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Ranking of general circulation models for Surat City by using a hybrid approach

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ABSTRACT

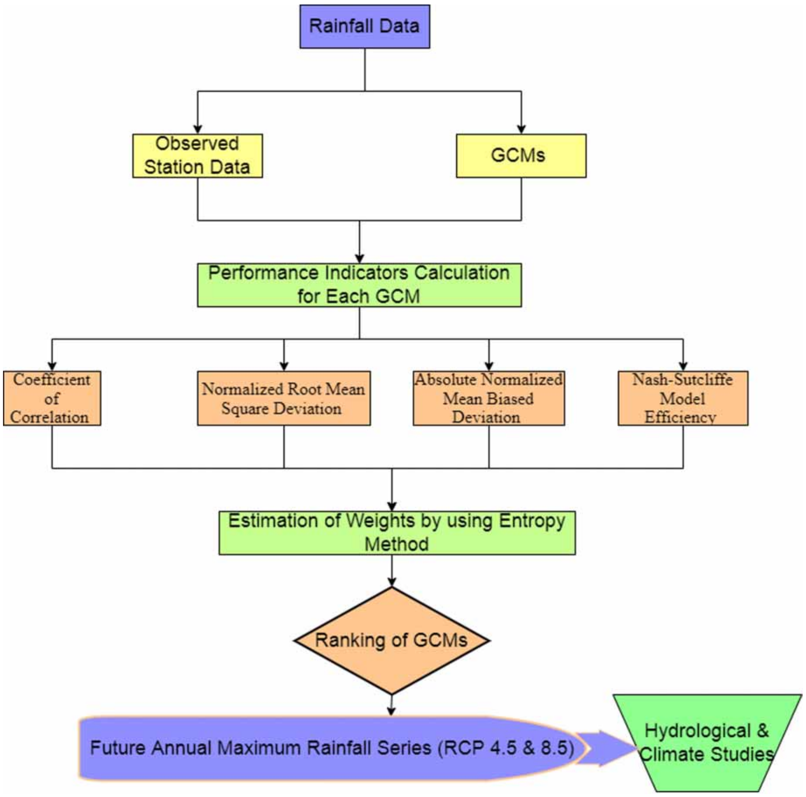
Climate change is expected to worsen flood risks by increasing precipitation in and around Surat City. Thus, to study the effect of climate change on Surat City's stormwater drainage network, ranking of general circulation models (GCMs) and generation of future annual maximum rainfall series is needed, which has not been performed by any reviewed study and is performed in the present study by using a hybrid approach. The 'hybrid approach' refers to the combination of past performance approach used for ranking of GCMs and envelope approach based on future climate projections. To rank 21 GCMs belonging to Coupled Model Intercomparison Project Phase 5, a past performance approach is employed by using four performance indicators, which are evaluated on the basis of Surat's simulated and observed monthly rainfall data corresponding to the period 1969–2005. By using an entropy method, weights are assigned to different performance indicators and then ranking of GCMs is performed by employing the TOPSIS method. The top five ranked GCMs are used to generate future annual maximum rainfall series by employing the Reliability Ensemble Averaging method corresponding to Representative Concentration Pathways scenarios 4.5 and 8.5. This study will be helpful for future climate and hydrologic studies to be performed in the study area.

Key words: climate change, general circulation model (GCM), hybrid approach, precipitation, reliability ensemble averaging (REA), TOPSIS

HIGHLIGHTS

- A hybrid approach is applied in the present study to generate future annual maximum rainfall series for Surat City corresponding to two climate change scenarios.
- The future annual maximum rainfall series generated in this study will be useful for various climatic and hydrologic studies to be performed in the study area.

GRAPHICAL ABSTRACT



INTRODUCTION

In hydrological designs for non-structural and structural flood control measures, especially in urban settings, quantifying precipitation extremes is essential. It is crucial to have reliable estimates of extreme rainfall intensities for efficient urban infrastructure design. Numerous examples abound in gross overestimation or underestimation of designs based on established techniques that lead to devastating consequences (Rupa *et al.* 2015). General circulation models (GCMs) are numerical illustrations of the land surface, ocean, and atmospheric processes developed based on physical-based empirical relationships and physical laws (Hassan *et al.* 2020). These can easily simulate/forecast different climatic parameters' present/future values. As a basis for evaluating impacts on hydrological systems, GCM outputs can be used. However, these outputs are significantly affected by uncertainties in development and application of GCMs, boundary condition, initial condition, emission scenarios, and model structure. This requires the selection of an appropriate GCM or set of GCMs (since sometimes no solitary model is found to be consistently supercilious) (Raju & Kumar 2015). The GCM ensemble subset selection needs a method tailored towards the efficiency of model performance or dependence in climate projection impact investigation. Usually, existing methods adopt two approaches. First is the 'past performance approach,' which relies on the ability of GCMs to imitate past climates but does not take future forecasts into account. Second is the 'envelope approach,' which selects GCMs but does not contemplate the potential of GCMs to replicate the past climate following their agreement with future climate projections. The 'hybrid approach' refers to combining the envelope approach with the past performance approach (Hassan *et al.* 2020). The hybrid approach takes past performance of GCMs and future climate projections of GCMs into account. Thus, the hybrid approach is used in the present study.

The NASA Ames Research Center and the Climate Analytics Group prepared the NEX-GDDP dataset by utilizing the NASA Earth Exchange. They distributed it through the NASA Center for Climate Simulation (NCCS) (https://developers.google.com/earth-engine/datasets/catalog/NASA_NEX-GDDP, accessed 5 May 2020; Thrasher *et al.* 2012). For various earth science groups, NEX-GDDP has considerable potential to become a widely used high-resolution dataset and a modern climate change standard (Bao & Wen 2017). Therefore, this dataset is used in the present study. India's coastal cities behave differently from the viewpoint of climate change, and one of them is Surat (Desai *et al.* 2015). Surat remains at high risk from flooding, and to address these risks, urban expansion has not been managed. Climate change is likely to worsen flood risks by incrementing precipitation in and around Surat City (Bhat *et al.* 2013). Thus, to study the effect of climate change on Surat City's stormwater drainage network, a selection of suitable ensemble of GCMs and generation future annual maximum rainfall series is necessary. Therefore, ranking of GCMs and generation of future annual maximum rainfall series is needed for Surat City.

Some recent studies have been carried out outside of India on the ranking of GCMs and/or the generation of future precipitation/rainfall time series by using suitable GCMs (Hassan *et al.* 2020; Khayyun *et al.* 2020; Rana *et al.* 2020; Salman *et al.* 2020). Various studies have also been carried out in India on the topic of Ranking of GCMs and/or generation of future precipitation/rainfall series by using suitable GCMs (Bal *et al.* 2016; Shashikanth & Sukumar 2017; Das *et al.* 2018; Hengade *et al.* 2018; Khan & Koch 2018; Thasneem *et al.* 2019). A few critical studies carried out in India are discussed below.

Rupa *et al.* (2015) considered 26 GCMs of Coupled Model Intercomparison Project Phase 5 (CMIP5) along with four Representative Concentration Pathways (RCP) scenarios for the case study of Bangalore City in India to study the climate change effects and to obain predicted IDF relationships.

Raju & Kumar (2015) used the skill score (SS) and performance indicator to rank 11 GCMs for the Upper Malaprabha catchment, two river basins, viz. Mahanadi and Krishna basins, and India corresponding to two variables, namely temperature and rate of precipitation. For the ranking of eleven GCMs, the TOPSIS technique was used.

Raju *et al.* (2016) assessed the minimum temperature (T_{min}) and maximum temperature (T_{max}) simulations for India, derived from 36 CMIP5 GCMs and corresponding data extending over 40 grid points. The correlation coefficient (CC), SS, and normalized root mean square error (NRMSE) were used for assessing GCMs. The entropy method was utilized to calculate the weights for the indicators mentioned above. However, equal weights were also considered as part of the sensitivity analysis tests. For the ranking of GCMs, the compromise programming (CP) technique was utilized.

From the reviewed literature the following research gaps are inferred: (i) none of the reviewed studies carried out ranking of GCMs for Surat City by using fine resolution dataset, (ii) none of the reviewed studies used a combination of ranking of GCMs (past performance) and reliability ensemble approach (REA) (envelope approach), i.e. hybrid approach for generation of future annual maximum rainfall series for Surat City to reduce the uncertainty in the projection of future annual maximum rainfall, (iii) none of the reviewed studies used the REA method for generation of future annual maximum rainfall series for Surat City.

All the aforesaid research gaps are addressed in the present study by: (i) ranking of GCMs for Surat City by using fine resolution dataset, (ii) combination of ranking of GCMs and REA method, i.e. hybrid approach for generation of future annual maximum rainfall series for Surat city to reduce uncertainty in the projection of future annual maximum rainfall and (iii) use of the REA approach for generation of future annual maximum rainfall series for Surat City (by using an ensemble of the top five ranked GCMs). Thus, in the current work, a hybrid approach is used to generate future annual maximum rainfall series for Surat City (having less uncertainty) based on RCP scenarios 4.5 and 8.5.

The methodology used in the present study consisted of firstly extracting CMIP5 GCMs data for the study area. Then, by applying performance criteria, performance indicators were evaluated for each GCM. The weight for each performance indicator was then determined by using the entropy approach. Each GCM was then ranked by applying these weights to each criterion by using TOPSIS algorithm. The top five GCMs were then used to generate future annual maximum rainfall series by using the REA method corresponding to RCP scenarios 4.5 and 8.5. Ranking of GCMs takes past performance into account while the use of REA for generation of future annual maximum rainfall series takes future climate projections of GCMs into account. Thus, a hybrid approach is used in the present study.

STUDY AREA

Surat city is situated in the Gujarat state covering an area of 326.515 km^2. It is located between longitudes 72°45′ to 72°54′ E and latitudes 21° 06′ to 21°15′ N. It is situated on the banks of the Tapi River with the coastline of the Arabian Sea on its west side (Joshi *et al.* 2012). According to the 2011 census, Surat city had a population of 4.5 million (Patel *et al.* 2017). The study area experiences hot summers with temperatures varying from 38 to 45 °C.

The winters are mild, but the month of January is specifically cold, with temperatures ranging from 10 to 15.5 °C. The mean annual rainfall is 1143 mm (Sharma *et al.* 2013). The study area is shown in Figure 1.

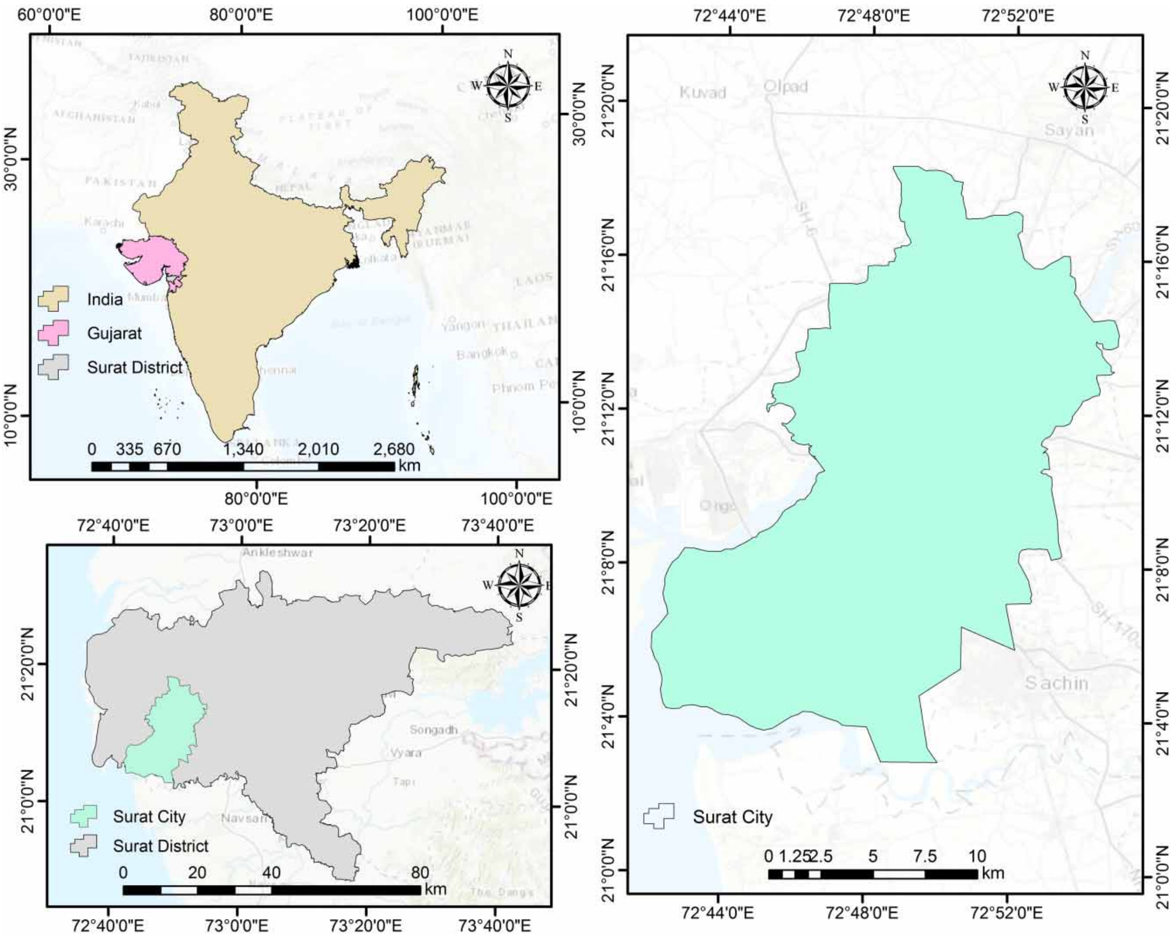


Figure 1 | Location of Surat city in the Gujarat state of India.

DATA COLLECTION

The NASA Earth Exchange-Global Daily Downscaled Projections (NEX-GDDP) dataset contains downscaled projections for RCPs 4.5 and 8.5, obtained from 21 models and scenarios corresponding to daily scenarios developed and disseminated under CMIP5. Each climate projection included a daily temporal scale data of minimum temperature, precipitation, and maximum temperature for the period 1950–2100. The spatial resolution of the dataset is 0.25° (nearly equal to 25×25 km) (NEX-GDDP India). The NEX-GDDP dataset is utilized in this study. India Meteorological Department (IMD), Pune, provided rainfall data of the Surat City's observation station corresponding to the period 1969–2005, which is utilized in the present study.

METHODOLOGY

Four indicators are used in the present study to evaluate the predictive ability of the GCMs, namely CC, normalized root mean square deviation (NRMSD), absolute normalized mean biased deviation (ANMBD), and Nash-Sutcliffe model efficiency (NSE). It is quite unlikely that the GCMs could be ranked based only on performance indicators. The relative ranking of the models is made possible via a method known as multicriteria decision-making (MCDM), which combines TOPSIS and entropy methods. The weights assigned to each of the GCM models' performance characteristics are evaluated by using the entropy method. These weights are then given as input to the TOPSIS method to rank the GCMs. In order to obtain a more accurate ranking by using the TOPSIS method, the weights of the criteria (i.e., performance indicators) are determined by using the entropy technique. The probability based Entropy-TOPSIS combination provided a tool for ranking of each GCM in the collection of GCMs according to their performance metrics. In this work, a hybrid technique is employed to generate future annual maximum rainfall series of Surat City, which included ranking of GCMs (past performance) and REA (envelope approach) of the top five ranked GCMs data to generate future annual maximum rainfall series for Surat City, which has not been performed by any reviewed study. Application of the hybrid approach in the generation of future annual maximum rainfall series for Surat City will reduce the uncertainty in the projected future annual maximum rainfall of Surat City. The suggested hybrid approach in the present study may be useful in a number of contexts, including investigations of hydrological, meteorological, and climatic models. The present work provides a precise and quantitative strategy (hybrid approach) for choosing appropriate GCM(s), thereby reducing the uncertainty in regional climate impact assessments. Figure 2 depicts the flow chart of the methodology (hybrid approach) used to rank GCMs and generate future annual maximum rainfall series.

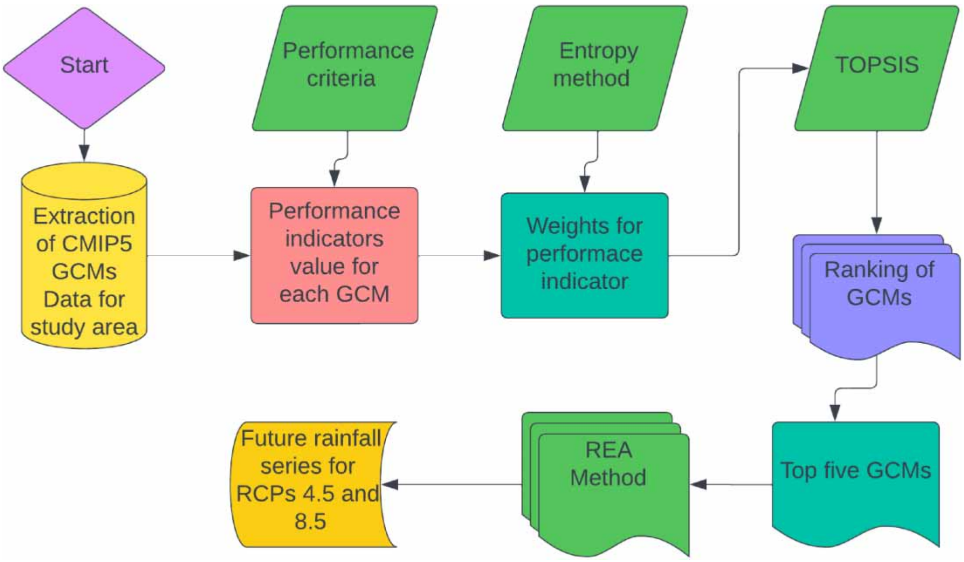


Figure 2 | Flow chart of the methodology.

Performance indicators

The CC, NRMSD, ANMBD and NSE are employed as statistical performance metrics in the present study.

For ANMBD and NRMSD indicators, a minimum value of 0 is ideal, while 1 is best for CC and NSE metrics (Sreelatha & Raj 2019). Equations (1)–(4) illustrate the expressions used to evaluate CC, NRMSD, ANMBD, and NSE (Sreelatha & Raj 2019):

$$CC = \frac{\sum_{i=1}^{x} (o_i - \bar{o})(s_i - \bar{s})}{(x-1)s_o s_s} \tag{1}$$

$$NRMSD = \frac{\sqrt{\left(\frac{1}{x}\right)\sum_{i=1}^{x} (o_i - s_i)^2}}{\bar{o}} \tag{2}$$

$$ANMBD = \left| \frac{\left(\frac{1}{x}\right)\sum_{i=1}^{x} (s_i - o_i)}{\bar{o}} \right| \tag{3}$$

$$NSE = 1 - \frac{\sum_{i=1}^{x} (o_i - s_i)^2}{\sum_{i=1}^{x} (o_i - \bar{o})^2} \tag{4}$$

where, s_i is the simulated value, and o_i is the historical value. $\bar{o}$ is the mean of historic values and $\bar{s}$ is the mean of simulated values. s_o is the standard deviation of historical values and s_s is the standard deviation of simulated values. The '*i*' indicates dataset tally, which can range between 1, 2……*x* (Sreelatha & Raj 2019).

Techniques used for ranking of GCMs

Entropy method

Regardless of the decision maker's point of view, the entropy approach is used to evaluate the weights of various indicators based on the specified payoff matrix. The entropy technique's analysis is based on the amount of available information (as measured by its entropy value) and its association with the importance of indicators (Raju *et al.* 2016). Below is an explanation of the entropy approach.

The entropy E_j for indicator j for the set of GCMs is determined by using the provided normalized payoff matrix, p_{ij} (where i represents the index for GCMs and j represents the index for indicators) (Raju & Kumar 2014). Equation (5) is used for computing E_j: is shown in Equation (5).

$$E_j = -\frac{1}{\ln(N)} \sum_{i=1}^{N} p_{ij} \ln(p_{ij}) \; for \; j = 1, \; \ldots, \; J \tag{5}$$

where $i = 1, \ldots, N$, N represents the number of GCMs, and j represents the number of indicators.

D_j is the degree of diversification of the information given by indicator j's results (Raju & Kumar 2014). The equation used for computing D_j is shown in Equation (6):

$$D_j = 1 - E_j \; for \; j = 1, \; \ldots, J \tag{6}$$

The normalized weights of indicators are calculated by using Equation (7):

$$w_j = \frac{D_j}{\sum_{j=1}^{j} D_j} \tag{7}$$

When the entropy value is large, the criteria vector contains high uncertainty, information diversification is low and criterion is less important (Raju & Kumar 2014).

TOPSIS

TOPSIS is based on the premise that the chosen option should have the shortest distance from the ideal solution and the greatest distance from the anti-ideal solution (Raju & Kumar 2015).

TOPSIS methodology is comprised of:

1. Calculation of the separation measure D_a^+ of every alternative a from the ideal solution, i.e., the Euclidean distance from the ideal value of each criterion and for all criteria (j is equal to 1, 2, 3, ….J), summing these for the particular alternative a, i.e. D_a^+ is calculated by using Equation (8) (Raju & Kumar 2015):

$$D_a^+ = \sqrt{\sum_{j=1}^{j} (w_j f_j(a) - w_j f_j *)^2} \tag{8}$$

where j is equal to 1, 2, …J; $f_j(a)$ = for criterion j, alternative a's normalized value.
f_j* = criterion's normalized ideal value j; w_j = assigned weight to the criterion j.

2. Calculation of separation measure D_a^- *for* every alternative a from the anti-ideal solution, i.e., Euclidean distance from the anti-ideal value of each criterion and for all criteria (j is equal to 1, 2, 3, ….J), summing

these for the particular alternative a, i.e. D_a^- is calculated by Equation (9) (Raju & Kumar 2015).

$$D_a^- = \sqrt{\sum_{j=1}^{j} (w_j f_j(a) - w_j f_j **)^2} \tag{9}$$

where f_j^{**} = Criterion j's normalized anti-ideal value

3. Calculation of relative closeness C_a for each alternative a by using Equation (10):

$$C_a = \frac{D_a^-}{(D_a^- + D_a^+)} \tag{10}$$

Based on the C_a values, alternatives are ranked. The higher the value of C_a, the superior is the alternative (Raju & Kumar 2015).

Reliability ensemble averaging (REA)

A quantitative approach called REA is used to assess the uncertainty in the GCMs' outputs and assign weights to various GCMs based on their bias relative to the observed data and the simulated modification convergence through GCMs. More reliable models are given higher weight, which minimizes the uncertainty related to multi-model analysis. Giorgi & Mearns (2002) initially developed REA, which was non-probabilistic. Later, Giorgi & Mearns (2003) proposed a probabilistic approach to this method (Das *et al.* 2018). Equations (11)–(15) illustrate the procedure used for REA:

$$R_i = R_{B,i} \times R_{D,i} \tag{11}$$

where for each ith model, $R_{B,i}$ is the bias reliability factor, $R_{D,i}$ is the convergence reliability factor and R_i is the REA (Riano 2013).

$$R_{B,i} = \frac{1}{S}\sum_{j=1}^{S} (P_{o,j} - P_{i,j})^2 \tag{12}$$

where $P_{o,j}$ is the observed precipitation maxima for the jth year, $P_{i,j}$ denotes the historical precipitation maxima output for the jth year and the ith model and S denotes the number of years in the series (Riano 2013):

$$R_{D,i} = \frac{1}{S}\sum_{j=1}^{S} (g_{i,j} - x_j)^2 \tag{13}$$

where g_{ij} is the precipitation forecast of the ith model's jth year, x_j is the REA-weighted average projection for the jth year for all models, and S is the number of years in the series (Riano 2013). The term x_j is defined in Equation (14):

$$x_j = \frac{\sum_{i=1}^{N} (R_i g_{i,j})}{\sum_{i=1}^{N} R_i} \tag{14}$$

where N is the number of models, $g_{i,j}$ denotes the projection of each *ith* model's *jth* year and R_i denotes the REA for *ith* model (Riano 2013):

$$w_i = \frac{R_i}{\sum_{i=1}^{N} R_i} \tag{15}$$

where w_i represents each model's weight in the ensemble, and R_i represents the REA (Thasneem *et al.* 2019).

RESULTS

Comparison of simulated and observed rainfall

A hybrid approach is used in the present study to generate future annual maximum rainfall series for Surat City corresponding to two climate change scenarios. A box plot is one way of representing past performance. In Figure 3, a box plot is shown for the annual rainfall of Surat city, which is prepared based on data obtained from 21 GCMs and station data of Surat City corresponding to the period 1969–2005. In Figure 4, a box plot is shown for the annual maximum rainfall of Surat City, which is prepared on the basis of data obtained from 21 GCMs and station data of Surat City corresponding to the period of 1969–2005. Simulated values are found to be reasonably close to the observed yearly rainfall. However, some models, such as the IP5L-CMSA-MR, underperformed in terms of annual maximum rainfall simulation. As a result, selecting the suitable set of GCMs for the study region based solely on the ranking is inappropriate. Therefore, the REA approach is also used in the present study to reduce future GCM data-related uncertainties. The uncertainty integrated into

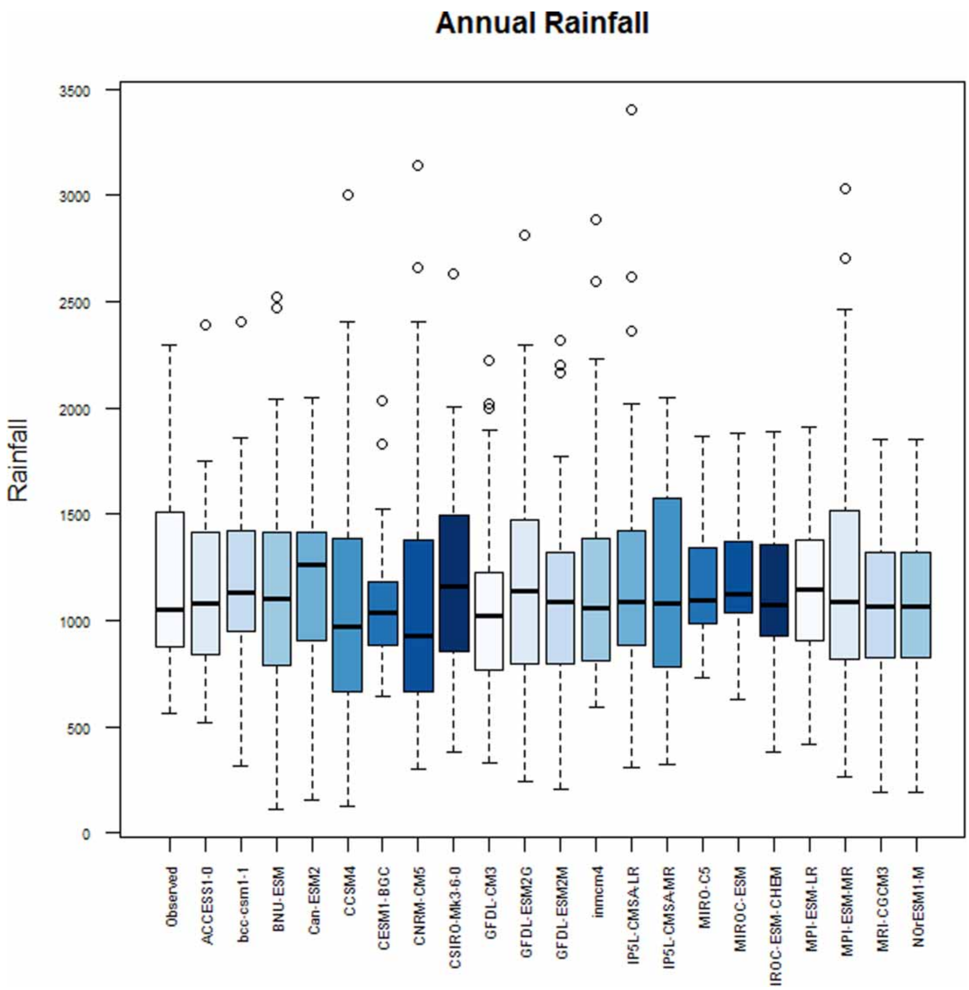


Figure 3 | Box plot of annual rainfall for Surat City corresponding to the period 1969–2005, prepared by using data of 21 GCMs and observed station data of Surat City.

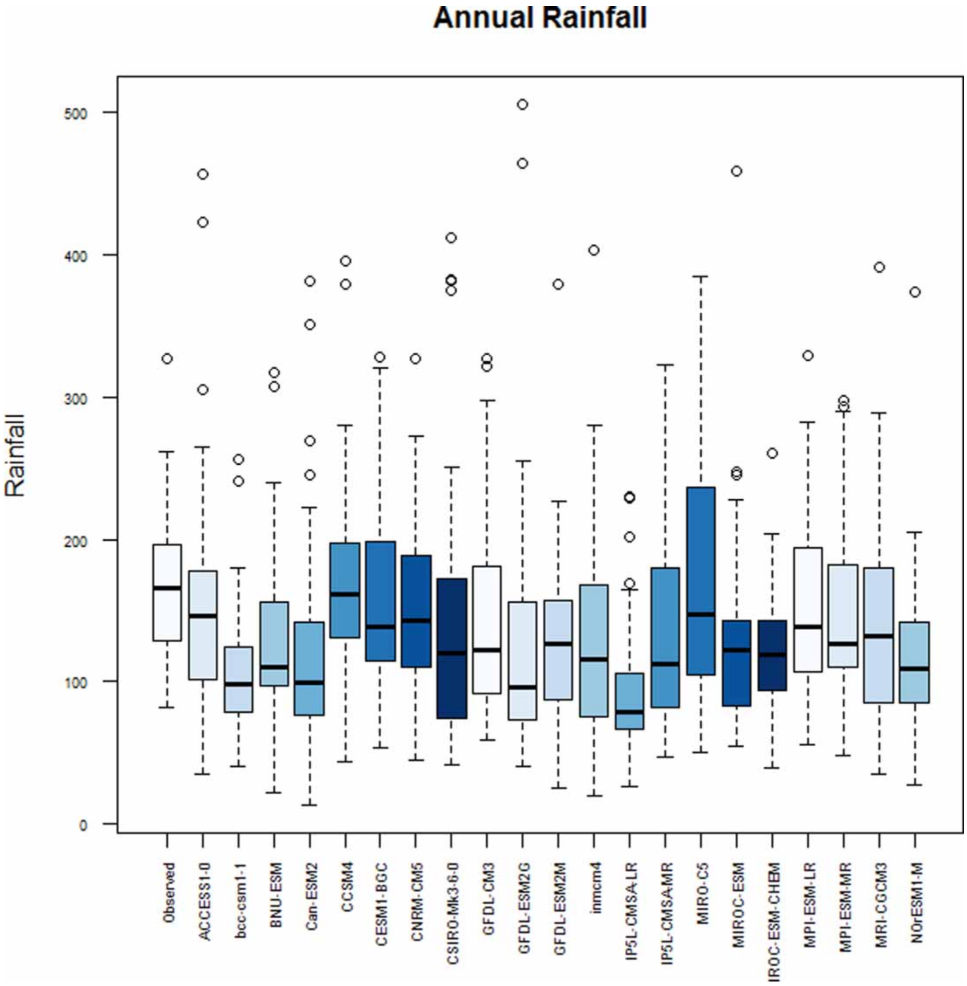


Figure 4 | Box plot of annual maximum rainfall for Surat City corresponding to the period 1969–2005, prepared by using data of 21 GCMs and observed station data of Surat City.

projected rainfall is reduced by using the REA approach, which is incorporated into projected rainfall because of the development and use of GCMs, initial condition, boundary condition, emission scenarios, and model structure. Thus, a hybrid approach is employed in the present study to forecast the future annual maximum rainfall series for Surat City corresponding to two climate change scenarios (RCP scenarios 4.5 and 8.5).

Assigning weights to the performance indicators

The entropy technique is used to assign weights to the performance indicators, with various weights being assigned to different performance indicators rather than equal weights. This, in turn, aids in the GCMs ranking. Table 1 shows the weights assigned by the entropy technique to four performance metrics, which are evaluated by comparing simulated and observed monthly rainfall data. Amongst the four performance indicators, NSE is found to have the highest weightage (0.79), which showed a significant impact on the ranking of GCMs. The combined contribution is found to be less than 21% for ANMBD, CC, and NRMSD.

Table 1 | Weights assigned by entropy method to different performance indicators

Performance Indicators	CC	NRMSD	ANMBD	NSE
Weight (%)	10.1784	5.7166	5.0040	79.1009

Assigning ranks to the GCMs

The TOPSIS technique takes the weights assigned by the entropy technique as input. Then ranks were assigned to each GCM according to TOPSIS metric values, and these metrics were determined by comparing simulated monthly rainfall data of 21 GCMs with observed monthly data of Surat City corresponding to the period 1969–2005. Table 2 displays the rankings given to 21 GCMs. TOPSIS metric values for the top five ranks are 0.986, 0.936, 0.910, 0.863, and 0.843, respectively. As a result, simulations of the top five GCMs are employed in the further analysis.

Table 2 | Values of performance indicators, TOPSIS metric values, and ranks of 21 GCMs

Sr. NO.	GCM Name	CC	NRMSD	ANMBD	NSE	TOPSIS METRIC	RANK
1	NorESM1-M	0.43	2.11	1.05	0.29	0.986	1
2	bcc-csm1-1	0.53	1.82	0.90	0.23	0.936	2
3	CNRM-CM5	0.50	1.95	0.98	0.21	0.910	3
4	MIROC-ESM	0.50	1.83	0.88	0.16	0.863	4
5	GFDL-CM3	0.44	2.03	0.94	0.14	0.843	5
6	IPSL-CMSA-LR	0.50	1.88	0.95	0.14	0.841	6
7	MIROC-ECM-CHEM	0.56	1.72	0.86	0.12	0.823	7
8	MIROC5	0.48	1.98	0.98	0.11	0.810	8
9	MPI-ESM-MR	0.59	1.66	0.84	0.08	0.781	9
10	GFDL-ESM2G	0.43	2.15	1.06	0.08	0.774	10
11	Can-ESM2	0.47	1.97	1.01	0.07	0.772	11
12	ACCESS1-0	0.57	1.96	1.02	0.06	0.754	12
13	CESM1-BGC	0.52	1.99	1.01	0.04	0.737	13
14	MPI-ESM-LR	0.52	1.83	0.88	0.02	0.715	14
15	inmcm4	0.39	2.27	1.16	−0.15	0.533	15
16	CCSM4	0.45	1.99	1.00	−0.18	0.506	16
17	BNU-ESM	0.47	1.99	1.03	−0.24	0.443	17
18	GFDL-ESM2M	0.45	2.07	1.03	−0.24	0.439	18
19	IPSL-CMSA-MR	0.45	1.99	0.99	−0.25	0.431	19
20	CSIRO-Mk3-′6-0	0.35	2.45	1.13	−0.90	0.165	20
21	MRI-CGCM3	0.43	2.19	1.01	−0.66	0.008	21

Assigning weights to the top five GCMs by using the REA method

The REA method was applied to assign weights to the top five GCMs corresponding to three time slices (2020–2049, 2050–2079, and 2070–2099) and RCPs 4.5 and 8.5 scenarios, respectively, and these weights are shown in Tables 3 and 4, respectively.

By using weights assigned to the top five GCMs, future annual maximum rainfall series (2023–2099) are generated for RCP 4.5 and RCP 8.5 by using the REA method, which are shown in Figure 5(a) and 5(b), respectively.

DISCUSSION ON RESULTS

In the present study, four statistical performance indicators, namely CC, NRMSD, ANMBD, and NSE, are employed, which are estimated based on observed monthly rainfall and GCM simulated monthly rainfall data for Surat city. By applying performance criteria, performance indicators are evaluated for each GCM. The weight for each performance indicator is then determined by using the entropy approach. GCMs are then ranked by applying these weights to each criterion by using the TOPSIS algorithm. The top five GCMs are then employed to generate future annual maximum rainfall series for Surat City by using the REA method corresponding to RCP scenarios 4.5 and 8.5. Thus, a combination of ranking of GCMs (past performance approach) and generation of future annual maximum rainfall series by using REA (envelope approach), i.e. the

Table 3 | Weights assigned to each of the selected top five GCMs for different time slices corresponding to the RCP 4.5 scenario

GCM/Year	NOrESM1-M	bcc-csm1-1	CNRM-CM5	MIROC-ESM	GFDL-CM3
2020–2049	0.1655	0.2194	0.2383	0.2074	0.1694
2050–2079	0.1713	0.2407	0.2176	0.2080	0.1623
2070–2099	0.1422	0.2406	0.2625	0.1886	0.1661

Table 4 | Weights assigned to each of the selected top five GCMs for different time slices corresponding to the RCP 8.5 scenario

GCM/Year	NOrESM1-M	bcc-csm1-1	CNRM-CM5	MIROC-ESM	GFDL-CM3
2020–2049	0.1179	0.1103	0.5224	0.1379	0.1116
2050–2079	0.2129	0.232	0.1991	0.1870	0.1691
2070–2099	0.1385	0.2426	0.2102	0.1826	0.2261

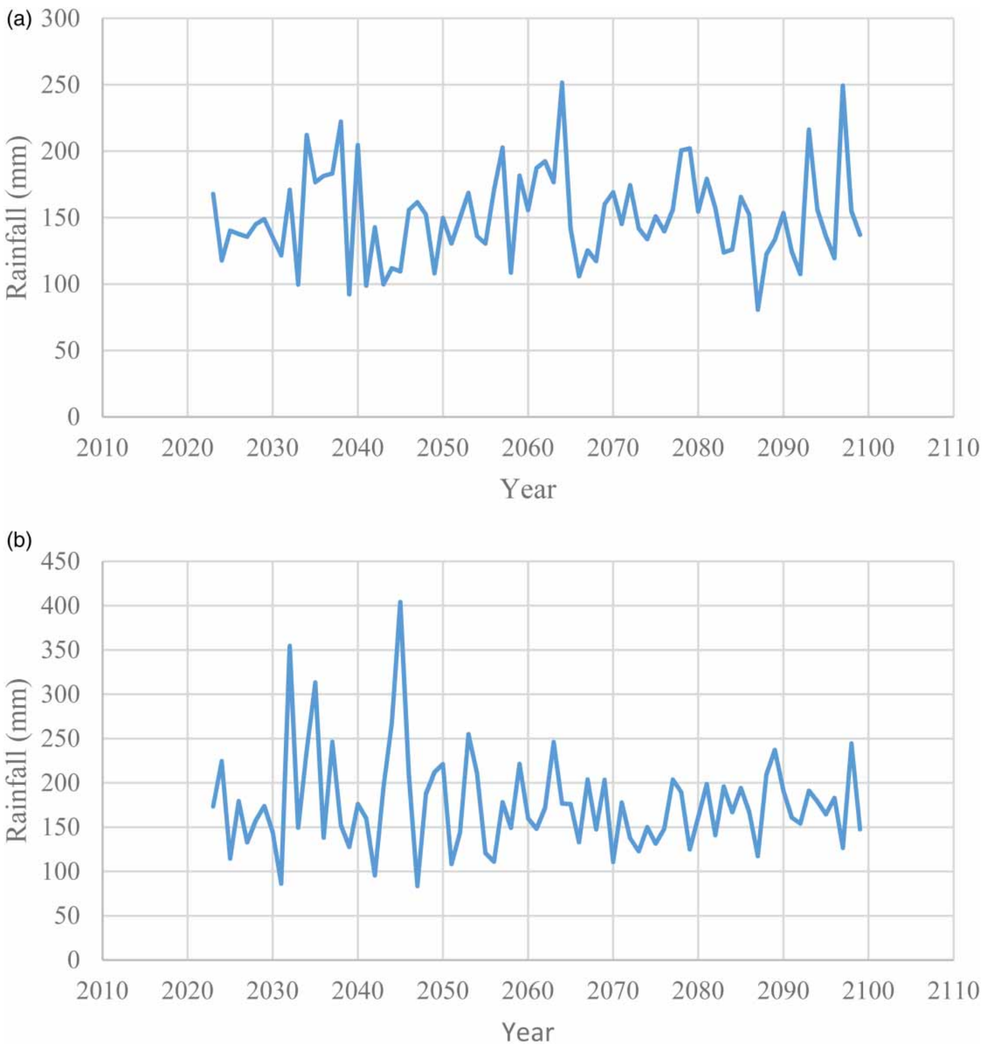


Figure 5 | (a) Time series of annual maximum rainfall for Surat City corresponding to the period 2023–2099 for the RCP 4.5 scenario (b) Time series of annual maximum rainfall for Surat City corresponding to the period 2023–2099 for the RCP 8.5 scenario.

hybrid approach is used in the present study to reduce uncertainty in the projected annual maximum rainfall for Surat City. The NSE is found to have a major influence on the GCM's ranking, which secured the highest weightage (0.79) amongst the four performance indicators. The top five ranked GCMs are NOrESM1-M, bcc-csm1–1, CNRM-CM5, MIROC-ESM, and GFDL-CM3. Future annual maximum rainfall series are then generated corresponding to two scenarios, RCP 4.5 and 8.5, by using an ensemble of the top five ranked GCMs through application of the REA technique. Based on the results of the projected annual maximum rainfall series, it can be found that for both the scenarios, i.e. RCP 4.5 and 8.5, the study area could experience more severe events in the future than in the past.

CONCLUSIONS

Climate change is likely to worsen flood risks by incrementing precipitation in and around Surat city. Thus, to study the effect of climate change on Surat City's stormwater drainage network, ranking of GCMs and generations of future annual maximum rainfall series are needed. A hybrid approach is used in the present study to generate future annual maximum rainfall series for Surat City corresponding to RCP 4.5 and 8.5 scenarios, which has not been performed by any reviewed study. The hybrid approach used in the present study consists of applying both a past performance approach through ranking of GCMs and an envelope approach through the REA technique for generation of future annual maximum rainfall series, which reduced the uncertainty in the projected future annual maximum rainfall of Surat City.

From the study, NSE is found to have a major impact on the ranking of GCMs. On the basis of projected annual maximum rainfall series, it can be found that, corresponding to RCP 4.5 and 8.5 scenarios, the study area could experience more severe events in the future than in the past. This can therefore increase the risk of flooding in the study area and affect the performance of the stormwater drainage network. The findings of the study can be used for flood risk analysis of Surat city, including stormwater drainage network assessment and urban flood assessment under climate change. The combined hydraulic and hydrological modelling can be used to evaluate the stormwater drainage system's capacity to handle floods under future climate change scenarios which can be generated by using annual maximum rainfall series derived in the present study for Surat City. The current study identified the best GCMs for Surat city and generated annual maximum rainfall series for the future by using an ensemble of top five ranked GCMs, which can be used in future hydrological or meteorological investigations.

DATA AVAILABILITY STATEMENT

Data cannot be made publicly available; readers should contact the corresponding author for details.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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