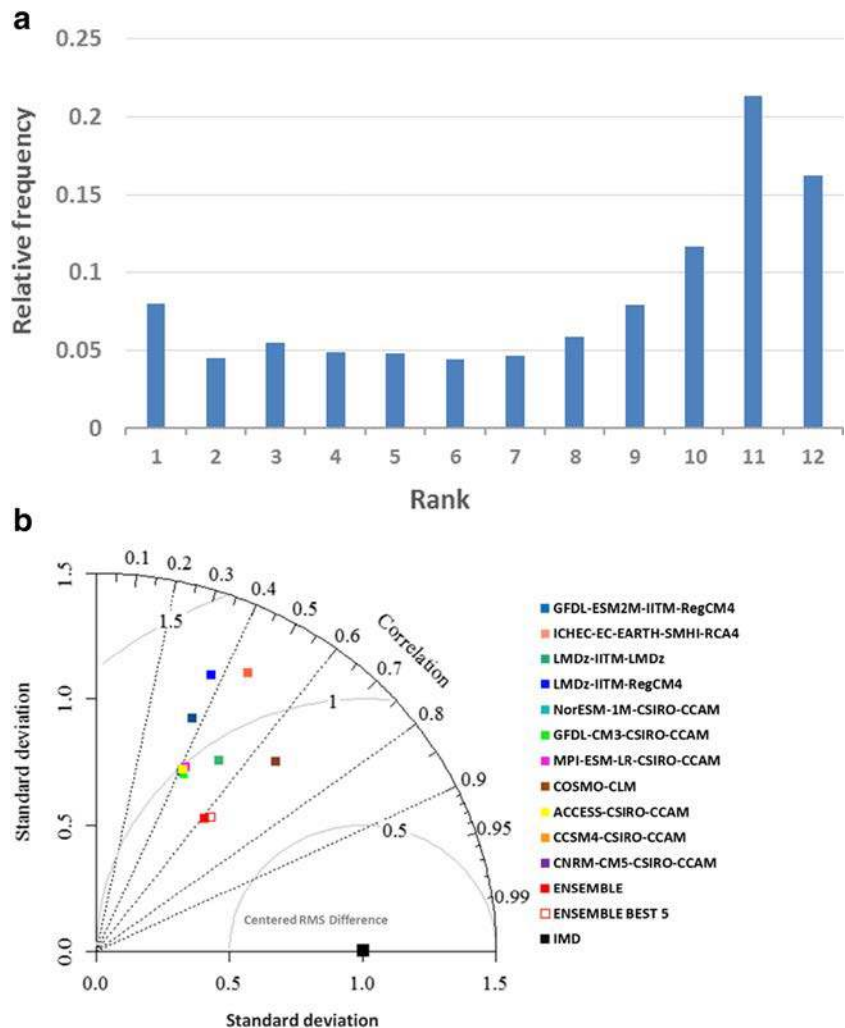
we call them as our Best 5 CORDEX-SA experiments. These experiments are the ones whose spatially averaged precipitation climatology comes within the ± 2 standard deviations from that of the IMD mean. They are: NorESM1-M-CSIRO-CCAM, LMDz-IITM-LMDz, LMDz-IITM-RegCM4, GFDL-ESM2M-IITM-RegCM4 and ICHEC-EC-EARTH-SMHI-RCA4. Three of these experiments also come within ± 1 standard deviation from IMD (Fig. 7c) which has been shown just to narrow down further on the better performing experiments but the aforementioned five experiments have been chosen ultimately so as to include more number of CORDEX-SA experiments in the ensemble. The metric may not be the only one to choose the better performing models but still we wanted to focus on the climatology so we stick to this method alone and it was beyond the scope of the present study to go for other metrics as it needs altogether a separate study to compare the different methods of selection of models.

The ranked histogram can be used as a diagnostic tool to assess the spread of an ensemble. (Hamill 2001). The underlying assumption is that the ensemble member results are distributed so as to delineate ranges or bins of the simulated variable

such that in each bin there is an equal probability of occurrence of observation. The histogram shows the probability of the total occurrences of observed values in each bin where bins are determined by ranking the ensemble member values from lowest to highest. The bins are fixed by ranking the ensemble member simulations from lowest to highest. A bin is formed by the interval between each pair of ranked values. There will be " $n + 1$ " bins if there are " n " ensemble members. For each case, observation will fall into a certain ranked bin. Therefore, for each bin there would be a number of total occurrences of observation which determines the histogram. As it can be seen in Fig. 8a, the IMD value too frequently occurs in the wettest (highest-valued) bins. Therefore, the ensemble tends to show dry bias as found in climatology analysis previously. There is also an uncertainty in the experiments with respect to IMD as histograms are not of same height.

Figure 8b presents the Taylor diagram showing the performances of experiments in simulating the spatial pattern of precipitation with IMD as reference. Here the JJAS mean precipitation values averaged over the study period (1971–2005) at each grid point present in the study area is considered

Fig. 8 **a** Ranked histogram showing the spread of the ensemble of 11 CORDEX-SA experiments with respect to IMD for JJAS mean precipitation (1970–2005). The histogram shows the probability of the total occurrences of IMD values in each bin where bins are determined by ranking the ensemble member values from lowest to highest. **b** Taylor diagram representing the normalized statistical comparison of spatial pattern of JJAS precipitation of the 11 CORDEX-SA experiments and their ensemble with that of IMD over India

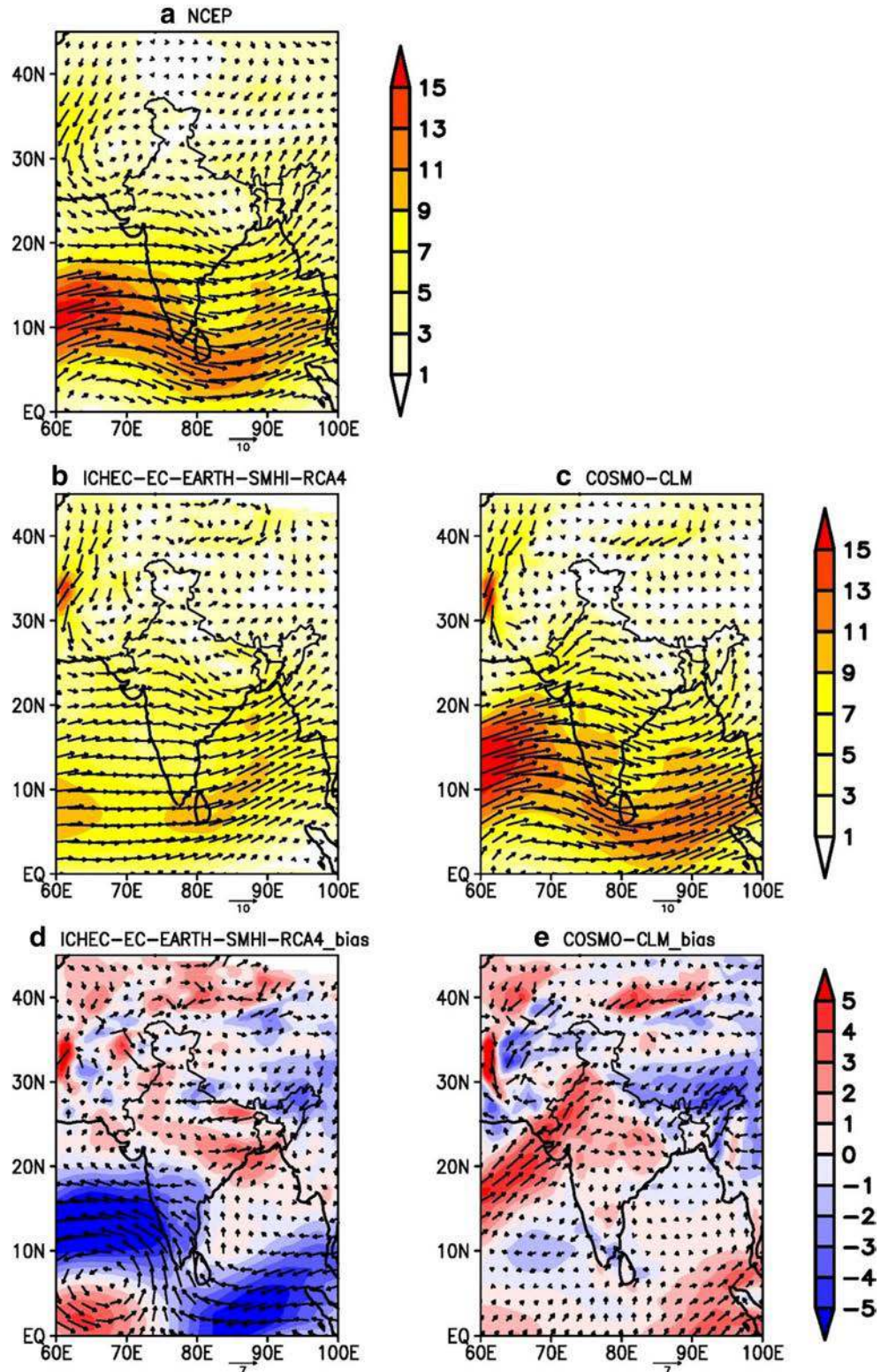


to calculate the Taylor diagram parameters. It can be noticed that the spatial pattern is captured up to an extent by all the experiments as none of them show negative correlation values. In particular, COSMO-CLM performs better than even ensemble in all aspects and shows smallest RMSE and highest

correlation (0.65) among all the experiments with respect to IMD.

During summer monsoon, a southwesterly low-level flow is established in the atmosphere—a part of large scale circulation in the atmosphere at around 850 hPa. Its formation

Fig. 9 JJAS mean climatology (1970–2005) of 850 hPa wind (m s^{-1}) from **a** NCEP reanalysis, **b, c** two CORDEX-SA experiments, and **d, e** their respective biases from NCEP reanalysis



involves processes such as the cross equatorial flow of zonal wind, which turns to the right due to the Coriolis force and develops as Findlater Jet. This transports moisture from the Arabian Sea to the Indian landmass and causes the precipitation during JJAS. These basic features of wind fields during monsoon are very important for a model to realistically simulate so as to accurately represent the monsoon dynamics and associated precipitation. In Fig. 9, the model simulated wind fields (Fig. 9b, c) are compared with that of NCEP reanalysis (Fig. 9a) along with the respective biases of models (Fig. 9d, e). The 850 hPa wind data was available for only two of these RCM experiments under CORDEX-SA. Of the two RCMs, COSMO-CLM is found to capture the spatial features of wind fields very well with the cross equatorial flow and the Findlater Jet very clearly represented along with the Bay of Bengal branch of the monsoonal flow. A strong wind core over the Arabian sea and over Bay of Bengal is realistically simulated by this RCM. The same RCM was earlier found to also capture the spatial distribution of precipitation over India very well in terms of a high spatial correlation (Fig. 8b). However, in terms of magnitude, the wind seems to be overestimated (Fig. 9e) over the central Indian region. Moisture riding on a strong wind tends to precipitate mostly along the Western Ghats by orographic forcing. The wind being still strong enough but with less moisture further moves inland but gets carried out of this region thus inhibiting the convergence. This could be linked with the precipitation as wet bias over the Western Ghats and the large dry bias over rest of India was found earlier in this model (Fig. 3k). On the other hand, ICHEC-EC-EARTH does not capture the observed spatial variability of wind field as good as COSMO-CLM with the former showing underestimation along the Western Ghats and overestimation over the foothills of Himalayas.

As it can be seen in Fig. 10a, the spread of the ensemble of Best experiments has reduced as all of these experiments climatologically lie within a boundary defined by standard deviation of the IMD. The spatial distribution of spread remains more or less same but the magnitude has reduced for whole of India and hence the certainty seems to be increased slightly. Figure 10b(a), b(b) shows the comparison of the JJAS precipitation bias for the ensemble of 11 experiments and that of the Best 5 experiments, respectively. A slight reduction in bias is seen over many places like central parts, and some parts of northern and eastern India. The reduction in bias is a direct result of the Best 5 experiments' closer resemblance with the observed precipitation climatology.

3.2 Indian monsoon core region

Model physics responds variably to the physiographic variations and hence its ability to reproduce the observed

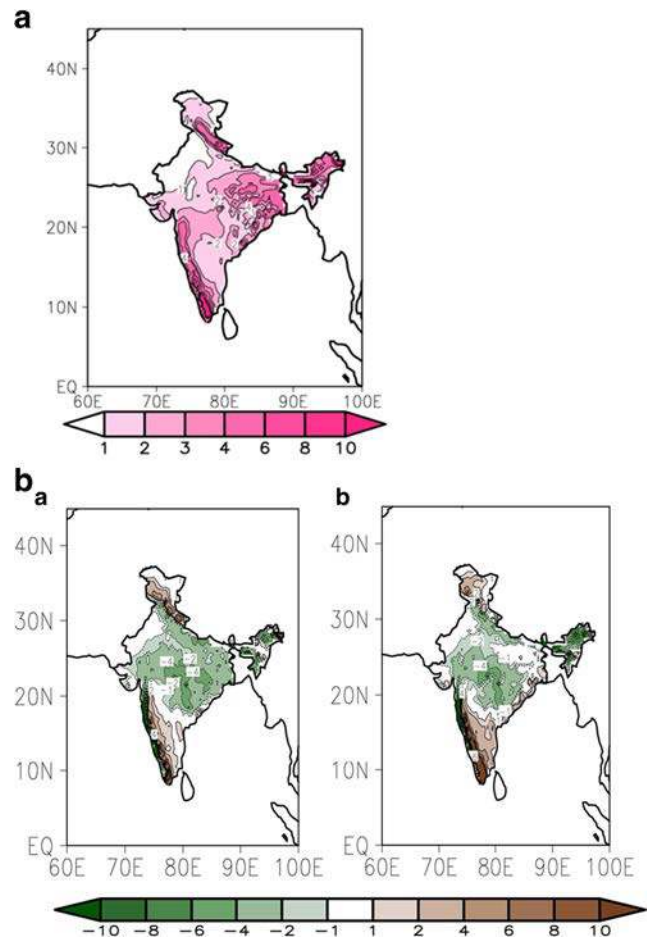
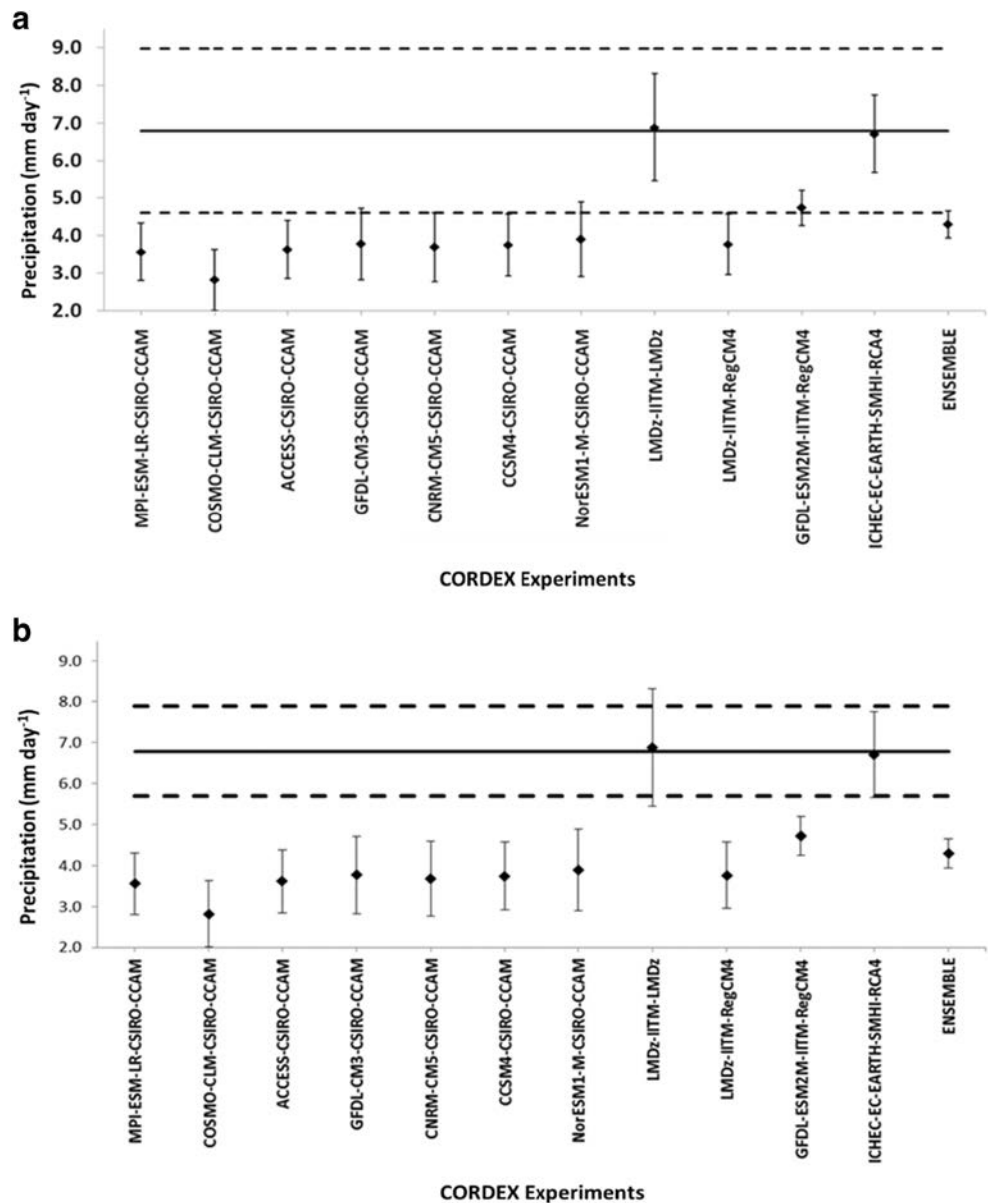


Fig. 10 a Spatial distribution of ensemble spread among the Best 5 CORDEX-SA experiments during JJAS mean precipitation (mm day^{-1}) for the period 1970–2005 over India. b JJAS mean precipitation bias (mm day^{-1}) for the period 1970–2005 for b(a) ensemble of 11 CORDEX-SA experiments and b(b) ensemble of Best 5 CORDEX-SA experiments with IMD over India

climate also varies spatially in a heterogeneous region like India. Therefore, in this section following the same approach as for all India, an attempt is made to have a focused study of the CORDEX-SA experiments for its ability in simulating the summer monsoon precipitation climatology by considering a homogeneous monsoon region of India which is called as Indian monsoon core region (or MCR) (as described in Section 2.1.1).

Figure 11a shows the best performing CORDEX-SA experiments over MCR as the ones whose mean climatology lie within ± 2 standard deviation from that of IMD. They are referred here as the Best 3 experiments. They are—LMDz-IITM-LMDz, ICHEC-EC-EARTH-SMHI-RCA4, and GFDL-ESM2M-IITM-RegCM4. Incidentally, these three experiments are also among the best performing experiments over the all India region. The first two experiments mentioned above have their climatology almost equal to that of IMD with LMDz-IITM-LMDz and ICHEC-EC-EARTH-SMHI-RCA4 showing 6.88 and 6.71 mm day^{-1}

Fig. 11 a JJAS precipitation climatology (black markers) for the period 1970–2005 over MCR of 11 CORDEX-SA experiments and their ensemble. The black horizontal line represents the precipitation climatology of IMD and the upper/lower dashed lines depict ± 2 standard deviation from the mean. Black markers with error bars represent mean and mean ± 1 standard deviation of the 11 CORDEX-SA experiments and their ensemble. **b** Same as **a** but the upper/lower dashed lines depicting ± 1 standard deviation from the mean



respectively and they also come within ± 1 standard deviation (Fig. 11b) from IMD (6.78 mm day^{-1}).

The Best 3 experiments show varying biases across the core region (Fig. 12a). Overall, they produce a dry bias over MCR as can be seen in the figure where the ensemble is showing an underestimation of precipitation climatology of upto 2 mm day^{-1} . Mishra et al. (2014) also reported similar findings based on the CORDEX-SA experiments two of which is included in the Best 3 set from the present study. They found that over the central part of India the experiments and their ensemble are showing dry bias although they studied annual maximum precipitation values only. The climatology of ensemble seems to be improved with reduced biases. The LMDz-IITM-LMDz and GFDL-ESM2M-IITM-RegCM4 which is although showing a wet bias within a small area at the bottom left region of the MCR box as a part of

Western Ghats induced orographic precipitation mainly produces dry bias over the larger part of core region. The dry bias in the RCMs as discussed before could be due to the excessive (orographic) precipitation along the west coasts and warm ocean regions (in Indian scenario, the Bay of Bengal) which seems to remove most of the moisture from the atmosphere and generate weaker precipitation over land (Rockel and Geyer 2008). In Fig. 12b, the variation of inter-model spread over space is described. The spread in the Best 3 experiments is reduced compared with 11 experiments or even the Best 5 over all-India region. There is an increased certainty and agreement in these set of three experiments. This may be just due to less number of experiments or due to the ability of experiments and nature of their selection based on resemblance with a common IMD data. Spatially the spread in the experiments is very less over MCR as

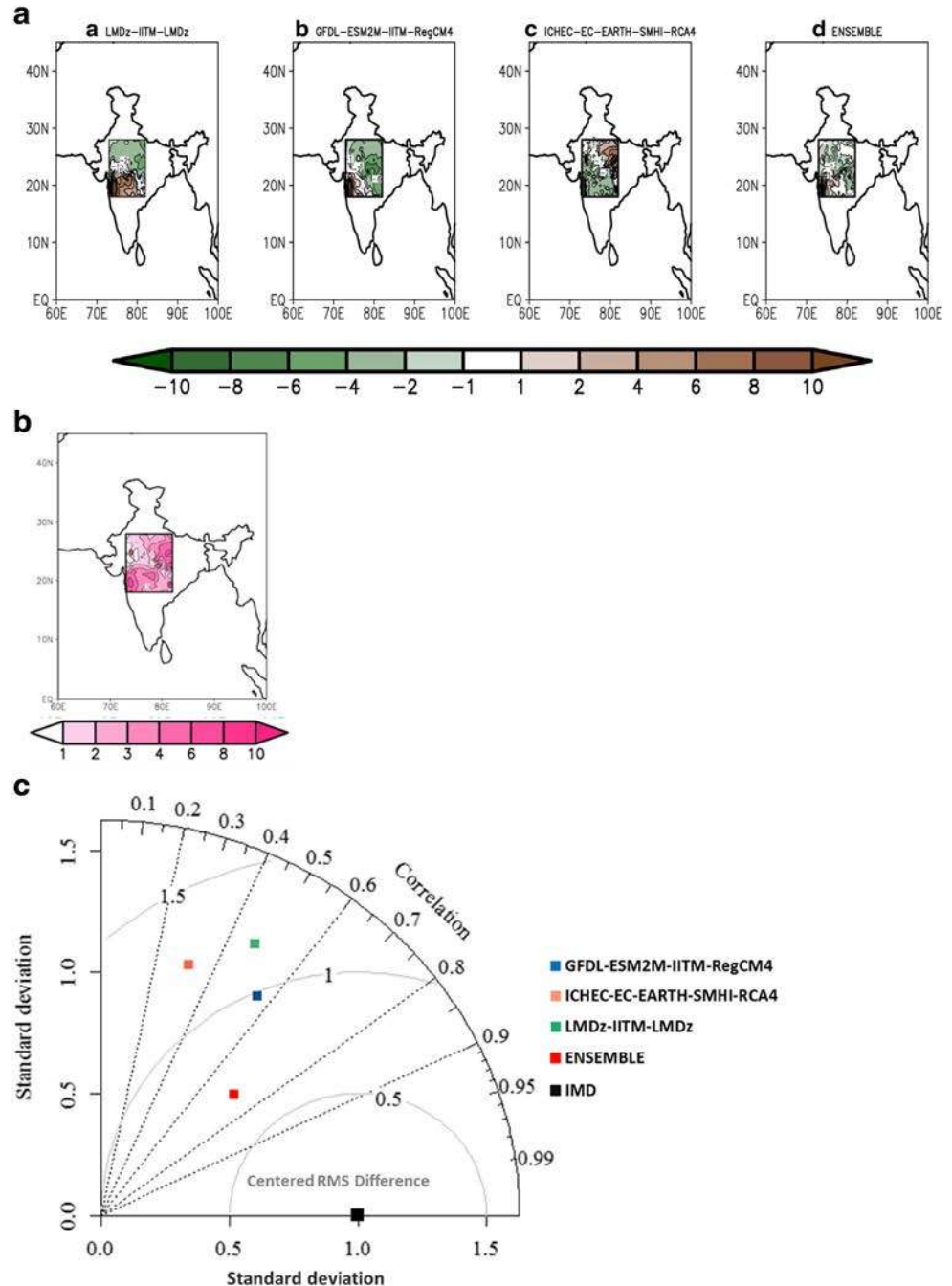
shown by standard deviations which vary between 0 and 3 mm day⁻¹ at most of the places with high degree of spread seen at places which seems to come under the influence of varying orography like, Western Ghats or Himalayan region. The Taylor diagram in Fig. 12c which represents the performance of experiments in simulating the precipitation spatially shows that the results are improved over MCR. The ensemble shows best correlation of about 0.7 with the member experiments also showing smaller but positive correlations. Two experiments GFDL-ESM2M-IITM-RegCM4 and ICHEC-EC-EARTH-SMHI-RCA4 show close spatial variation with IMD as indicated by

their corresponding standard deviations in the diagram. Interestingly, over MCR the ICHEC-EC-EARTH-SMHI-RCA4 and the ensemble shows better resemblances in various aspects of Taylor diagram with the reference when compared with their respective performance over all India region.

3.3 Skill score and model weighting

Weighting of individual climate models of an ensemble is a widely used method to reduce uncertainty in climate projections (Giorgi and Mearns 2002, 2003, Murphy et al. 2004,

Fig. 12 **a** JJAS precipitation bias (mm day⁻¹) averaged over the period 1970–2005 of only Best 3 CORDEX-SA experiments (a(a)–(c)) and their ensemble (a(d)) with IMD over MCR (box). **b** Spatial distribution of ensemble spread among the Best 3 CORDEX-SA experiments during JJAS precipitation (mm day⁻¹) for the period 1970–2005 over MCR (box). **c** Taylor diagram representing the normalized statistical comparison of spatial pattern of JJAS mean precipitation (1970–2005) of only the Best 3 CORDEX-SA experiments and their ensemble with that of IMD over MCR



Tebaldi et al. 2005, Tebaldi and Knutti 2007, Knutti et al. 2010). The basic idea behind weighting is that the higher performing models in an ensemble are given higher weightage in calculating the mean of all models, which would result in a better performing ensemble. As the ensemble members in the present set of CORDEX-SA experiments are not completely independent (common RCM/GCM in some experiments), the equally weighted ensemble mean are considered throughout the study. Moreover, equally weighted ensemble is considered to consistently outperform the individual members of ensemble (Knutti et al. 2010). However, considering the relative impacts of joint model errors and model noise on the performance of ensemble mean, a knowledge of relative performance of individual model is also required (Weigel et al. 2010). Taking this into consideration, as an additional part of the present study a comparison of the basic climatology of weighted ensemble mean with the earlier used simple ensemble mean (equally weighted or average) is made. For this purpose, first we have calculated a “combined” skill score of each individual

model and then the relative (combined) skill score of a model is used as a weighing factor for that model in calculating the weighted ensemble mean.

The model “combined” skill score is the combination of two separate skill scores—(i) model “performance” skill score and (ii) model “convergence” skill score. The idea of this method is based on the “reliability ensemble averaging method” of Giorgi and Mearns (2002). We have followed the approach of Dessai et al. (2005) in calculating these skill scores but without area averaging of the scores so as to show spatial variation of model skills. The method relies on the modified version of least complicated skill score used by Taylor (2001) and Murphy (1988). Model “performance” skill score (Fig. 13a) is calculated as:

$$S.S.performance = \frac{|\bar{x}_{obs}|}{\left[\frac{1}{N} \sum_{i=1}^N (x_{imod} - x_{iobs})^2\right]^{1/2}} \quad (1)$$

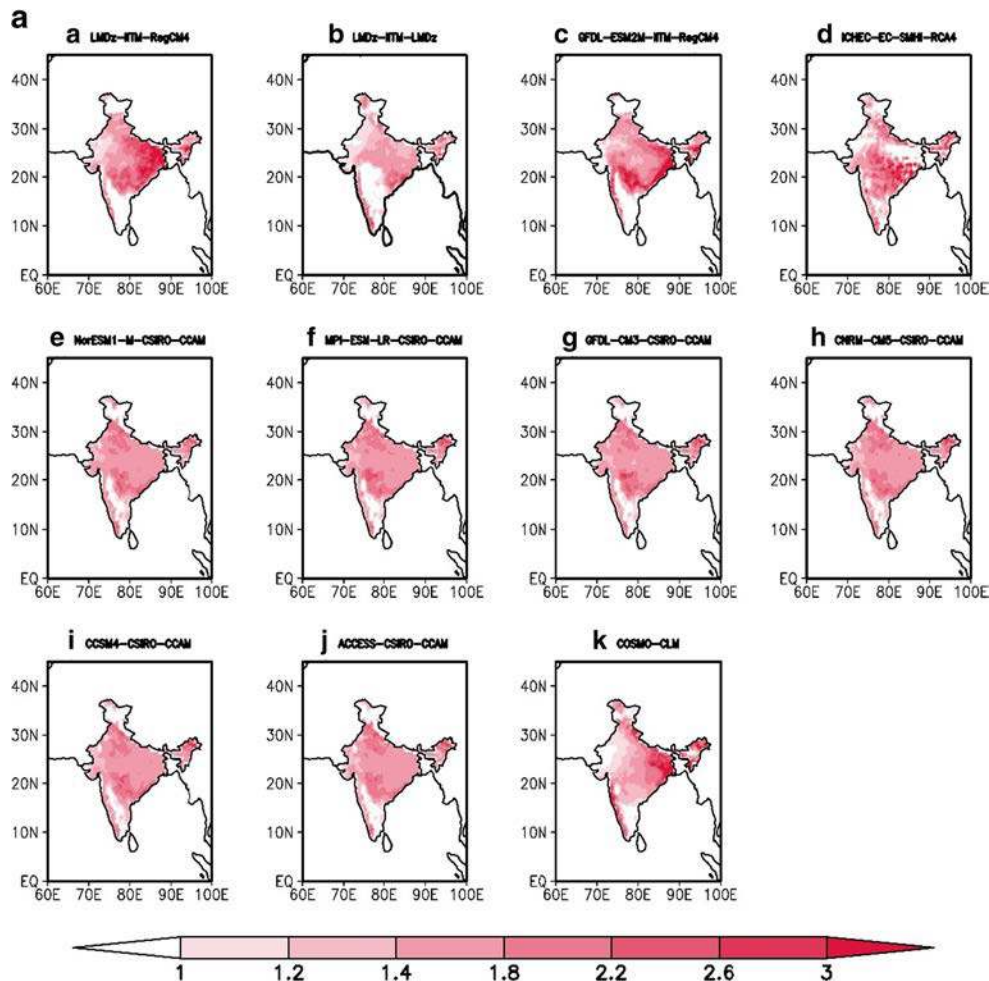


Fig. 13 Skill scores for 11 CORDEX-SA experiments, for **a(a)–(k)** model “performance” (with respect to IMD), **b(a)–(k)** model “convergence” (with respect to simple ensemble mean), and **c(a)–(k)** combined skill score for JJAS precipitation over India

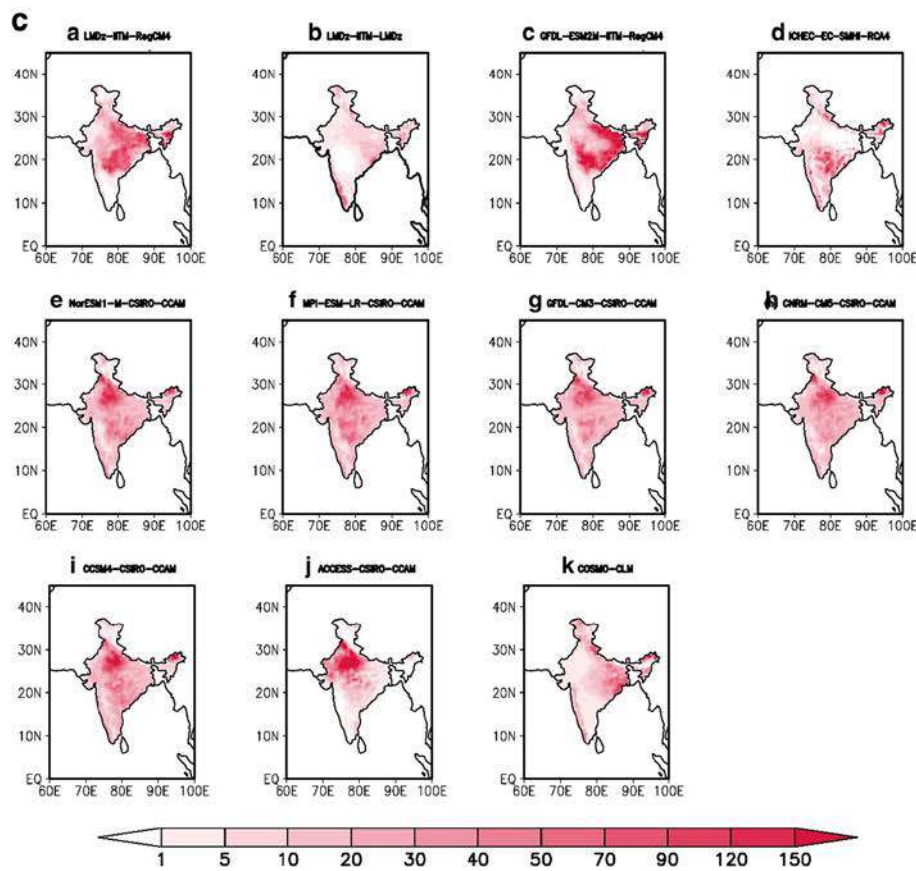
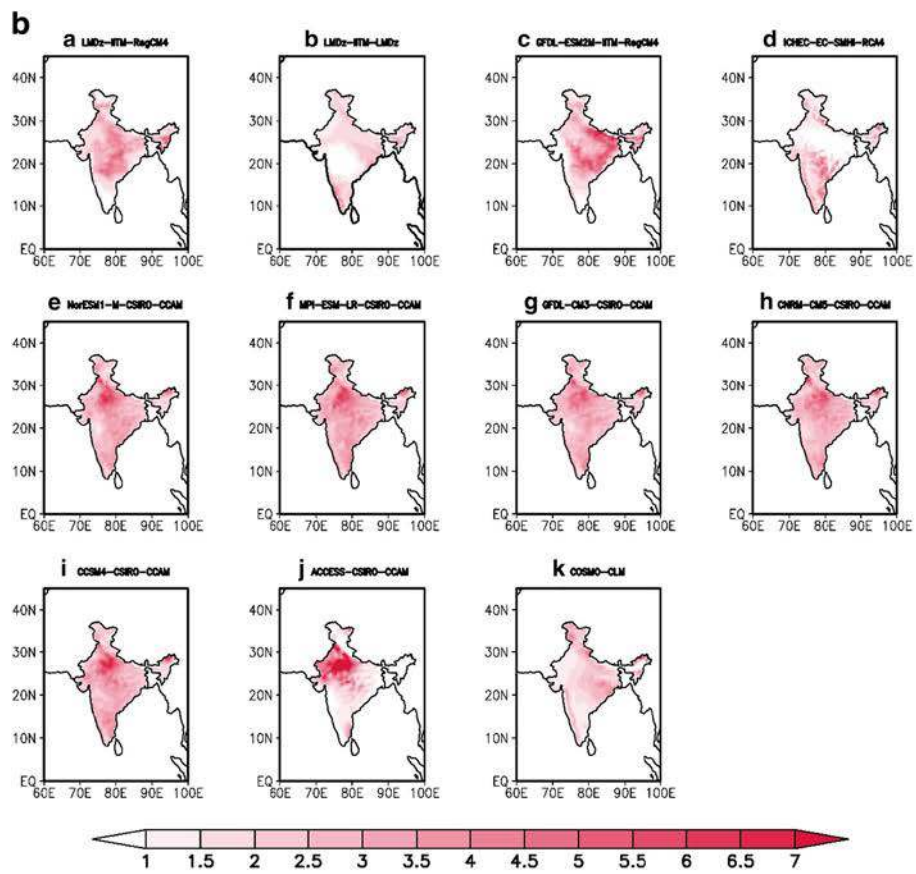


Fig. 13 (continued)

where

- S.S. _{performance} = model “performance” skill score,
- N = number of time points, here 35 for 35 years (1971–2005)
- $x_{i\text{mod}}$ = i th data point of model simulation for variable x , here variable is JJAS mean precipitation
- $x_{i\text{obs}}$ = i th data point of observation (here, IMD) for variable x , here variable is JJAS mean precipitation
- x_o : average of observations for variable x .

This skill score gives an overall measurement of model bias, variance and spatial correlation. Therefore, it is considered as an integrated index of measurement of model performance.

Similarly, the model “convergence” skill score (Fig. 13b) is calculated as:

$$S.S.\text{convergence} = \frac{|\bar{x}_{\text{ens}}|}{\left[\frac{1}{N} \sum_{i=1}^N (x_{i\text{mod}} - x_{i\text{ens}})^2\right]^{1/2}} \quad (2)$$

where

- S.S. _{convergence} model “convergence” skill score,
 - N number of time points, here 35 for 35 years (1971–2005)
 - $x_{i\text{mod}}$ i th data point of model simulation for variable x , here variable is JJAS mean precipitation
 - $x_{i\text{ens}}$ i th data point of the ensemble average for variable x , here variable is JJAS mean precipitation
 - x_o multi-model ensemble average for variable x .
- Finally, the combined skill score is calculated as:

$$S.S.\text{combined} = \left(\sqrt{S.S.\text{performance}} \times \sqrt{S.S.\text{convergence}}\right)^4 \quad (3)$$

where S.S. combined = model “combined” skill score.

From Fig. 13b as well as Table 4 it is found that there is a wide variation in convergence skill scores among the

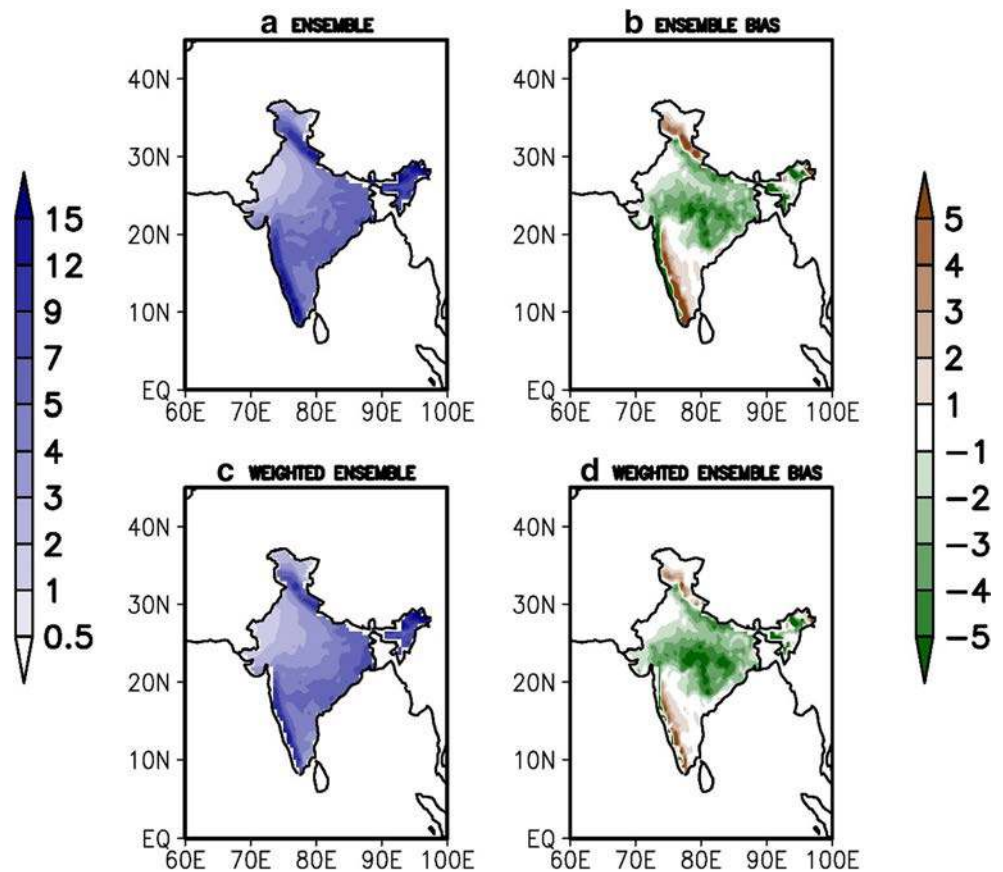
individual experiments suggesting discrepancy between the models or the inter-model spread. This also point towards the uncertainty among the experiments which was discussed earlier in Fig. 7a. The skill also varies spatially for each model. For e.g. we find that the experiments which involves CCAM as RCM shows particularly a high skill in north-western part of India and a similar distribution to each other at other regions. For ICHEC-SMHI-RCA4 the skill drastically reduces along the Indo-Gangetic plains. This indicates that in this region the model has a large deviation from the ensemble. Overall, the MPI-ESM-LR-CCAM agrees best with the multi-model ensemble which is indicated by highest mean convergence skill core of 3.0. As it was found in the bias study also, the model performance varies in space and from each other again indicating discrepancy or uncertainty in simulations. A wet bias along the west coast of India results in a reduced skill of less than one in almost all models in that region. As seen in climatological comparison of models Fig. 7b, the GFDL-ESM2M-RegCM4 experiment lies closest to the mean observation line, here also it shows the highest “performance” skill of 1.52 as well as the combined skill of 37.82 although in ‘convergence’ it does not emerges to be the highest skilled model.

Based on the relative combined skill score, weights are assigned to different experiments and then weighted ensemble mean is calculated. In Fig. 14, the climatology and the respective bias (with IMD) of the weighted ensemble mean (Fig. 14c, d) and simple ensemble mean (Fig. 14a, b) which is simply the multi-model average that we used earlier in all our analysis are compared. A clear difference that is seen in weighted mean climatology is the reduction of bias along the western coastline, on both windward and leeward side of Western Ghats where reduction in dry bias as well as wet bias

Table 4 Mean skill score (for Performance, Convergence, and Combined) for each CORDEX-SA experiment (averaged over India) for JJAS precipitation

S. no.	Model	Skill score		
		Performance	Convergence	Combined
1	GFDL-ESM2M-IITM-RegCM4	1.52	2.59	37.82
2	ICHEC-EC-EARTH-SMHI-RCA4	1.41	1.72	13.51
3	LMDz-IITM-LMDz	1.22	1.70	7.36
4	LMDz-IITM-RegCM4	1.52	2.41	27.46
5	CCSM4-CSIRO-CCAM	1.41	2.97	25.22
6	CNRM-CM5-CSIRO-CCAM	1.42	2.81	21.76
7	GFDL-CM3-CSIRO-CCAM	1.43	2.84	21.61
8	MPI-ESM-LR-CSIRO-CCAM	1.43	3.00	24.86
9	NorESM1-M-CSIRO-CCAM	1.41	2.88	23.59
10	ACCESS-CSIRO-CCAM	1.39	2.30	26.01
11	COSMO-CLM	1.48	2.02	15.36

Fig. 14 Comparison of JJAS precipitation climatology (mm day^{-1}) over India for the period 1970–2005 of **a** simple ensemble mean, **b** weighted ensemble mean of 11 CORDEX-SA experiments, and **c, d** their respective biases with respect to IMD



takes place, respectively. This indicates a regional skill of weighted ensemble mean. A slight reduction in wet bias is also found in parts of western Himalayan region. On the other hand, in the central part of India, the dry bias is getting enhanced. This could be due to higher convergence of those models and hence a higher “combined” skill in this region which was showing dry bias. Summarizing, the weighted ensemble definitely exhibits an improved performance in capturing the climatology though the skill is localized.

4 Conclusions

In this study, a comprehensive evaluation of the ability and uncertainty of an ensemble of 11 RCM experiments under CORDEX-SA in representing seasonal mean summer monsoon precipitation climatology over India is presented. In general, most of the simulations were able to capture the important features of summer monsoon precipitation climatology over India especially the high precipitation over the western coast and northeast India and low precipitation over Rajasthan. However, there also exists a very wide spread dry bias in simulations which used a particular regional model (CCAM) that affects the performance of ensemble in capturing the spatial pattern of precipitation. Individual model skill varies from each

other and also spatially in capturing precipitation climatology over India but in general most of the experiments tend to underestimate the monsoonal mean precipitation over a larger part of India including the MCR. This reflects in their ensemble also though with slightly reduced bias due to cancelation of opposite signed biases. In fact, paired difference Student’s t-test reveals that a significant dry bias is seen in all the simulations over India spatially except for RCA4 regional model which shows a significant wet bias. This suggests a common deficiency in the present set of CORDEX-SA experiments in simulating the summer monsoon precipitation over India. Such systematic biases could be removed by applying bias correction methodology to improve accuracy (Dobler and Ahrens 2008; Piani et al. 2010). About the added value of RCM over its parent GCM, it can be concluded that the benefit of downscaling can vary spatially over a geographically heterogeneous region like India with the possibility of both improvement and worsening of results. A considerable uncertainty is found in the present ensemble of experiments which varies in space where in some parts it is as large as 5 mm day^{-1} . This is reflected in their convergence skill score where some models skill gets highly reduced in particular region over India. On an average, the uncertainty between the models in simulating the mean precipitation is around $2\text{--}3 \text{ mm day}^{-1}$. The reason for such differences in model results could be lying in the variation in

parameterization physics like convection, planetary boundary layer assumption, and land-surface schemes, etc. to which the simulation of monsoon dynamics could be very sensitive especially where they play an important role like over regions where local forcings are relevant (Solman et al. 2013). Other sources of uncertainty could also exist such as differences in model's configuration- numerical techniques, vertical resolution and different forcings which can explain differences in simulated precipitation climatology (Solman and Pessacg 2012). To conclusively comment on the reasons behind the uncertainty would require analysis of other variables and their physical linkages together with the information of simulation design in hand. This is beyond the scope of present study. Moreover, from this study we can definitely say that large uncertainty together with large bias at a place which results in a reduced combined skill of model suggests that the reliability in simulating the monsoonal mean precipitation features is degraded at that place. One other noticeable finding is that though the experiments are not able to capture the actual strength of long-term seasonal mean precipitation as seen in climatology bias but it shows good ability in capturing its spatial distribution (variation along the grid points) as shown by the positive signs of spatial correlation values in Taylor diagrams. Further, with the selection of better performing CORDEX-SA experiments by the method we used, their ensemble average shows only a slight improved performance in various aspects—reduced biases, improved certainty and correlations. This suggests that only a mean climatology based identification of good performing models is not comprehensive enough for making a reliable ensemble.

To investigate the individual models in depth is beyond the scope of the present study as this would require detailed analysis of how each model has been configured, how sensitive they are to different parameterization schemes and associated dynamics along with their interactions. Unavailability of this information under CORDEX-SA is a major limitation in interpreting the results. We have made no attempt in the present study to identify the reasons behind the agreement or disagreement in the experiments. Though RCMs are thought to be portable in the sense that they can be used to generate climate information for any region across the world but the quality of their results depends on regions as found by Takle et al. (2007). The current analysis which documents the assessment of 11 experiments—their common weaknesses and strengths that may be informative for identification of individual models and their improvement to give reliable future projections of precipitation over Indian region.

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