Deciphering the projected changes in CMIP-6 based precipitation simulations over the Krishna River Basin

Suram Anil and Anand Raj P.
Department of Civil Engineering, National Institute of Technology Warangal, Telangana 506004, India
*Corresponding author. E-mail: sanil@student.nitw.ac.in

ABSTRACT

The impact of climate change on the Krishna River Basin (KRB) is significant due to the semi-arid nature of the basin. Herein, 21 global climate models (GCMs) of Coupled Model Intercomparison Project Phase 6 (CMIP6) were examined to simulate the historical monthly precipitation over the 1951–2014 period in the KRB. The symmetrical uncertainty (SU) method and the multi-criteria decision method (MCDM) were employed to select the suitable GCMs for projecting possible changes in precipitation over the KRB. The biases in the climate projections were removed by using the empirical quantile mapping method. The reliability ensemble averaging (REA) method was used to generate the multi-model ensemble (MME) mean of projections and to analyse the spatio-temporal changes of precipitation under different shared socioeconomic pathways (SSPs). BCC-CSM2-MR, IPSL-CM6A-LR, MIROC6, INM-CM5-0, and MPI-ESM1-2-HR were found to be the most suitable GCMs for the KRB. The MME mean of the chosen GCMs showed significant changes in precipitation projection that occurs for a far future period (2071–2100) over the KRB. The projection changes of precipitation range from −36.72 to 83.05% and −37.68 to 95.75% for the annual and monsoon periods, respectively, for various SSPs. Monsoon climate projections show higher changes compared with the annual climate projections, which reveals that precipitation concentration is more during the monsoon period over the KRB.

Key words: global circulation models, Krishna River Basin, precipitation projection, reliable ensemble average, shared socioeconomic pathways, symmetric uncertainty

HIGHLIGHTS

- The impact of climate change on the KRB is significant due to its semi-arid nature.
- Climate change impact assessment using recently launched CMIP6 climate models over the KRB is not performed.
- The most popular concept of symmetric uncertainty is used to find suitable GCMs over the KRB.
- The selected GCMs agree with those of past studies, which can be used for further hydrological studies, and these results are helpful to policymakers.
INTRODUCTION

Climate change is a multidimensional complex global phenomenon leading to hydro-climatological extreme events, thereby motivating the research community to study it since the past few decades (Sheffield & Wood 2008; Cameron 2011; Ahmed et al. 2019a). The changes in precipitation can affect many sectors, including agriculture, hydrological cycle, environment, health, and power (Ahmed et al. 2018; Mohsenipour et al. 2018; Shiru et al. 2018). Generally, the atmospheric conditions of semi-arid regions are sensitive to the variability of regional climate, especially for precipitation (Ye & Chen 1992; Gong et al. 2004; Xing & Wang 2017). Sometimes, even a slight deficit in rainfall can cause heavy drought, affecting agricultural plants specifically during summertime.

Since the past few decades, the potential impact of precipitation due to climate changes is being assessed by using various climate models for future prediction of climate. Global climate models (GCMs) are numerical models that represent the various physical systems of the earth’s climate with respect to the surface of the land, oceans, atmosphere, and cryosphere, and these are employed to provide likely changes in future climate projections (Gouda et al. 2018; Reshmidevi et al. 2018). These future climate projections play a crucial role in understanding the possible climate change impacts and in taking various mitigation steps and making recommendations to policymakers (Nashwan & Shahid 2020). However, the estimation of climate change on a regional scale is encumbered due to the various uncertainties that are involved in obtaining GCM outputs. However, the performance of the climate model varies between the regions and within the models due to the uncertainties associated with the model parameterisation, calibration, boundary conditions, structure, etc. (IPCC 2013; Tiwari et al. 2014; McSweeney et al. 2015). Apart from these uncertainties, reference datasets and performance evaluation metrics also influence the performance of GCMs (Anil et al. 2021) used. Due to all these uncertainties associated with GCMs, the selection of GCMs is becoming a challenge in terms of ranking them using the simulation of the current climate (Raju et al. 2017; Kamworapan & Surussavadee 2019). A number of works have been attempted to rank GCMs in Indian river basins using CMIP5 (Raju et al. 2017; Das et al. 2018) and CMIP3 (Rajeevan & Nanjundiah 2009; Raju & Nagesh Kumar 2014; Anandhi & Nanjundiah 2015) phase models. Recently, the Coupled Model Intergovernmental Panel on Climate Change Phase 6-based climate model data was made available for the evaluation of climate change studies (Eyring et al. 2016), but very meagre studies have been conducted based on Coupled Model Intercomparison Project Phase 6 (CMIP6; Anil et al. 2021) climate models in India. The CMIP6 climate data differ in terms of carbon emissions and forcing scenarios compared with CMIP5 and CMIP3 phases. These CMIP6 projects provided nine shared socioeconomic pathway (SSP) scenarios based on the future concentration of greenhouse gas. From the total of nine scenarios, high-prioritised five SSPs are comprised...
in which four are grouped in ‘Tier 1 (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5)’ mentioned in ScenarioMIP (O’Neill et al. 2016; Meinshausen et al. 2019) along with SSP1-1.9 as per Assessment Report 6 (AR6).

Generally, a set of suitable GCMs will be preferred from the large pool of GCMs for the area of interest for performing climate change impact studies by excluding those that have a greater degree of uncertainty (Lutz et al. 2016; Khan et al. 2018). The selected GCMs are employed to develop the multi-model ensemble (MME) mean, which can strengthen the prediction reliability by using information from the variable of interest (Knutti et al. 2010). The performance of the MME depends upon the performance of GCM ensembles in mimicking past climates (Pour et al. 2018). Various approaches involved in GCM performance evaluation, ranking, and development of the MME for different geographical locations have been discussed and segregated very clearly, which helps in the easy understanding of GCM selection for a region (Raju & Nagesh Kumar 2020). However, this selection of GCMs is becoming challenging for developing future climate projections (Salman et al. 2018; Noor et al. 2019). GCM selection can be done in four ways. (i) By considering the latest phase of GCMs, (ii) By considering the finer spatial resolution of GCMs, (iii) By validity, where GCM performance is considered, and (iv) By representativeness and climate variability of interest, where a wide range of future GCM projections are made available (Mendlik & Gobiet 2016). In the present study, a hybrid approach is followed by considering the latest CMIP6 based models with different spatial resolutions, covering four SSPs of future precipitation projections and evaluating the performance of GCMs.

From the development of GCMs, continuous efforts are being reported for assessing GCM performance (Phillips 1956; Xu 1999) using various filters, including the weighted skill score (Perkins et al. 2007; Maxino et al. 2008; Anandhi & Nanjundiah 2015), Brier score (Fu et al. 2013; Ruan et al. 2018; Jia et al. 2019), clustering analysis (Yokoi et al. 2011; Knutti et al. 2013; Raju & Nagesh Kumar 2016), information entropy (Shukla et al. 2006), and Bayesian weightage (Min & Hense 2006). Apart from these metrics, a composite metric is also used by collecting the metrics in evaluating climate models (Taylor 2001; Murphy et al. 2004; Gleckler et al. 2008; Reichler & Kim 2008; Fu et al. 2013; Raju & Nagesh kumar 2014; Ahmadalipour et al. 2017; Raju et al. 2017). All these performance metrics are purely dependent on time mean state of climate, which is a major drawback of these indicators (Reichler & Kim 2008; Rathinasamy et al. 2014). Most of the time-domain metrics are very sensitive to outliers and extreme events. Therefore, most of them cannot capture the frequencies of climate extremes in terms of temporal variability, which are also essential in model performance evaluation.

In recent years, symmetrical uncertainty (SU) has become very popular in selecting a variable (Khan et al. 2018; Salman et al. 2018; Shiru et al. 2019a). SU is a filter-based tool that tracks the dissimilarity and similarity between the dependent variable and the independent variable such as observed variables and GCMs in terms of information entropy throughout the time series and selects the most relevant GCMs in an unbiased manner. The advantage of SU is that it will provide a general measure of alliance among the observed and the model variables irrespective of underlying distributions and various conditional dependences of data (Wu & Zhang 2004a, 2004b). The high dissimilarity in the time series of model and observed datasets can be reduced by information gain in SU, thereby ranking GCMs based on the capability to replicate reference data time series; by this way, multiple statistical metrics can be avoided.

The Krishna River Basin (KRB) is one of the most important river basins in the Indian subcontinent and the fifth largest in the subcontinent. The KRB is highly sensitive to climate variability, especially in terms of precipitation, due to its semi-arid nature and due to its fast-approaching physical water scarcity (WWAP 2012). The KRB is expected to experience regular and seasonal water-stressed conditions due to the reduction in precipitation in the future (Gosain et al. 2006). In contrast to this statement, a few studies have concluded that an increasing trend in precipitation levels is being seen in the basin, resulting in more water yield in the future (Kulkarni et al. 2014; Mishra & Lilhare 2016), and these studies have used different SRES and RCP scenarios, respectively. Therefore, it is necessary to understand the spatio-temporal variation of precipitation using CMIP6 GCM projections for performing further climate impact studies over the KRB for the purpose of regional sustainability. The prime objectives of the current study are (i) using SU to choose the most skilful GCMs from CMIP6 GCMs for precipitation over the KRB and (ii) developing the MME mean of precipitation using the reliability ensemble average (REA) method for climate impact studies. An analysis of spatio-temporal variation in projections of precipitation over semi-arid regions like the KRB is essential to policymakers in formulating various planning and management strategies.

**Study area**

The KRB is the most important and the fifth-largest river basin in the Indian peninsula and lies between 73°20’ and 81°E longitude and 13°5’–19°24’N latitude covering a geographical area of 2, 58,948 km², which is almost 8% of the total geography of
the country. A large part of the basin is covered by agricultural land (75.86%), and only 4% of the basin is occupied by water bodies (NRAA 2011). Most of the basin is flat terrain and has a semi-arid nature (according to Koppen Classification), dominated by the southwest monsoon rainfall (nearly 90%). The entire KRB is classified into three major climate zones as tropical monsoon climate (Am), tropical savanna climate (Aw), and hot (semi-arid) steppe climate (BSh) as per the Koppen–Geiger climate classification system (Kottek et al. 2006; Chen & Chen 2013). The whole KRB is divided into three major elevation zones such as low (−8 to 356.7 m), medium (356.8–609.7 m), and high (609.8–1,890 m) using ArcMap classification for easy analysis of results. Figure 1 represents the location map of the KRB with Koppen climate classification.

Four different seasons can be observed in the catchment: cold weather is from December to February (DJF), pre-monsoon is from March to May (MAM), monsoon from June to September (JJAS), and finally, post-monsoon from October to November (ON). A spatially distributed map of precipitation over the catchment for pre-monsoon, monsoon, and annual periods using IMD data from 1985 to 2014 is presented in Figure 2. The annual precipitation of the basin varies from 403 mm South-East to 3,108 mm South-West.

Data

Gridded precipitation data

Precipitation data with 0.25°×0.25° spatial resolution are available from the Indian Meteorological Department (IMD), which are taken as a reference dataset for the current study. The major advantage of this precipitation dataset is that it is compiled from 6,955 rain gauge stations (Pai et al. 2014) and has no missing value, and the data can be accessed from https://www.imdpune.gov.in/. The monthly precipitation data covering the duration from 1951 to 2014 at 348 grid locations that cover the full catchment were used to evaluate the CMIP6 climate models.

CMIP6 GCM datasets

The CMIP6 GCM datasets were obtained from the Earth System Grid Federation (ESGF) (https://esgf-node.llnl.gov/search/cmip6/) portal. A total of 21 GCMs were selected for the KRB, which had long-term projections under different SSP scenarios. In order to rank the performance of earlier studies, GCM outputs were spatially re-gridded to a common grid resolution of 2°×2° (Ahmed et al. 2019b; Noor et al. 2019), 2.5°×2.5° (Johnson & Sharma 2009; Eghdamirad et al. 2017; Raju et al. 2017; Jiang et al. 2019), and 3°×3° (Woldemeskel et al. 2014). Due to the fact that some researchers preferred to re-grid the GCM data into a resolution of the observed gridded dataset (Tiwari et al. 2014; Pour et al. 2018; Hassan et al. 2020; Homsi et al. 2020; Anil et al. 2021), the collected GCM outputs were spatially re-gridded to 0.25°×0.25°.
However, the GCM outputs were bias-corrected using the empirical quantile mapping method after re-gridding the raw GCM outputs to the spatial resolution of 0.25° × 0.25° to remove the inherent biases. The name, their developing centres, countries, and the resolutions of different GCMs used for the evaluation are listed in Table 1.

**METHODOLOGY**

The goal of the current study is to select the most suitable GCMs from the CMIP6 phase and to project the precipitation over the KRB using the MME. This is because precipitation is a key climate variable that can influence the characteristics of catchments like floods and droughts. Therefore, the selected GCMs can be applied for further analysis of climate studies over the basin. The procedure involving the selection of GCMs and spatio-temporal projections of the precipitation changes is outlined below:

1. Precipitation simulations of 21 GCMs were re-gridded to a reference dataset of IMD spatial resolution at 0.25° × 0.25° using the bilinear interpolation technique and bias-corrected using the quantile mapping method.
2. The performance of the 21 GCMs was evaluated against IMD as reference data by applying SU at 348 grid points covering the KRB, for the period of 1951–2014.
3. GCM rankings were estimated based on the aggregated score at all grids obtained using the pattern of ranking scores using MCDA over the KRB.
4. The top five GCMs were selected based on the aggregated score, and future precipitation simulations for different SSPs were bias-corrected using the same quantile method.
5. Development of the MME of the top five GCMs using the REA method to reduce the uncertainty in projections.
6. Evaluation of spatio-temporal changes of precipitation over the KRB during 2015–2040, 2041–2070, and 2071–2100.
7. The procedure used for the selection of GCMs using SU is given below.

**Selection of GCM ensemble**

Nowadays, the selection of relevant GCMs for climate studies is becoming a major challenge in projecting the climate. SU is an information entropy theoretical filter-based method that computes the similarity between the observed and the simulated time series in terms of mutual information (MI) entropies (Witten & Frank 2005). If \( P(O) \) and \( P(S) \) denote the probability density functions (PDF) of observed and simulated variables, the joint PDF will be \( P(A,B) \), and then the MI between \( A \) and \( B \) can be quantified as follows:

\[
\text{MI}(O; S) = \sum P(O, S) \log \frac{P(O, S)}{P(O) \cdot P(S)}
\]  

(1)
From the properties of MI, it can be written as differences in the sum of individual entropies and joint entropy:

\[
\text{MI}(O; S) = H(O) + H(S) - H(O, S) = \frac{H(O) + H(S)}{C_0}
\]

where \(H(O)\), \(H(S)\), and \(H(O, S)\) represent the entropies of \(O\), \(S\), and joint entropy of \(O\) and \(S\), respectively.

The SU can overcome the drawback of the MI which is biased to a higher number of values by normalising the MI with the entropies of individual variables, as given in Equation (3). Therefore, SU is an unbiased estimation of similarity between two time series with a range of 0 and 1. The advantage of SU is that it will provide a general measure of alliance among the observed and the model variables irrespective of underlying distribution shapes and various conditional dependences of data (Wu & Zhang 2004a, 2004b). The high dissimilarity of the time series of the data can be reduced by MI in SU, thereby ranking the GCMs based on the capability to replicate reference data time series; by this way, multiple conventional statistical metrics can be avoided. SU is also effective for feature selection in large datasets (Press et al. 1996; Wu & Zhang 2004b; Pour et al. 2018; Salman et al. 2018; Homsi et al. 2020):

\[
\text{SU} = 2 \times \frac{\text{MI}(O; S)}{H(O) + H(S)}
\]
If the SU between two variables is 0, it means there is no agreement between two random variables, and this occurs if and only if the two variables are statistically independent. If the SU value is 1, it means there is perfect agreement between two variables (Shreem et al. 2016).

GCMS ranking using MCDM

The aggregation of information from different sources using MCDM is effective for ranking and selecting the variables (Raju et al. 2017; Salman et al. 2019). At a single grid point, ranking of GCM can be assessed easily. When multiple grids are involved, it is difficult to select GCMs, because various results will be given by GCMs at different grid locations. MCDM techniques will be effectively employed to overcome this complexity and used for GCM ranking for the KRB. The following steps are involved in the MCDM technique:

(i) GCMs are ranked 1st, 2nd, 3rd, etc., at each grid point using a score obtained by using SU.
(ii) Specified weight \( w_i \) is given to each GCM in such a way that inverse weight is applied to the ranking of GCMs.
(iii) The frequency \( F_i \) of each GCM for each rank is calculated. Also, the total ranking weight (TRW) of each GCM is calculated using MCDM, which is given in the following equation:

\[
TRW = \sum_{i=1}^{5} F_i \times w_i
\]  

(iv) The GCM final ranking is determined by sorting the TRW from the highest to the lowest (descending) order. In the present study, GCM rankings only up to the 5th position in each grid are considered and the remaining are ignored because it is assumed that they cannot simulate the precipitation well at that grid point.

Quantile mapping bias correction

However, GCMs are extracted and re-gridded to the spatial resolution of the observed dataset of 0.25° x 0.25°, and there will be bias in the extreme events. Hence, this bias should be corrected before GCM performance assessment for better matching of simulations with the observed dataset. In the present study, a non-parametric quantile mapping (QM) method (Gudmundsson et al. 2012; Cannon et al. 2015; Cannon 2016) is employed to remove the bias in each month of GCMs. The QM technique adopts the cumulative distribution function (CDF) of simulated data to that of observed data. The transformed function for correcting the bias in simulated data is shown in the following equation:

\[
R_o = F_o^{-1}(F_m(R_m))
\]  

where \( R_m \) and \( R_o \) are the modelled and observed rainfall, \( F_m \) denotes the CDF of \( R_m \), and \( F_o^{-1} \) denotes the inverse CDF (quantile function) corresponding to \( R_o \). The empirical CDF of the simulated and observed data is estimated and is applied for simulated GCM data.

Ensemble projection of precipitation

With more GCMs, the projections will vary from one GCM to other because of structural differences (Sachindra et al. 2014). The MME mean will reduce the uncertainty involved in the individual GCM and can enhance the accuracy of projections (Tebaldi & Knutti 2007; Pour et al. 2018; Iqbal et al. 2020). MME approaches are categorised into two types: (i) simple ensemble average (SEM) and (ii) weighted ensemble method (WEM). Equal weightage is allotted to each GCM in SEM, whereas in WEM, the weights are allocated based on the historical association between observations and GCMs (Sanchez-Gomez et al. 2009). Even though both approaches have pro and cons, the WEM was found to be better than SEM (Sachindra et al. 2014; Crawford et al. 2019). The reliability ensemble averaging (REA) method is used to find the weights of the selected five GCMs and projections of different SSP scenarios. REA can be used to quantify the uncertainty of multiple GCMs prior to hydrological modelling, which reduces the vagueness of using projections of multimodels (Chandra et al. 2015). The REA method incorporates two reliability directives for assigning weights to GCMs, and these are ‘model performance’, where the capability of the model lies in capturing the observed data series, and ‘model convergence’, where the model simulation is converging to a specified forcing scenario. The procedure involved in the REA method to get the weighted GCM projection time series is as follows:
1. The RMSE is estimated by considering CDF deviations for the observed precipitation and all GCM simulations for the
control time period. The inverse of the RMSE values is treated as weight proportionality, and the weighted sum across
all the GCMs is equal to 1. The higher weights are assigned to the best-performing GCMs.
2. Weights that are obtained through criteria called model performance are treated as initial weights, which can be used for
performing respective GCM model convergences.
3. The weighted mean CDF (CDF\textsubscript{FM}) for a future scenario is estimated by multiplying the respective initial weight (W\textsubscript{i}) with
the CDF of the future simulation of \textit{i}th GCM (CDF\textsubscript{Fi}):
\[
CDF_{FM} = \sum_{i=1}^{n} W_i \times CDF_i
\]
4. Now, the RMSE will be computed between the CDF of individual GCM projections and the future weighted mean CDF.
5. Next, the mean of the RMSE inverse estimated using steps 1 and 4 is averaged; therefore, the new weights allocated to the
GCMs are proportionally used, such that the sum of new weights will become 1 for all GCMs.
6. Steps 2–5 can be repeated until the previous weight and new weight are the same so that it completes the criteria of model
convergence.

The REA method is applied at 348 grid points over the KRB for determining the variable precipitation, and the
final weights obtained are multiplied by the corresponding scenarios at a grid; therefore, the summation of weighted scenario values will be
considered as an ensemble average to that specified grid location.

The spatio-temporal variation of precipitation of the KRB was evaluated from the MME precipitation projections for the
near future 2015–2040, against the historical period 1989–2014, mid-future (2041–2070), and end future (2071–2100) against
1985–2014.

RESULTS
Selection of GCM ensemble
The concept SU is applied to rank the GCMs at 348 grid points over the entire KRB. The spatial distribution of the 1st-, 2nd-, and
3rd-ranked GCMs in the KRB is shown in Figure 3. Distinct colour ramps are used for representing the top-ranked
GCMs. From the figure of the 1st-ranked GCMs, it is revealed from the BSh climate zone that most of the grid points of
higher and medium elevations BCC-CSM2-MR, MIROC6, and INM-CM5-0 are the best-ranked GCMs, followed by IPSL-
CM6A-LR in lower elevation. From the Aw climate zone, it is found that IPSL-CM6A-LR and BCC-CSM2-MR are performing
well in lower elevations and higher elevations, respectively, and at the higher elevation zone of the southern part at some grid
points, GFDL-CM4 is performing well. It is found that BCC-CSM2-MR is the best GCM in the Am climate zone (consisting of
only 10 grid points). From the 2nd-ranking positions, it can be observed that in most of the grid points in the BSh climate
zone, the 1st-ranked GCMs, MIROC6, INM-CM5-0, and BCC-CSM2-MR are dominating. INM-CM5-0, MIROC6, and
MPI-ESM1-2-LR are performing well in the lower elevation of the Aw climate zone, and at higher elevations, MPI-ESM1-2-HR and MIROC6 are the best-performing GCMs. From 3rd-ranking positions, it can be observed that INM-CM5-0, MPI-
ESM1-2-HR, BCC-CSM2-MR, IPSL-CM6A-LR, and MIROC6 are the best GCMs, performing well at most of the grids in
different elevations of climate zones of the study area.

Finally, it is very clear that BCC-CSM2-MR, IPSL-CM6A-LR, MIROC6, INM-CM5-0, and MPI-ESM1-2-HR are the most
dominating GCMs in three ranking positions. These GCMs were chosen as the top five GCMs over the entire study area
after applying the MCDM technique as discussed in the methodology. Figure 4 shows the TRW using the MCDM technique
and ranks obtained from different GCMs for precipitation.

Multi-model ensemble generation
The MME average of bias-corrected precipitation at each grid was developed by using the REA method for the selected top
five GCMs, for estimating the future possible variations in precipitation over the KRB. The selection of GCMs for developing
the MME is clearly discussed for different geographical locations (Raju & Nagesh Kumar 2020). Some of the studies reported
that full uncertainty can be better addressed only by considering all GCMs (Venkataraman et al. 2016; Bannister et al. 2017;
Saeed & Athar 2018; Ongoma et al. 2019). Some studies suggest taking 50% of GCMs in developing the MME (Ahmed et al.
However, many of the previous studies suggest that omitting of GCMs is necessary for the preparation of the MME as they influence the skill of the MME by making it biased (Perkins et al. 2007). As there is no rule to select the number of GCMs, the top GCMs were selected to develop the MME (Tian et al. 2016; Wang et al. 2016; Khan et al. 2018; Latif et al. 2018; Ahmed et al. 2019a, 2019b; Noor et al. 2019; Shiru et al. 2019b; Homsi et al. 2020; Iqbal et al. 2020). As part of preliminary analysis, we have obtained the weights of all GCMs in a historical scenario. It was found that most of the weights of the top five GCMs account for more than 80% of uncertainty (the cumulative weight of the top five GCMs is greater than 0.8) in 236 out of 348 grids. This result made us to choose the top five GCMs for preparing the MME.

The ability of the REA method to develop the MME was correlated by the scatter plots of observed spatially averaged monthly rainfall, with individual and MME of GCMs for the period 1985–2014 shown in Figure 5. The scatter plots show that the individual GCMs and the MME average of GCMs are in satisfactory alignment with the 45° line, and compared with individual GCMs, the MME mean shows better alignment with the correlation coefficient and is found to be 0.6055, which means that the accuracy of the MME mean for precipitation projections can be improved by reducing the uncertainty associated in the individual GCMs.

As the correlation coefficient alone cannot decide the performance of the MME, the efficiency of the REA-based MME mean was evaluated against the observed precipitation during 1985–2014. Three statistical parameters, namely index of agreement (MD), percentage bias (Pbias), and normalised root mean square error (NRMSE), were computed over all the grid locations, and the obtained results were represented in boxplots shown in Figure 6. The box plot represents the range of interquartile and median of precipitation. It is revealed from the box plots that the median of the MME shows satisfactory improvement with the interquartile range compared with selected individual GCMs for all the statistics.
Changes in annual rainfall

The changes of annual precipitation (%) over the KRB for three future periods, namely near future (2015–2040), mid-future (2041–2070), and far future (2071–2100), were assessed using the MME against the observed precipitation of 1989–2014 for near future 1985–2014 for the rest of the period for four SSPs. The projected precipitation for three future periods at all grid locations of climate zones was averaged to find out the rainfall changes in the region. Significant changes occurred in the projected precipitation in future periods for all SSPs in most regions of the KRB. The future changes in precipitation and uncertainty levels were computed using the mean of the MME and the 95% confidence interval band, as shown in Figure 7.

It is found that the precipitation variation changes from period to period and zone to zone under all SSPs. More changes occur in the end period (2071–2100) under SSP5-8.5, followed by all other SSPs. The highest uncertainty levels are noticed in the Am climate zone, which covers only 10 grids in the entire study area under all SSP scenarios. The higher uncertainty level band is more than zero and the lower band is lower than zero for different SSPs. This indicates that there is an increase and decrease in precipitation of the KRB for different SSPs at a 95% level of confidence.

For a clear understanding of the possible annual precipitation changes, the spatial distribution plots were drawn, as shown in Figure 8. The changes in annual rainfall are in the range of $-36.72$ to $38.97\%$ during the near future (2015–2040), $-51.61$ to $45.24\%$ during the mid-future (2041–2070), and $-30.63$ to $83.05\%$ in the far future (2071–2100) for different SSPs. The map shows that the highest precipitation decreases and increases are in the ranges of $-23.97$ to $-36.72\%$ and $29.03$ to $83.05\%$, respectively, for three future periods under different SSPs. Significant changes occur under the SSP5-8.5 scenario. The maximum increase in the precipitation is found to be $83.05\%$, in the far future at the higher elevation part of the BSh and Aw climate zones, and a higher decrease of $-36.7\%$ is found to be in the near future at the higher elevation of the Aw and Am climate zones under SSP5-8.5, respectively. It can be observed from the figure that the near-future and mid-future precipitation projections show similar results under SSP 2-4.5, 3-7.0, and 5-8.5. In some of the grid points in the central part of the BSh zone and along the southeast regions of the Aw and BSh climate zones, the change in projections ranges from $-20$ to $0\%$ during the near and mid-futures for all SSPs, which indicates the probability of drought in those regions. But in SSP1-2.6 at most grids, the change in projection is in the range of $-20$ to $60\%$ during the near period. The major changes in the projections are found in the far future. There is a greater decrease ($-31$ to $0\%$) in most of the grid points for all climate zones,
indicating the expected droughts in the far future under the SSP1-2.6 scenario. In SSP2-4.5 and SSP3-7.0, the lower elevations of the BSh and Aw regions may experience drought in the future, but the remaining portions of the basin will experience an increasing trend in precipitation. Finally, it can be found from the figure that there will be an increasing trend in precipitation projections (from 0 to 83%) for the far future under the SSP5-8.5 scenario.

**Changes in seasonal rainfall**

The monthly precipitation projections for all grid locations of the climate zone were averaged for assessing the changes in the projection of seasonal precipitation, as given in Figure 9. From the figure, it can be clearly understood that the monsoon period (June–October) is more influential than the other months, and future precipitation is underestimating the observed
precipitation under all SSPs. As the monsoon period is dominating for the occurrence of precipitation (90%) over the study area, only future changes in the monsoon period are discussed. The spatial distribution of precipitation changes for the monsoon period under different SSPs is shown in Figure 10. There is a similar trend in the results that were found in monsoon precipitation projections compared with annual change. But the increasing percentage rate of precipitation projections is more than the decreasing rate under all SSPs for all future periods. The BSh climate zone is the most influencing zone in the monsoon period. It is found from the figure that most of the grids are experiencing increasing precipitation trends, and only in a few grid locations, the projections are reduced to less than zero in all climate zones. The projected precipitation
changes in the monsoon period are in the range of −37.68 to 64.56% during the near future, −36.72 to 70.73% during the mid-future, and −37.42 to 95.75% during the far future. The results show that the higher increase of 95.75% and decrease of 37.66% in projected rainfall occur at the higher elevation zones of BSh and Aw under SSP5-8.5 and SSP2-4.5, respectively. The major increases occur in the far future under SSP5-8.5 compared with the near and mid-futures and all other SSPs. SSP2-4.5 and SSP1-2.6 show more influence in the future projections as there is an increment of up to 80% in most of the grids, except in the far future. There is a similar increment of up to 80% for the near future under three future scenarios, except for SSP5-8.5.

DISCUSSIONS
The study over the KRB is most significant due to its semi-arid nature and vulnerability to climate change, owing to an uneven distribution of precipitation. The amount of precipitation has an imperative role in the availability of water in the KRB. Therefore, it is very important to assess the variation of precipitation due to changes in climate over the KRB. Generally, GCMs are developed to project climate variables at global scales, so they show huge uncertainty for climate simulations over various regions (Raju et al. 2017; Xu et al. 2019). In previous studies, researchers recommended that the selection of suitable GCMs can reduce the uncertainty in projections of climate change (Raju & Nagesh Kumar 2014). In the present study, GCMs were selected using SU, which has been found to be the most robust method for overcoming the disadvantage of using multiple conventional statistical performance matrices for selecting GCMs in recent years (Pour et al. 2018; Salman et al. 2018; Shiru et al. 2019).

The GCMs that are selected as the most suitable for this study can be compared with those in previous studies. Raju & Nagesh Kumar (2015) used the TOPSIS method for ranking GCMs all over India and in the KRB. From their results, it
can be found that they ranked MIROC3 and BCCR as the top-ranked GCMs in the KRB. Similar results were found in this study, as testified by the fact that GCMs belonging to the same family were in the top five. Babar et al. (2015) found that MIROC5 was the best GCM for annual precipitation projection in India. MIROC5 was found to be the best GCM to project precipitation in India, which has also been found in the list of top five GCMs in the present study. Sarthi et al. (2016) used conventional statistical metrics, skill scores, and Taylor diagrams, which found BCCCSM1.1(m) as the most preferable GCM among 34 GCMs for India in projecting precipitation. The same family group GCM, BCC-CSM2-MR, is the top GCM in the present study.

The projection of the MME shows that there is an uneven distribution of precipitation throughout the basin under four SSP scenarios for future slices. The results of MME mean projections can be compared with those of the previous studies. From Figures 9 and 10, the future projections revealed that there is a probability of water scarcity and drought in the future at some of the grid locations of the semi-arid BSh climate zone under four SSPs, except the SSP5-8.5 scenario for the far future. This is due to a reduction of precipitation, which agrees with the results of the previous study (Gosain et al. 2006). According to Kulkarni et al. (2014) who considered only one SRES scenario, the annual precipitation for the mid-future (2041–2070) follows an increasing trend, which is true for some grids in the present study. But for the SSP5-8.5 scenario, an increasing trend in the far period can be found, which agrees with that of past studies (Mishra & Lilhare 2016).

CONCLUSION

In this study, a multi-model ensemble of CMIP-6-based precipitation projections for different scenarios was generated to assess the variability of precipitation over the KRB. The ability of GCMs to reproduce the observed precipitation is ranked using the concept of SU BCC-CSM2-MR, IPSL-CM6A-LR, MIROC6, INM-CM5-0, and MPI-ESM1-2-HR, which were the most preferable GCMs for projecting the precipitation in the KRB. The REA method was used to develop the MME for the projection of precipitation. A weighted average ensemble of selected GCM precipitation simulation using the REA
method showed satisfactory performance in mimicking observed precipitation. This confirms the fidelity of the selected GCMs to project precipitation. Based on these results, the following are the conclusions made in the present study. The increases in annual projection are higher in the far future, except SSP1-2.6, compared with the near and mid-futures. The results revealed that there is an increase in annual precipitation in almost the entire study area (except 11 grid points) in the far future under the SSP5-8.5 scenario, which is true from previous study results (Mishra & Lilhare 2016). However, in the near future, the projections at almost 81% of grids in the study area show a negative trend under the SSP5-8.5 scenario. The declination in precipitation projections in the near future can be observed in the range of 56% (192 grid points) to 81% (283 grid points) in the KRB, especially in the BSh climate zone under different SSP scenarios. This result suggests the vulnerability of the study area to droughts in the near future in those locations due to the reduction in the precipitation projections, which was found to be true in previous studies (Gosain et al. 2006). The MME of the seasonal precipitation changes also follows an increasing trend in the far future in the entire KRB under all scenarios. SSP5-8.5 shows an increase in precipitation over most of the grids in the basin in the far future. In contrast to the annual precipitation trends projected by the MME, the seasonal precipitation increases in the near future, showing that the precipitation patterns will get intensified in the future over the KRB. Therefore, from this study, the selected GCMs can be used for further climate impact studies over the KRB. In light of this, this study is expected to assist policymakers in devising various water resource management strategies and planning applications over the KRB.

**DATA AVAILABILITY STATEMENT**

All relevant data are available from an online repository or repositories.
REFERENCES

Ahmadalipour, A., Rana, A., Moradkhani, H. & Sharma, A. 2017 Multi-criteria evaluation of CMIP5 GCMs for climate change impact analysis. *Theoretical and Applied Climatology* 128 (1–2), 71–87.

Ahmed, K., Shahid, S. & Nawaz, N. 2018 Impacts of climate variability and change on seasonal drought characteristics of Pakistan. *Atmospheric Research* 214, 364–374. https://doi.org/10.1016/j.atmosres.2018.08.020.

Ahmed, K., Sachindra, D. A., Shahid, S., Demirel, M. C. & Chung, E.-S. 2019a Selection of multi-model ensemble of general circulation models for the simulation of precipitation and maximum and minimum temperature based on spatial assessment metrics. *Hydrology and Earth System Sciences* 23 (11), 4803–4824.

Ahmed, K., Shahid, S., Sachindra, D. A., Nawaz, N. & Chung, E.-S. 2019b Fidelity assessment of general circulation model simulated precipitation and temperature over Pakistan using a feature selection method. *Journal of Hydrology* 573, 281–298. https://doi.org/10.1016/j.jhydrol.2019.03.052.

Ahmed, K., Sachindra, D. A., Shahid, S., Iqbal, Z., Nawaz, N. & Khan, N. 2020 Multi-model ensemble predictions of precipitation and temperature using machine learning algorithms. *Atmospheric Research* 236, 104806. https://doi.org/10.1016/j.atmosres.2019.104806.

Anandhi, A. & Nanjundiah, R. S. 2015 Performance evaluation of AR4 climate models in simulating daily precipitation over the Indian region using skill scores. *Theoretical and Applied Climatology* 119 (3), 551–566. https://doi.org/10.1007/s00704-013-1045-5.

Anil, S., Manikanta, V. & Pallakury, A. R. 2021 Unravelling the influence of subjectivity on ranking of CMIP6 based climate models: a case study. *International Journal of Climatology* https://doi.org/10.1002/joc.7164.

Babbar, Z. A., Zhi, X. F. & Fei, G. 2015 Precipitation assessment of Indian summer monsoon based on CMIP5 climate simulations. *Arabian Journal of Geosciences* 8 (7), 4379–4392. https://doi.org/10.1007/s12517-014-1518-4.

Bannister, D., Herzog, M., Graf, H. F., Scott Hosking, J. & Short, C. A. 2017 An assessment of recent and future temperature change over the Siachuan basin, China, using CMIP5 climate models. *Journal of Climate* 30 (17), 6701–6722. doi:10.1175/JCLI-D-16-0536.1.

Cameron, F. 2011 Guest editorial: climate change as a complex phenomenon and the problem of cultural governance. *Museum and Society* 9, 84–89.

Cannon, A. J. 2016 Multivariate bias correction of climate model output: matching marginal distributions and intervariable dependence structure. *Journal of Climate* 29 (19), 7045–7064. https://doi.org/10.1175/JCLI-D-15-0679.1.

Cannon, A. J., Sobie, S. R. & Murdock, T. Q. 2015 Bias correction of GCM precipitation by quantile mapping: how well do methods preserve changes in quantiles and extremes? *Journal of Climate* 28 (17), 6938–6959. https://doi.org/10.1175/JCLI-D-14-00754.1.

Chandra, R., Saha, U. & Mujumdar, P. P. 2015 Model and parameter uncertainty in IDF relationships under climate change. *advances in Water Resources* 79, 127–139. https://doi.org/10.1016/j.adwres.2015.02.011.

Chen, D. & Chen, H. W. 2013 Using the Köppen classification to quantify climate variation and change: an example for 1901–2010. *Environmental Development* 6, 69–79. https://doi.org/10.1016/j.envdev.2013.03.007.

Crawford, J., Venkataraman, K. & Booth, J. 2019 Developing climate model ensembles: a comparative case study. *Journal of Hydrology* 568, 160–173. https://doi.org/10.1016/j.jhydrol.2018.10.054.

Das, L., Dutta, M., Mezghani, A. & Benestad, R. E. 2018 Use of observed temperature statistics in ranking CMIP5 model performance over the Western Himalayan Region of India. *International Journal of Climatology* 38 (2), 554–570. https://doi.org/10.1002/joc.5193.

Eghdamirad, S., Johnson, F. & Sharma, A. 2017 How reliable are GCM simulations for different atmospheric variables? *Climatic Change* 145 (1–2), 237–248. https://doi.org/10.1007/s10584-017-2086-x.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J. & Taylor, K. E. 2016 Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development* 9 (5), 1957–1958. https://doi.org/10.5194/gmd-9-1937-2016.

Fu, G., Liu, Z., Charles, S. P., Xu, Z. & Yao, Z. 2015 A score-based method for assessing the performance of GCMs: a case study of southeastern Australia. *Journal of Geophysical Research: Atmospheres* 118, 4154–4167. https://doi.org/10.1002/jgrd.50269.

Gleckler, P. J., Taylor, K. E. & Doutriaux, C. 2008 Performance metrics for climate models. *Journal of Geophysical Research: Atmospheres* 113 (D6). https://doi.org/https://doi.org/10.1029/2007JD008972.

Gong, D. Y., Shi, P. J. & Wang, J. A. 2004 Daily precipitation changes in the semi-arid region over northern China. *Journal of Arid Environments* 59 (4), 771–784. https://doi.org/10.1016/j.jaridenv.2004.02.006.

Gosain, A. K., Rao, S. & Basuray, D. 2006 Climate change impact assessment on hydrology of Indian river basins. *Current Science* 90 (3), 346–353.

Gouda, K. C., Nahak, S. & Goswami, P. 2018 Evaluation of a GCM in seasonal forecasting of extreme rainfall events over continental India. *Weather and Climate Extremes* 21, 10–16. https://doi.org/j.wace.2018.05.001.

Gudmundsson, L., Bremnes, J. B., Haugen, J. E. & Engen-Skaugen, T. 2012 Technical note: downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods. *Hydrology and Earth System Sciences* 16 (9), 3383–3390. https://doi.org/10.5194/hess-16-3383-2012.

Hassan, I., Kalin, R. M., White, C. J. & Aladejana, J. A. 2020 Selection of CMIP5 GCM ensemble for the projection of Spatio-temporal changes in precipitation and temperature over the Niger Delta, Nigeria. *Water* 12 (2), 385.

Homsi, R., Shiru, M. S., Shahid, S., Ismail, T., Harun, S. B., Al-Ansari, N., Chau, K.-W. & Yaseen, Z. M. 2020 Precipitation projection using a CMIP5 GCM ensemble model: a regional investigation of Syria. *Engineering Applications of Computational Fluid Mechanics* 14 (1), 90–106. https://doi.org/10.1080/19942060.2019.1683076.
IPCC 2013 AR5 – Citations. CLIMATE CHANGE 2013 – The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. 3. https://doi.org/10.1017/CBO9781107415324.Summary.

Iqbal, Z., Shahid, S., Ahmed, K., Ismail, T., Khan, N., Virk, Z. T. & Johar, W. 2020 Evaluation of global climate models for precipitation projection in sub-Himalaya region of Pakistan. Atmospheric Research 245, 105061. https://doi.org/10.1016/j.atmosres.2020.105061.

Jia, K., Ruan, Y., Yang, Y. & Zhang, C. 2019 Assessing the performance of CMIP5 global climate models for simulating future precipitation change in the Tibetan Plateau. Water 11 (9), 1771.

Jiang, Z., Sharma, A. & Johnson, F. 2019 Assessing the sensitivity of hydro-climatological change detection methods to model uncertainty and bias. Advances in Water Resources 134, 103430. https://doi.org/10.1016/j.advwatres.2019.103430.

Johnson, F. & Sharma, A. 2009 Measurement of GCM skill in predicting variables relevant for hydroclimatological assessments. Journal of Climate 22 (16), 4373–4382. https://doi.org/10.1175/2009JCLI2681.1.

Kamworapan, S. & Surussavadee, C. 2019 Evaluation of CMIP5 global climate models for simulating climatological temperature and precipitation for Southeast Asia. Advances in Meteorology 2019, 1–18. https://doi.org/10.1155/2019/1067365.

Khan, N., Shahid, S., Ahmed, K., Ismail, T., Nawaz, N. & Son, M. 2018 Performance assessment of general circulation model in simulating daily precipitation and temperature using multiple gridded datasets. Water 10 (12), 1793.

Knutti, R., Abramowitz, G., Collins, M., Eyring, V., Gleckler, P. J., Hewitson, B. & Mearns, L. 2010 Good practice guidance paper on assessing and combining multi model climate projections. In: IPCC Expert Meeting on Assessing and Combining Multi Model Climate Projections. p. 15.

Knutti, R., Masson, D. & Gettelman, A. 2013 Climate model genealogy: generation CMIP5 and how we got there. Geophysical Research Letters 40 (6), 1194–1199. https://doi.org/10.1002/grl.50256.

Kottek, M., Grieser, J., Beck, C., Rudolf, B. & Rpefl, F. 2006 World Map of the Köppen-Geiger Climate Classification Updated. Kulkarni, B. D., Deshpande, N. R., Patwardhan, S. K. & Bansod, S. D. 2014 Assessing hydrological response to changing climate in the Krishna Basin of India. Journal of Earth Science & Climatic Change 05 (07). https://doi.org/10.4172/2157-7617.1000211.

Latif, M., Hannachi, A. & Syed, F. S. 2018 Analysis of rainfall trends over Indo-Pakistan summer monsoon and related dynamics based on CMIP5 climate model simulations. International Journal of Climatology 38, e577–e595. https://doi.org/10.1002/joc.5391.

Lutz, A. F., ter Maat, H. W., Biemans, H., Shrestha, A. B., Wester, P. & Immerzeel, W. W. 2016 Selecting representative climate models for climate change impact studies: an advanced envelope-based selection approach. International Journal of Climatology 36 (12), 3988–4005. https://doi.org/10.1002/joc.4608.

Maxino, C. C., McAvaney, B. J., Pitman, A. J. & Perkins, S. E. 2008 Ranking the AR4 climate models over the Murray-Darling Basin using simulated maximum temperature, minimum temperature and precipitation. International Journal of Climatology 28 (8), 1097–1112. https://doi.org/10.1002/joc.1612.

McSweeney, C. F., Jones, R. G., Lee, R. W. & Rowell, D. P. 2015 Selecting CMIP5 GCMs for downscaling over multiple regions. Climate Dynamics 44 (11–12), 3237–3260. https://doi.org/10.1007/s00382-014-2418-8.

Mehnsouan, M., Nicholls, Z., Lewis, J., Giddens, M., Vogel, E., Freund, M., Beyerle, U., Gessner, C., Nauels, A., Bauer, N., Canadell, J., Daniel, J., John, A., Krummel, P., Luderer, G., Meinshausen, N., Montzka, S., Rayner, P., Reimann, S., Wang, H. J. et al. 2019 The SSP greenhouse gas concentrations and their extensions to 2500. Geoscientific Model Development Discussions 1–77. https://doi.org/10.5194/gmdd-2019-222.

Mendlik, T. & Gobiet, A. 2016 Selecting climate simulations for impact studies based on multivariate patterns of climate change. Climatic Change 135 (3–4), 381–393. https://doi.org/10.1007/s10584-015-1582-0.

Min, S.-K. & Hense, A. 2006 A Bayesian approach to climate model evaluation and multi-model averaging with an application to global mean surface temperatures from IPCC AR4 coupled climate models. Geophysical Research Letters 33 (8). https://doi.org/10.1029/2006GL025779.

Mishra, V. & Lillhare, R. 2016 Hydrologic sensitivity of Indian sub-continental river basins to climate change. Global and Planetary Change 139, 78–96. https://doi.org/10.1016/j.gloplacha.2016.01.003.

Mohsenipour, M., Shahid, S., Chung, E.-s. & Wang, X.-j. 2018 Changing pattern of droughts during cropping seasons of Bangladesh. Water Resources Management 32 (5), 1555–1568. https://doi.org/10.1007/s11269-017-1940-9.

Murphy, J. M., Sexton, D. M. H., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M. & Stainforth, D. A. 2004 Quantification of modelling uncertainties in a large ensemble of climate change simulations. Nature 430 (7001), 768–772. https://doi.org/10.1038/nature02771.

Nashwan, M. S. & Shahid, S. 2020 A novel framework for selecting general circulation models based on the spatial patterns of climate. International Journal of Climatology 40 (10), 4422–4443. https://doi.org/10.1002/joc.6465.

Noor, M., Ismail, T., Shahid, S., Nashwan, M. S. & Ullah, S. 2019 Development of multi-model ensemble for projection of extreme rainfall events in Peninsular Malaysia. Hydrology Research 50 (6), 1772–1788. https://doi.org/10.2166/nh.2019.097.

O’Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtz, G., Knutti, R., Kriegler, E., Lamarque, J. F., Lowe, J., Meinsh, G. A., Moss, R., Riahi, K. & Sanderson, B. M. 2016 The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6. Geoscientific Model Development 9 (9), 3461–3482. https://doi.org/10.5194/gmd-9-3461-2016.

Ongoma, V., Chen, H. & Gao, C. 2019 Evaluation of CMIP5 twentieth century rainfall simulation over the equatorial East Africa. Theoretical and Applied Climatology 135 (3–4), 893–910. https://doi.org/10.1007/s00704-018-2392-x.

Pai, D. S., Sridhar, L., Rajeevran, M., Sreejith, O. P., Satthai, N. S. & Mukhopadhyay, B. 2014 Development of a new high spatial resolution (0.25 × 0.25) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. Mausam 65 (1), 1–18.
Parth Sarthi, P., Kumar, P. & Ghosh, S. 2016 Possible future rainfall over Gangetic Plains (GP), India, in multi-model simulations of CMIP3 and CMIP5. *Theoretical and Applied Climatology* 124 (3-4), 691–701. https://doi.org/10.1007/s00704-015-1447-5.

Perkins, S. E., Pitman, A. J., Holbrook, N. J. & McAneney, J. 2007 Evaluation of the AR4 climate models’ simulated daily maximum temperature, minimum temperature, and precipitation over Australia using probability density functions. *Journal of Climate* 20 (17), 4356–4376. https://doi.org/10.1175/JCLI4253.1.

Phillips, N. A. 1956 The general circulation of the atmosphere: a numerical experiment. *Quarterly Journal of the Royal Meteorological Society* 82 (352), 123–164. https://doi.org/10.1002/qj.49708235202.

Pour, S. H., Shahid, S., Chung, E. S. & Wang, X. J. 2018 Model output statistics downscaling using support vector machine for the projection of spatial and temporal changes in rainfall of Bangladesh. *Atmospheric Research* 213, 149–162. https://doi.org/10.1016/j.atmosres.2018.06.006.

Press, W. H., Teukolsky, S. A., Vetterling, W. T. & Flannery, B. P. 1996 *Numerical Recipes: The Art of Scientific Computing with IBM PC or Macintosh*. Cambridge University Press.

Rajeevan, M. & Nanjundiah, R. S. 2009 Coupled model simulations of twentieth century climate of the Indian summer monsoon. *Current Trends in Science: Platinum Jubilee Special* 537–567.

Raju, K. S. & Nagesh kumar, D. 2014 Ranking of global climate models for India using multicriterion analysis. *Climate Research* 60 (2), 103–117.

Raju, K. S. & Nagesh Kumar, D. 2015 Ranking general circulation models for India using TOPSIS. *Journal of Water and Climate Change* 6 (2), 288–299. https://doi.org/10.2166/wcc.2014.074.

Raju, K. S. & Nagesh Kumar, D. 2016 Selection of global climate models for India using cluster analysis. *Journal of Water and Climate Change* 7 (4), 764–774. https://doi.org/10.2166/wcc.2016.112.

Raju, K. S. & Nagesh Kumar, D. 2020 Review of approaches for selection and ensembling of GCMs. *Journal of Water and Climate Change* 11 (3), 577–599. https://doi.org/10.2166/wcc.2020.128.

Raju, K. S., Sonali, P. & Nagesh kumar, D. 2017 Ranking of CMIP5-based global climate models for India using compromise programming. In: *Theoretical and Applied Climatology*. pp 563–574. https://doi.org/10.1007/s00704-015-1721-6.

Rathinasamy, M., Khosa, R., Adamowski, J., Sudheer, C., Partheepan, G., Anand, J. & Narsimlu, B. 2014 Wavelet-based multiscale performance analysis: an approach to assess and improve hydrological models. *Water Resources Research* 50 (12), 9721–9737. https://doi.org/10.1002/2013WR014650.

Reichler, T. & Kim, J. 2008 How well do coupled models simulate today’s climate? *Bulletin of the American Meteorological Society* 89 (3), 303–311. https://doi.org/10.1175/BAMS-89-3-303.

Rashidievi, T. V., Nagesh Kumar, D., Mehrotra, R. & Sharma, A. 2018 Estimation of the climate impact and change on crop water balance using an ensemble of GCMs. *Journal of Hydrology* 556, 1192–1204. https://doi.org/10.1016/j.jhydrol.2017.02.016.

Ruan, Y., Yao, Z., Wang, R. & Liu, Z. 2018 Ranking of CMIP5 GCM skills in simulating observed precipitation over the Lower Mekong Basin, using an improved score-based method. *Water*, 10, 12. https://doi.org/10.3390/w10121868.

Sachindra, D. A., Huang, F., Barton, A. F. & Perera, B. J. C. 2014 Multi-model ensemble approach for statistically downscaling general circulation model outputs to precipitation. *Quarterly Journal of the Royal Meteorological Society* 140 (681), 1161–1178. https://doi.org/10.1002/qj.2205.

Saeed, F. & Athar, H. 2018 Assessment of simulated and projected climate change in Pakistan using IPCC AR4-based AOGCMs. *Theoretical and Applied Climatology* 134 (3-4), 967–980. https://doi.org/10.1007/s00704-017-2320-5.

Salman, S. A., Shahid, S., Ismail, T., Ahmed, K. & Wang, X.-J. 2018 Selection of climate models for projection of spatiotemporal changes in temperature of Iraq with uncertainties. *Atmospheric Research* 173–174, 509–522. https://doi.org/10.1016/j.atmosres.2018.07.008.

Salman, S. A., Shahid, S., Ismail, T., Al-Abadi, A. M., Wang, X. & Chung, E.-S. 2019 Selection of gridded precipitation data for Iraq using compromise programming. *Measurement* 132, 87–98.

Sanchez-Gomez, E., Somot, S. & Déqué, M. 2009 Ability of an ensemble of regional climate models to reproduce weather regimes over Europe-Atlantic during the period 1961–2000. *Climate Dynamics* 33 (5), 723–736. https://doi.org/10.1007/s00382-008-0502-7.

Sheffield, J. & Wood, E. F. 2008 Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. *Climate Dynamics* 31 (1), 79–105. https://doi.org/10.1007/s00382-007-0340-z.

Shiru, M. S., Shahid, S., Alias, N. & Chung, E. S. 2018 Trend analysis of droughts during crop growing seasons of Nigeria. *Sustainability (Switzerland)* 10 (3), 1–13. https://doi.org/10.3390/su10030871.

Shiru, M. S., Shahid, S., Chung, E. S., Alias, N. & Scherer, L. 2019 A MCDM-based framework for selection of general circulation models and projection of spatio-temporal rainfall changes: a case study of Nigeria. *Atmospheric Research* 225, 1–16. https://doi.org/10.1016/j.atmosres.2019.03.033.

Shiru, M. S., Shahid, S., Chung, E.-S., Alias, N. & Scherer, L. 2019a A MCDM-based framework for selection of general circulation models and projection of spatio-temporal rainfall changes: a case study of Nigeria. *Atmospheric Research* 225, 1–16. https://doi.org/10.1016/j.atmosres.2019.03.033.

Shreem, S. S., Abdullah, S. & Nazi, M. Z. A. 2016 Hybrid feature selection algorithm using symmetrical uncertainty and a harmony search algorithm. *International Journal of Systems Science* 47 (6), 1312–1329. https://doi.org/10.1080/00207721.2014.924600.

Shukla, J., DeSole, T., Fennessy, M., Kinter, J. & Paolino, D. 2006 Climate model fidelity and projections of climate change. *Geophysical Research Letters* 33 (7). https://doi.org/10.1029/2006GL025579.
Taylor, K. E. 2001 Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research: Atmospheres* **106** (D7), 7183–7192. https://doi.org/10.1029/2000JD900719.

Tebaldi, C. & Knutti, R. 2007 The use of the multi-model ensemble in probabilistic climate projections. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **365** (1857), 2053–2075. https://doi.org/10.1098/rsta.2007.2076.

Tian, Y., Xu, Y. P., Booij, M. J. & Cao, L. 2016 Impact assessment of multiple uncertainty sources on high flows under climate change. *Hydrology Research* **47** (1), 61–74. https://doi.org/10.2166/nh.2015.008.

Tiwari, P. R., Kar, S. C., Mohanty, U. C., Kumari, S., Sinha, P., Nair, A. & Dey, S. 2014 Skill of precipitation prediction with GCMs over north India during winter season. *International Journal of Climatology* **34** (12), 3440–3455.

Venkataraman, K., Tummuri, S., Medina, A. & Perry, J. 2016 21st century drought outlook for major climate divisions of Texas based on CMIP5 multimodel ensemble: implications for water resource management. *Journal of Hydrology* **534**, 300–316. https://doi.org/10.1016/j.jhydrol.2016.01.001.

Witten, I. H. & Frank, E. 2005 Credibility: evaluating what's been learned. In *Data Mining: Practical Machine Learning Tools and Techniques*.

Woldemeskel, F. M., Sharma, A., Sivakumar, B. & Mehrotra, R. 2014 A framework to quantify GCM uncertainties for use in impact assessment studies. *Journal of Hydrology* **519**, 1453–1465. https://doi.org/10.1016/j.jhydrol.2014.09.025.

Wu, Y. & Zhang, A. 2004a Feature selection for classifying high-dimensional numerical data. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2. https://doi.org/10.1109/cvpr.2004.1315171.

Wu, Y. & Zhang, A. 2004b Feature selection for classifying high-dimensional numerical data. In: *Proceedings of the 2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2004. CVPR 2004, 2, II–II*.

WWAP 2012 *World Water Assessment Programme: The United Nations World Water Development Report 4: Managing Water under Uncertainty and Risk*. UNESCO, Paris.

Xing, W. & Wang, B. 2017 Predictability and prediction of summer rainfall in the arid and semi-arid regions of China. *Climate Dynamics* **49** (1–2), 419–431. https://doi.org/10.1007/s00382-016-3351-9.

Xu, C. 1999 Climate change and hydrologic models: a review of existing gaps and recent research developments. *Water Resources Management* **13** (5), 369–382.

Xu, K., Xu, B., Ju, J., Wu, C., Dai, H. & Hu, B. X. 2019 Projection and uncertainty of precipitation extremes in the CMIP5 multimodel ensembles over nine major basins in China. *Atmospheric Research* **226**, 122–137. https://doi.org/10.1016/j.atmosres.2019.04.018.

Ye, D. Z. & Chen, P. Q. 1992 *Global Change in China: A Preliminary Study*. Meteorological Press, Beijing. (In Chinese).

Yokoi, S., Takayabu, Y. N., Nishii, K., Nakamura, H., Endo, H., Ichikawa, H., Inoue, T., Kimoto, M., Kosaka, Y., Miyasaka, T., Oshima, K., Sato, N., Tsuchima, Y. & Watanabe, M. 2011 Application of cluster analysis to climate model performance metrics. *Journal of Applied Meteorology and Climatology* **50** (8), 1666–1675. https://doi.org/10.1175/2011JAMC2643.1.

First received 29 September 2021; accepted in revised form 12 January 2022. Available online 10 February 2022