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Evaluation of the CORDEX regional climate models (RCMs) for simulating climate extremes in the Asian cities

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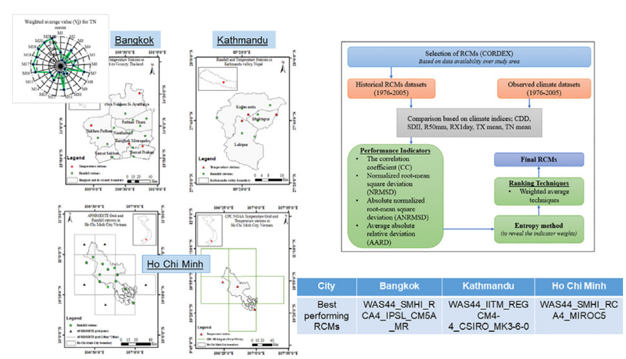
HIGHLIGHTS

- We evaluated 21 Regional Climate Models (RCMs) to simulate future climate extremes in Asian cities.
- Different RCMs performed differently to simulate future climate extremes.
- RCM WAS44_SMHI_RCA4_IPSL_CM5A_MR performs the best in Bangkok city.
- RCM WAS44_SMHI_RCA4_MIROC5 performs the best in Ho Chi Minh City.
- RCM WAS44_IITM_REGCM4-4_CSIRO_MK3-6-0 performs the best in Kathmandu.

GRAPHICAL ABSTRACT



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ABSTRACT

This study evaluates the ability of 21 Regional Climate Models (RCMs) from the Coordinated Regional Climate Downscaling Experiment (CORDEX) in simulating climate extremes in the fast growing Asian cities which are highly vulnerable to climate change. The three Asian cities have two different climate characteristics, namely Bangkok and its vicinity and Ho Chi Minh City in tropical climate region and Kathmandu in sub-tropical and temperate climate region. The RCMs were evaluated to simulate the six climate indices; Consecutive Dry Days (CDD), Simple Daily Intensity Index (SDII), Number of extremely heavy precipitation days (R50mm), Maximum 1-day precipitation amount (RX1day), Mean of daily maximum temperature (TX mean) and Mean of daily minimum temperature (TN mean). The performance indicators used were correlation coefficient, normalized root mean square deviation, absolute normalized root mean square deviation and average absolute relative deviation. The Entropy method was endorsed to acquire weights of these four indicators and weightage average techniques were used for ranking of 21 RCMs. The result demonstrated that the best model for one climate index is not the same best model for other climate indices. The 3 RCMs; WAS44_SMHI_RCA4_IPSL_CM5A_MR, WAS44_SMHI_RCA4_MIROC5, and WAS44_IITM_REGCM4-4_CSIRO_MK3-6-0 are the best performing RCMs for simulating future climate extremes in Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley, respectively. Therefore, they are recommended to use for climate change impact and adaptation studies in water resources management in the selected cities.

1. Introduction

The increasing water demand due to rapid population growth, urbanization, and industrialization along with global warming in the

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past few decades are making water a precious, but not always available asset (Beran et al., 2016; Gosling and Arnell, 2016). Climate change has become a serious threat to water resources. The world climate is changing at full tilt in recent years (Vijaya et al., 2012). As reported by Intergovernmental Panel on Climate Change (IPCC), the global temperature has risen by 0.3-0.6 °C and will pick up to rise between 1.4 and 5.8 °C by 2100 relative to 1900 (IPCC, 2013). Under these circumstances, the hydrological cycle experience significant impacts with furthermore change in precipitation and evaporation (Shrestha et al., 2020). The release of greenhouse gases like nitrous oxide, carbon dioxide and methane in the atmosphere by the virtue of several human exercise are the main factor that influence on climate change and will have impact in climate, such as changing the patterns and quantity of rainfall, and increasing the global temperature (IPCC, 2013). Climate change results in increase or decrease in the temperature and other climatic variable, which will affect the hydrologic cycle of a watershed by altering evaporation, precipitation, infiltration, recharge, etc.

Climate models are widely relied upon to investigate the response of the climate system to various forcing, for making climate predictions on seasonal to decadal time scales and for making projection of future climate over coming century and beyond (Flato et al., 2013). Future climate projections provided by general circulation models (GCMs) can serve as the basic input for climate change impact studies on water resources (Stefanidis et al., 2020). However, the coarser resolution of the GCMs output prohibits it from providing a precise description of extreme events with respect to the regional and local impact of climate variability and change (Giorgi et al., 2009). In addition, they cannot precisely simulate regional scale phenomena due to local conditions and peculiarities, such as the complex topography, lakes, and small islands (Zanis et al., 2015). Hence, they have to be downscaled in most cases to appropriate (higher) resolutions. Such a downscaling can be done either through applying statistical downscaling or through dynamic downscaling via use of Regional Climate models (RCMs) embedded in a larger GCMs (Khan and Koch, 2018; Xue et al., 2014; Rummukainen, 2010). RCMs are higher resolution nested regional climate modelling technique which consists of using initial condition, time dependent lateral meteorological conditions and surface boundary conditions derived from GCMs (Giorgi et al., 2001). To advance the distribution of atmosphere and diverse climatic variable at higher resolution, RCMs considered the land cover, topographical features within individual grids of GCMs. The resolution of RCMs ranges from 10 to 50 km (Mariotti et al., 2014). In addition, RCMs are useful for understanding the local climate in region that has complex topography (Endris, 2013) and they account for land surface heterogeneity (Gbobaniyi, 2014).

Many researchers from around the world have evaluated the climate models for future climate change projection studies using several techniques. Some of which are mentioned below: Raju and Kumar (2014) considered 5 performance indicators (R, NMRSD, ANMRSD, AARD and SS) to rank 11 GCMs for India for precipitation as a given climate variable. They used Entropy method to determine the weights of the indicators and an outranking based Multi Criteria Decision Making (MCDM) method, PROMETHEE-2. They found that the addition of more indicators, more climate variable, different GCMs and change in indicator weight changed the resulting ranking pattern. Fordham et al. (2011) used an ensemble of 20 GCMs over Australia by applying the range of skill and convergence metrics for precipitation according to their skill in reproducing 20-year observed patterns of regional and global climate of interest. They concluded that model ranking (match of simulate to observed conditions) differs according to skill metric used, as well as the climate variable and season considered. According to Perkins et al. (2007), skill score approach was applied to evaluate 14 RCMs peculiar to the ability of GCMs to resemble daily rainfall, daily minimum, and maximum temperature for 12 regions of Australia. The assessment was in regard to how properly individual GCMs could arrest the observed probability density function for each individual variable and each region. Ojha et al. (2014) employed an ensemble of 17 GCMs and ranked 10 variables by applying the Variable Convergence Score (VCS) method for the case of India. A higher consistency was indicated for pressure and temperature and lower consistency for precipitation and related variable across GCMs. The overall result indicated low convergence in atmospheric attributes for northeastern part of India. According to Wilcke and Barring (2016), clustering method was used to reduce ensembles of climate simulation and select the suitable subsets of climate models for impact modelling studies in Europe. This method includes identifying user requirements (variables), transforming variables into orthogonal and therewith uncorrelated variables, calculating the optimum number of clusters, using hierarchical clustering to group the simulation, and selecting the simulation closest to the group's mean as representative.

Regardless of the availability of large number of RCMs in CORDEX archive, and the ongoing enhancements in their process representation, issues of large uncertainties with regard to future climate are not yet avoidable. The inherent uncertainties, along with other factor such as time limitations, human resource availability, or computational constraints make it imperative to sort out the most appropriate set of RCMs for the assessment of climate change impacts in the region (Khan and Koch, 2018). Therefore, the evaluation of RCMs is very necessary prior to their use in impact assessment study (Anagnostopoulos et al., 2010; Koutsoyiannis et al., 2007). The main objective of this study is to evaluate the RCMs for simulating climate extreme in the Asian cities namely Bangkok and its vicinity, Ho Chi Minh City, and Kathmandu valley. The specific objectives are, (a) to evaluate the skills of climate models in simulating the past climate using performance indicators, (b) to reveal weightage of performance indicators using entropy method and, (c) to select the best performing RCMs based on ranking techniques. The main hypothesis of this research is that the climate models with a higher ability in reproducing historical climate yield better performance in the evaluation of future climate trend.

2. Data and methodology

2.1. Description of study area

The study area consists of fast growing three Asian cities; Bangkok, Ho Chi Minh City, and Kathmandu Valley (Fig. 1). Bangkok and its vicinity, Thailand, consist of 7 provinces: Bangkok, Nonthaburi, Pathum Thani, Nakhon Pathom, Samut Sakhon, Samut Prakan and Phra Nakhon Si Ayutthaya. The city and its surrounding province are located along the bank of the Chao Phraya river, Noi river, Pasak river, Mae Klong river, Prachin river and Tha Chin river. Bangkok lies in the humid tropics and is hot throughout the year with a tropical wet-and-dry climate, which is under the influence of the South Asian monsoon system. The average temperature is 30 °C and average rainfall is 1500 mm/yr. The total population of 11.3 million and population density of 300-3600 persons/km^2 is already recorded in the study area.

Ho Chi Minh City (HCMC) is the largest city in Vietnam located in the southeast region 1760 km south of Hanoi. The city covers an area of 2095 km^2 and is home to over 7.95 million people (in 2014), accounting for approximately 0.6% of total area and 8.79% of the total population of Vietnam. It is the most important economic center, contributing 20% of the country's GDP. The average elevation of the entire city ranges from 0.5 to 1.0 masl. The climate is tropical, specifically tropical wet and dry, with an average humidity of 75% and an average temperature of 27 °C. It receives an average annual rainfall of 1946 mm, of which 1130 mm is lost in evaporation.

Kathmandu, the capital city of Nepal located in central Nepal, covering almost 656 km^2 is the largest metropolitan city in Nepal. According to the 2011 census, it is the home of almost 2.5 million people with an average population density of 29 person/km^2 (including the urban and rural area of Kathmandu valley). Kathmandu valley falls under warm temperate zone have an elevation range of 1205 –2713 masl

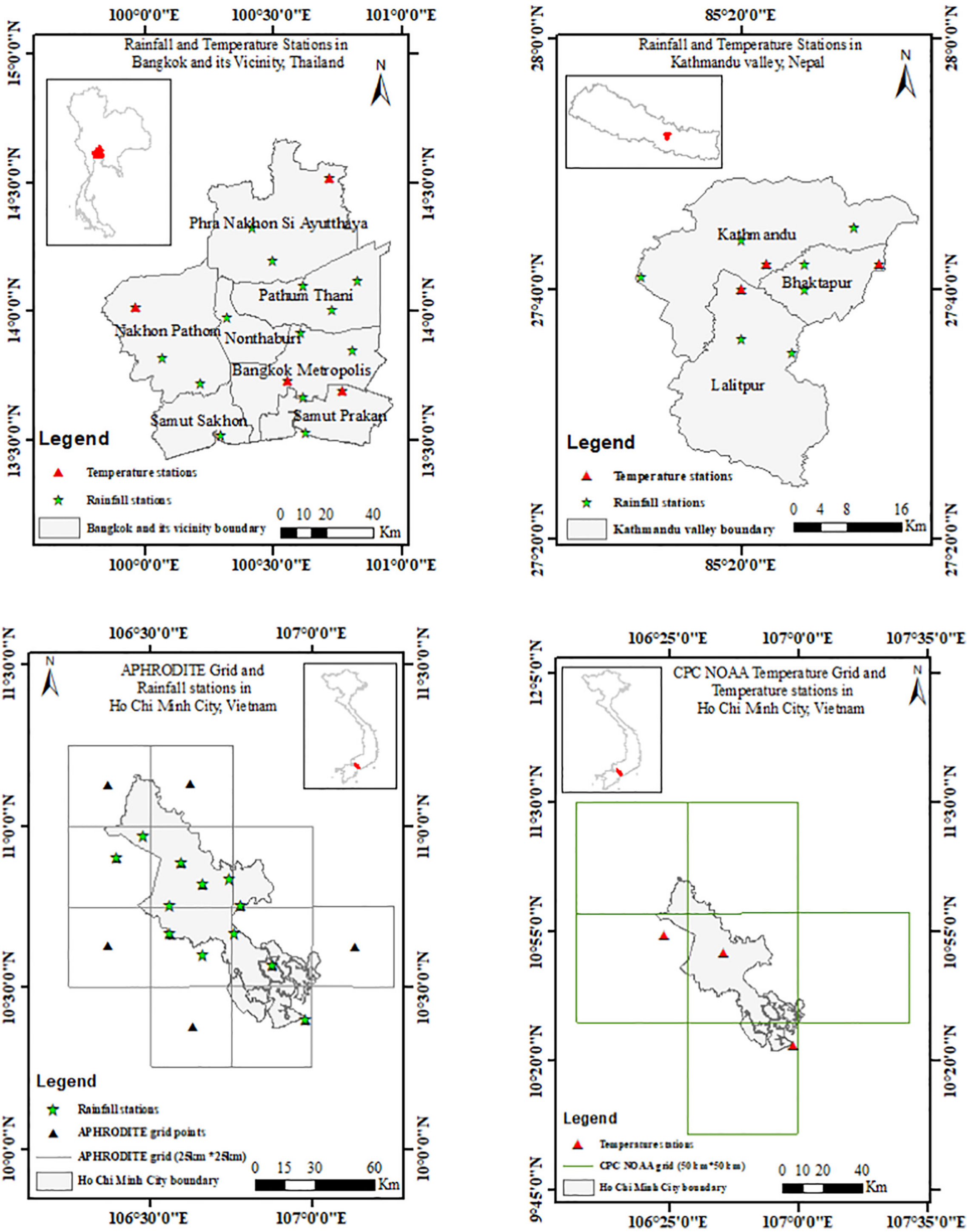

Fig. 1. Study area map of Bangkok and its vicinity, Kathmandu valley showing meteorological stations and Ho Chi Minh city with APHRODITE (Asian Precipitation - Highly-Resolved Observational Data Integration Towards Evaluation) grid and CPC NOAA (Climate Prediction Center- National Oceanic and Atmospheric Administration) temperature grid and meteorological stations, respectively.

with significance difference in summer (28-30 °C) and winter (10 °C) average temperature. It has an average rainfall of 1455 mm/yr, 65% of which falls during the period of June to August.

2.2. Data

For Bangkok and its vicinity, Thailand, observed rainfall data (1976–2005) for 17 rainfall station and temperature data (1976–2005) for 4 temperature station was collected from the Thai Meteorological Department (TMD), Thailand. Likewise, for Kathmandu valley, Nepal, observed rainfall data (1976-2005) for 10 rainfall station and temperature data (1976–2005) for 3 temperature station was collected from the Department of Hydrology and Meteorology (DHM), Nepal. Because of the inaccessibility of the observed rainfall and temperature data in Ho Chi Minh city, Vietnam, gridded precipitation data (APHRODITE) and gridded temperature data (CPC NOAA) were used. In this study, simulation of 21 RCMs (M1 to M21) from Coordinated Regional Climate Downscaling Experiment (CORDEX) were extracted. RCMs were selected based on their data availability over the study region (Table 1). The selected RCMs were downloaded from the CORDEX data portal (https://esgf-data.dkrz.de/search/cordex-dkrz/) and were further evaluated. All three Asian cities in this study refers to the region containing the city and surrounding areas. The simulation performed for this study were executed by three RCMs: RegCM4-4, RCA4 and CCAM which offers different land surface scheme such as Community Land Model (CLM 3.5) (Oleson et al., 2008), Tile approach (Samuelsson et al., 2006) and Soil canopy scheme (Kowalczyk et al., 1994) respectively. All these land surface scheme includes parameterizations of the urban canopy. The detail model configuration is shown in supplementary Table 11.

2.3. Methodology

The overall methodological framework adopted in this study is depicted in Fig. 2. In this study, twenty one RCMs with gridded resolution of 0.44° × 0.44° from the CORDEX data portal were accessed for six climate indices; Consecutive Dry Days (CDD), Simple Daily Intensity Index (SDII), Number of extremely heavy precipitation days (R50mm), Maximum 1-day precipitation amount (RX1day), Mean of daily maximum temperature (TX mean) and Mean of daily minimum temperature

Table 1
Data used in the study with their corresponding sources.

Data type	Frequency/time	Unit/Format	Resolution	Source		
				Bangkok	HCMC	Kathmandu
Data required for evaluation of RCMs						
Observed Rainfall	Daily/1976–2005	Mm	–	TMD	DWRPIS	DHM
Observed maximum and minimum temperature	Daily/1976–2005	°C	–	TMD	DWRPIS	DHM
RCMs data	Daily/1976–2005	Mm	–	CORDEX data portal (https://esgf-data.dkrz.de/search/cordex-dkrz/)		
APHRODITE data	Daily/1976–2005	Mm	–	Research Institute for Humanity and Nature (http://www.chikyu.ac.jp)		
NOAA climate data sets	Daily/1976–2005	°C	–	NOAA's National Centers for Environmental Information (NCEI) (https://www.ncdc.noaa.gov/cdo-web/)		

RCMs, their domain, driving model and driving model institute

Model Serial	Domain	Model	Driving Model	Driving Model Institute
M1	South Asia	RegCM4-4	CCCma-CanESm2	Canadian Centre for Climate Modelling and Analysis, Canada
M2	South Asia	RegCM4-4	CERFACS-CNRM-CM5	Center National de Recherches Meteorologiques and Center Europeen de Recherche et Formation Avancees en Calcul Scientifique, France
M3	South Asia	RegCM4-4	CSIRO-MK3-6-0	Queensland Climate Change Center of Excellence and Commonwealth Scientific and Industrial Research Organization, Australia
M4	South Asia	RegCM4-4	GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA
M5	South Asia	RegCM4-4	IPSL-CM5A-LR	Institut Pierre Simon Laplace, France
M6	South Asia	RegCM4-4	MPI-ESM-MR	Helmholtz-Zentrum Geesthacht, Climate Service Center, Max Plank Institute for Meteorology
M7	South Asia	RCA4	CCCma-CanESM2	Canadian Centre for Climate Modelling and Analysis, Canada
M8	South Asia	RCA4	CNRM-CM5	Center National de Recherches Meteorologiques and Center Europeen de Recherche et Formation Avancees en Calcul Scientifique, France
M9	South Asia	RCA4	CSIRO-MK3	Queensland Climate Change Center of Excellence and Commonwealth Scientific and Industrial Research Organization, Australia
M10	South Asia	RCA4	ICHE-EC-EARTH	A European Community Earth-System Model
M11	South Asia	RCA4	IPSL-CM5A-LR	Institut Pierre Simon Laplace, France
M12	South Asia	RCA4	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine Earth Science and Technology.
M13	South Asia	RCA4	MPI-ESM-LR	Helmholtz-Zentrum Geesthacht, Climate Service Center, Max Plank Institute for Meteorology
M14	South Asia	RCA4	NCC-NorESM1-M	Norwegian Climate Center
M15	South Asia	RCA4	NOAA-GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory, USA
M16	South Asia	CSIRO-CCAM	ACCESS 1.0	Collaboration for Australia Weather and Climate Research, Australian Government
M17	South Asia	CSIRO-CCAM	CCSM4	US National Center for Atmospheric Research
M18	South Asia	CSIRO-CCAM	CNRM-CM5	Center National de Recherches Meteorologiques and Center Europeen de Recherche et Formation Avancees en Calcul Scientifique, France
M19	South Asia	CSIRO-CCAM	GFDL-CM3	NOAA Geophysical Fluid Dynamics Laboratory, USA
M20	South Asia	CSIRO-CCAM	MPI-ESM-LR	Helmholtz-Zentrum Geesthacht, Climate Service Center, Max Plank Institute for Meteorology
M21	South Asia	CSIRO-CCAM	NORESM-1 M	Norwegian Climate Center

Note: TMD: Thai Meteorological Department, DWRPIS: Department of Water Resource Planning in South of Vietnam, DHM: Department of Hydrology and Meteorology.

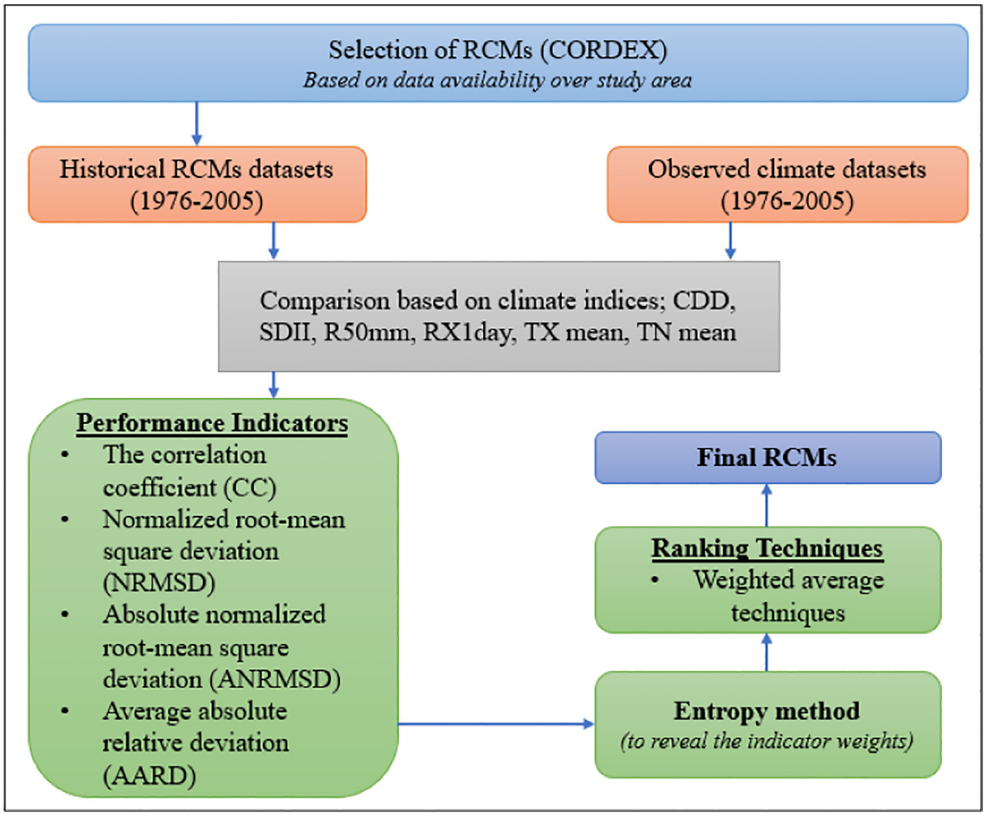

Fig. 2. Overall methodological framework for evaluation of RCMs in selected Asian cities. (Note: RCMs: Regional Climate Models, CORDEX: Coordinated Regional Climate Downscaling Experiment, CDD: Consecutive Dry Days, SDII: Simple Daily Intensity Index, R50mm: Number of extremely heavy precipitation days, RX1day: Maximum 1-day precipitation amount, TX mean: Mean of maximum temperature, TN mean: Mean of minimum temperature).

(TN mean) using four performance indicators. The performance indicators used were correlation coefficient, normalized root mean square deviation, absolute normalized root mean square deviation and average absolute relative deviation. The Entropy method was endorsed to acquire weights of these 4 indicators and weightage average techniques was used for ranking of 21 RCM's in all three Asian cities.

2.4. Climate indices

Six climate indices; Consecutive Dry Days (CDD), Simple Daily Intensity Index (SDII), Number of extremely heavy precipitation days (R50mm), Maximum 1-day precipitation amount (RX1day), Mean of daily maximum temperature (TX mean) and Mean of daily minimum temperature (TN mean) were used to compare the observed climate datasets (1976–2005) with the historical RCMs datasets (1976–2005) (Table 2). To keep the work manageable, we only analyzed for six indices in total, four indices to represent change in precipitation and two indices to represent change in temperature. The climate indices are selected from the set of indices described by the Joint CCI/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) (Zhang et al., 2011) and Southeast Asia Regional Climate Downscaling Project (SEACLID) (ARCP2015-04CMY-Tangang).

2.5. Performance indicators

A performance indicator or metric is a quantifiable measure for any RCM to determine how well it simulates the observed data. Four performance indicators; correlation coefficient, normalized root mean square deviation, absolute normalized root mean square deviation and average absolute relative deviation were selected to evaluate the RCMs (Raju and Kumar, 2014).

2.5.1. The correlation coefficient (CC)

The correlation coefficient provides information on the strength of relationship between the observed and the simulated value. The value of correlation coefficient ranges from -1 to +1 such that -1 < CC < +1. A CC value close to 1 indicates perfect positive fit or good model performance whereas, a CC closer to 0 means there is no linear correlation or weak correlation. The correlation coefficient (CC) is computed as:

$$CC = \frac{\sum_{i=1}^{T}(x_i - \bar{x})(y_i - \bar{y})}{(T-1)\sigma_{obs}\sigma_{sim}} \quad (1)$$

Table 2
Description of ETCCDI (Expert Team on Climate Change and Detection precipitation indices) indices used in this study.

ID	Indicator Name	Indicator Definition	Units
CDD	Consecutive dry days	Maximum number of consecutive days when precipitation <1 mm in a year.	days
R50mm	Number of extremely heavy precipitation days	Annual count when precipitation ≥50 mm	days
RX1day	Maximum 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
SDII	Simple daily intensity index	The ratio of annual total precipitation to the number of wet days (≥ 1 mm)	mm/days
TX mean	Mean of T_{max}	Monthly mean of daily maximum temperature	°C
TN mean	Mean of T_{min}	Monthly mean of daily minimum temperature	°C

2.5.2. Normalized root mean square deviation (NRMSD)

NRMSD is a measure of the difference between the observed values and the model projected values and can be expressed as:

$$\text{NRMSD} = \frac{\sqrt{\frac{1}{T}\sum_{i=1}^{T}(x_i - y_i)^2}}{\bar{x}} \quad (2)$$

Smaller values of NRMSD indicate better performance or predictive power of the model. Ideally, a value of 0 is preferred.

2.5.3. Absolute normalized root mean square deviation (ANRMSD)

ANRMSD is defined as the ratio of the mean of difference between simulated and observed value to the mean of observed value and is expressed as:

$$\text{ANRMSD} = \left| \frac{\frac{1}{T}\sum_{i=1}^{T}(y_i - x_i)}{\bar{x}} \right| \quad (3)$$

Here again, smaller values indicate better performance of the model, and ideally, a value of 0 is preferred (Chai and Draxler, 2014).

2.5.4. Average absolute relative deviation (AARD)

AARD is defined as the average of the absolute values of relative errors and is expressed as:

$$\text{AARD} = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{y_i - x_i}{x_i}\right| \quad (4)$$

Smaller values again indicate better performance of the model, and a value of 0 is preferred (Willmott and Matsuura, 2005).

For Eqs. (1)–(4), x_i and y_i are the observed and simulated value, $\bar{x}$ and $\bar{y}$ are averages of observed and simulated values, whereas σ_{obs} and σ_{sim} and are the standard deviations of observed and simulated value and T is the number of time steps or number of observations (Sharifi et al., 2016).

2.6. Entropy method

The Entropy method was applied to determine the weights of indicators (Pomerol and Romero, 2000; Raju and Nagesh, 2010). The weights of the indicators for each grid rely on the formulated grid wise payoff matrix, i.e., RCMs versus performance indicator array. The main benefit of the Entropy method is that the weights are determined for each indicator without the involvement of a decision maker, which is expected to reduce the undue bias towards any indicator. An added advantage of this method is that the variation of weights of indicators across the various grid points provides a convenience for the water resources planner to recognize their importance to the outcome. The application steps of Entropy method are presented in the following (Li et al., 2011). Firstly, it is assumed that there is a set of 'm' feasible alternatives, Ai ($i = 1, 2...., m$) and 'n' evaluation criteria Cj ($j = 1, 2..., n$) in the problem.

Step 1: Formation of decision matrix which shows the performances of different alternatives (RCMs) with respect to various evaluation criteria (performance indicators).

$$X = [X_{ij}]_{matrix} = \begin{bmatrix} X_{11} & \cdots & X_{1n} \\ \vdots & \ddots & \vdots \\ X_{m1} & \cdots & X_{mn} \end{bmatrix} \text{ where, } i = 1, 2 \ldots, m; j = 1, 2 \ldots, n \quad (5)$$

X_{ij} presents the performance value of i^{th} alternative on j^{th} criteria.

Step 2: Normalization of the decision matrix (r_{ij}). Beneficial (maximization) and non-beneficial (minimization) criteria are normalized by Eqs. (6) and (7), respectively. Maximization means, if the increase in indictor value increase the better performance of model and minimization refers that the decrease in indicator value increases the better performance of model. To have the performance measures comparable and dimensionless, all the entries of the decision matrix are linear normalized using the following two equations:

$$r_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \text{ where, } i = 1, 2 \ldots, m; j = 1, 2 \ldots, n \quad (6)$$

$$r_{ij} = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \text{ where, } i = 1, 2 \ldots, m; j = 1, 2 \ldots, n \quad (7)$$

Step 3: Determination of Entropy value (ej) for each evaluation criteria (performance indicators).

$$e_j = \frac{-1}{\ln(m)}\sum_{i=1}^{m} f_{ij} * \ln\left(f_{ij}\right) \text{ where, } i = 1, 2 \ldots, m; j = 1, 2 \ldots, n \quad (8)$$

$$f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} \text{ where, } i = 1, 2...., m;\ j = 1, 2..., n \text{ and } 0 < e_j < 1 \quad (9)$$

Step 4: Calculation of Entropy weights (Wj) based on degree of diversification (Dj).

$$Dj = 1 - ej \quad (10)$$

$$W_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \text{ where, } \sum_{j=1}^{n} W_j = 1 \quad (11)$$

The smaller the value of the entropy, the larger the entropy-based weight, then the specific criterion provides more information, and this criterion becomes more important than the other criteria in the decision making process (Wu et al., 2011).

2.7. Weighted average technique

Weighted average technique was applied to rank the alternatives (RCMs) in Bangkok and its vicinity and this technique depends on the weight of indicator for CC, NRMSD, ANRMSD and AARD (Raju and Kumar, 2014). It is the utility related technique as is applied as:

$$V_j = \sum_{j=1}^{n} r_{ij} W_j \text{ where, } j = 1, 2..., n;\ \sum_{j=1}^{n} W_j = 1; W_j > \ = 0 \quad (12)$$

3. Results and discussions

3.1. Calculation of performance indicators

Table 3 demonstrate the value obtained for the four performance indicators (CC, NRMSD, ANRMSD and AARD) (Eqs. (1)–(4)) for the selected 21 RCMs in 3 Asian cities (Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley) for Consecutive Dry Days (CDD). Minimum or zero error is desirable in case of NRMSD, ANRMSD and AARD whereas an ideal value of 1 is desirable for CC.

For Bangkok and its vicinity, in the case of CC as obtained from Eq. (1), M11 was correlated well with the observed data with a value of 0.206, whereas a minimum CC was observed for M19 with a value of -0.203. In the case of the NRMSD indicator (Eq. (2)), M11 is the preferred RCM, with a NRMSD value of 0.526, whereas M3 is the least preferred (NRMSD = 0.968). For ANRMSD (Eq. (3)) as well, M11 is the preferred RCM (0.139) whereas M3 is the least preferred (0.795). For AARD (Eq. (4)), M8 and M3 are the most and least preferred RCMs, respectively.

Table 3
Rectangular matrix of four performance indicators (Correlation coefficient (CC), Normalized root mean square deviation (NRMSD), Absolute normalized root mean square deviation (ANRMSD) and Average absolute relative deviation (AARD)) obtained for 21 chosen RCMs for consecutive dry days (CDD) in three Asian cities; Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley. (Green color indicates good performance and blue color indicates bad performance).

Modal Serial	Bangkok and its vicinity				Ho Chi Minh City				Kathmandu Valley			
	CC	NRMSD	ANRMSD	AARD	CC	NRMSD	ANRMSD	AARD	CC	NRMSD	ANRMSD	AARD
M1	0.029	0.593	0.166	0.547	0.077	0.580	0.294	0.453	0.047	0.876	0.686	0.639
M2	0.014	0.626	0.257	0.642	-0.298	0.627	0.149	0.575	0.102	0.818	0.611	0.577
M3	0.174	0.968	0.795	1.193	0.054	1.186	0.967	1.359	0.065	0.690	0.415	0.445
M4	0.059	0.764	0.378	0.810	0.171	0.854	0.361	0.866	-0.025	0.864	0.669	0.614
M5	0.001	0.618	0.198	0.601	0.065	0.627	0.240	0.627	0.000	0.832	0.628	0.593
M6	0.008	0.718	0.371	0.792	-0.029	0.848	0.496	0.936	0.188	0.835	0.645	0.604
M7	0.090	0.632	0.407	0.447	0.091	0.659	0.479	0.502	0.091	1.061	0.648	1.059
M8	0.151	0.582	0.317	0.423	-0.299	0.705	0.474	0.544	-0.013	1.036	0.347	0.442
M9	0.029	0.553	0.147	0.571	0.269	0.609	0.245	0.619	-0.127	1.618	1.261	1.832
M10	0.187	0.631	0.429	0.452	-0.204	0.770	0.611	0.645	0.181	0.898	0.521	0.881
M11	0.206	0.526	0.139	0.429	0.200	0.551	0.253	0.462	0.331	0.898	0.541	0.852
M12	0.138	0.584	0.217	0.471	0.008	0.687	0.264	0.616	0.227	0.881	0.488	0.814
M13	-0.054	0.634	0.352	0.460	0.015	0.628	0.428	0.469	0.048	0.970	0.396	0.856
M14	0.138	0.537	0.156	0.425	0.058	0.604	0.261	0.497	0.048	0.970	0.396	0.856
M15	0.158	0.589	0.249	0.450	0.262	0.660	0.197	0.623	0.051	0.837	0.285	0.732
M16	0.044	0.625	0.378	0.432	-0.152	0.773	0.612	0.682	0.112	0.760	0.502	0.541
M17	0.081	0.675	0.420	0.512	-0.034	0.795	0.625	0.739	-0.055	0.747	0.470	0.509
M18	0.018	0.650	0.372	0.499	-0.021	0.752	0.609	0.582	-0.117	0.785	0.541	0.529
M19	-0.203	0.719	0.427	0.584	-0.155	0.782	0.631	0.596	-0.006	0.781	0.552	0.514
M20	0.000	0.667	0.414	0.487	0.009	0.783	0.659	0.614	0.005	0.766	0.511	0.502
M21	0.039	0.624	0.356	0.459	-0.042	0.743	0.615	0.597	-0.153	0.784	0.537	0.509
Max	0.206	0.968	0.795	1.193	0.269	1.186	0.967	1.359	0.331	1.618	1.261	1.832
Min	-0.203	0.526	0.139	0.423	-0.299	0.551	0.149	0.453	-0.153	0.690	0.285	0.442
Max-Min	0.408	0.441	0.656	0.771	0.568	0.635	0.818	0.906	0.484	0.928	0.977	1.390

Table 4
Rectangular matrix of normalized performance indicators (Correlation coefficient (CC), Normalized root mean square deviation (NRMSD), Absolute normalized root mean square deviation (ANRMSD) and Average absolute relative deviation (AARD)) for 21 chosen RCMs, total entropy (ej) of each indicator, the degree of diversification (Dj) of each indicator, weight of each indicator (Wj), weighted average value (Vj) of each RCMs, and the rank of each RCMs for consecutive dry days (CDD) in Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley. (Green color indicates top 5 performing RCMs and blue color indicates bad performing RCM).

dal Serial	Bangkok and its vicinity						Ho Chi Minh City						Kathmandu Valley					
	CC	NRMSD	ANRMSD	AARD	(V_j) (eq.12)	Rank	CC	NRMSD	ANRMSD	AARD	(V_j) (eq.12)	Rank	CC	NRMSD	ANRMSD	AARD	(V_j) (eq.12)	Rank
M1	0.566	0.848	0.958	0.838	0.790	8	0.663	0.954	0.822	1.000	0.802	4	0.413	0.800	0.589	0.858	0.573	12
M2	0.529	0.774	0.820	0.716	0.700	13	0.002	0.880	1.000	0.865	0.526	14	0.525	0.862	0.666	0.903	0.661	7
M3	0.923	0.000	0.000	0.000	0.272	21	0.621	0.000	0.000	0.000	0.270	21	0.450	1.000	0.866	0.998	0.691	6
M4	0.641	0.461	0.635	0.498	0.566	18	0.827	0.523	0.741	0.544	0.712	8	0.264	0.812	0.607	0.876	0.503	18
M5	0.498	0.794	0.909	0.769	0.730	12	0.642	0.880	0.889	0.808	0.767	6	0.315	0.848	0.648	0.892	0.544	16
M6	0.515	0.566	0.645	0.520	0.560	19	0.475	0.532	0.576	0.467	0.508	16	0.703	0.844	0.631	0.884	0.743	3
M7	0.716	0.761	0.591	0.968	0.752	9	0.687	0.830	0.596	0.946	0.728	7	0.503	0.601	0.628	0.556	0.547	15
M8	0.865	0.874	0.728	1.000	0.863	5	0.000	0.758	0.603	0.900	0.412	19	0.288	0.628	0.936	1.000	0.561	14
M9	0.568	0.940	0.988	0.808	0.813	7	1.000	0.908	0.882	0.816	0.927	1	0.053	0.000	0.000	0.000	0.028	21
M10	0.953	0.764	0.557	0.962	0.813	6	0.168	0.656	0.435	0.788	0.410	20	0.690	0.776	0.758	0.684	0.713	4
M11	1.000	1.000	1.000	0.992	0.998	1	0.879	1.000	0.873	0.990	0.914	3	1.000	0.776	0.738	0.705	0.875	1
M12	0.834	0.869	0.881	0.937	0.877	4	0.540	0.786	0.859	0.820	0.702	9	0.785	0.794	0.792	0.732	0.779	2
M13	0.364	0.755	0.675	0.951	0.665	16	0.552	0.878	0.659	0.982	0.699	10	0.414	0.699	0.886	0.702	0.581	10
M14	0.835	0.977	0.974	0.997	0.939	2	0.628	0.917	0.863	0.952	0.783	5	0.414	0.699	0.886	0.702	0.581	11
M15	0.883	0.858	0.831	0.965	0.883	3	0.988	0.828	0.942	0.813	0.923	2	0.421	0.842	1.000	0.791	0.639	8
M16	0.604	0.776	0.635	0.988	0.738	10	0.259	0.650	0.434	0.748	0.442	18	0.546	0.925	0.777	0.929	0.704	5
M17	0.694	0.664	0.571	0.884	0.699	14	0.466	0.615	0.418	0.684	0.513	15	0.201	0.939	0.810	0.952	0.535	17
M18	0.539	0.721	0.644	0.901	0.689	15	0.489	0.683	0.437	0.857	0.565	11	0.073	0.898	0.737	0.938	0.448	19
M19	0.000	0.564	0.561	0.791	0.449	20	0.253	0.637	0.411	0.842	0.446	17	0.303	0.902	0.727	0.949	0.569	13
M20	0.497	0.680	0.581	0.917	0.655	17	0.542	0.634	0.377	0.822	0.560	12	0.326	0.919	0.768	0.957	0.591	9
M21	0.593	0.779	0.669	0.953	0.736	11	0.453	0.697	0.430	0.841	0.548	13	0.000	0.899	0.742	0.952	0.413	20
e_j (eq.8)	0.973	0.979	0.977	0.979	-	-	0.942	0.978	0.967	0.979	-	-	0.937	0.981	0.981	0.980	-	-
D_j (eq.10)	0.027	0.021	0.023	0.021	-	-	0.058	0.022	0.033	0.021	-	-	0.063	0.019	0.019	0.020	-	-
W_j (eq.11)	0.295	0.229	0.249	0.227	-	-	0.435	0.163	0.247	0.156	-	-	0.522	0.154	0.161	0.162	-	-

For Ho Chi Minh City, in case of CC (Eq. (1)), M9 is associated well with the observed data with value of 0.268, whereas a least CC of -0.299 was observed for M8. For NRMSD (Eq. (2)), M11 is the desired RCM, with a NRMSD value of 0.551 and M3 is the least desired RCM with value of 1.186. In case of ANRMSD (Eq. (3)) M2 is the preferred RCM (0.149) and M3 is the least preferred RCM (0.967). For AARD (Eq. (4)), M1 and M3 are the most and least preferred RCMs, respectively.

For Kathmandu valley, in case of CC (Eq. (1)), M11 is correlated well with the observed data with value of 0.331, whereas a lowest CC of -0.153 was noted for M21. For NRMSD (Eq. (2)), M3 is the desired RCM, with a NRMSD value of 0.690 and M9 is the least desired RCM with value of 1.618. In case of ANRMSD (Eq. (3)) M15 is the preferred RCM (0.285) and M9 is the least preferred RCM (1.261). For AARD (Eq. (4)), M8 and M9 are the most and least preferred RCMs with value of 0.442 and 1.832, respectively.

3.2. Application of entropy method and weighted average techniques

Table 4 depicts the normalized performance indicators (Eqs. (6) and (7)), total entropy (ej) of each indicator (Eq. (8)), the degree of diversification (Dj) of each indicator (Eq. (10)), weight of each indicator (Wj) (Eq. (11)), weighted average value (Vj) of each RCMs (Eq. (12)) and the rank of each RCMs for consecutive dry days (CDD) in three Asian cities.

For Bangkok and its vicinity, CC has the highest importance value or weightage (29.5%) which means that its effect on ranking of RCMs is significant. The total contribution of NRMSD, ANRMSD and AARD are 22.9%, 24.9% and 22.7% respectively. Ideal RCMs are the one with the supreme weighted average value (Vj). For consecutive dry days, RCMs; M11, M14, M15, M12, and M8 with the convenience value of 0.998, 0.939, 0.883, 0.877, and 0.863 occupies 1st, 2nd, 3rd, 4th, and 5th positions respectively, whereas M3 with the weighted average value of 0.272 occupies 21st position.

Table 5
Rank of 21 RCMs for all six climate indices in all three Asian cities; Bangkok and its vicinity, Ho Chi Minh city and Kathmandu Valley with their rank sum. (Note: CDD: Consecutive Dry Days, SDII: Simple Daily Intensity Index, R50mm: Number of extremely heavy precipitation days, RX1day: Maximum 1-day precipitation amount, TX mean: Mean of maximum temperature, TN mean: Mean of minimum temperature).

Modal Serial	Rank in Bangkok and its vicinity							Rank in Ho Chi Minh City							Rank in Kathmandu Valley						
	CDD	SDII	R50mm	Rx1day	TX mean	TN mean	Rank Sum	CDD	SDII	R50mm	Rx1day	TX mean	TN mean	Rank Sum	CDD	SDII	R50mm	Rx1day	TX mean	TN mean	Rank Sum
M1	8	8	7	19	16	12	70	4	2	15	21	1	9	52	12	2	12	16	18	1	61
M2	13	7	13	12	20	18	83	14	1	13	7	8	18	61	7	1	4	11	20	17	60
M3	21	6	4	14	15	9	69	21	21	21	8	12	19	102	6	3	1	6	10	2	28
M4	18	13	18	20	21	20	110	8	17	19	18	6	12	80	18	9	15	18	21	18	99
M5	12	21	20	21	19	10	103	6	20	20	9	9	6	70	16	5	14	12	15	8	70
M6	19	1	3	4	17	13	57	16	4	6	5	4	11	46	3	4	7	15	12	11	52
M7	9	2	8	5	12	7	43	7	9	9	11	2	7	45	15	7	3	9	3	9	46
M8	5	10	9	6	11	21	62	19	7	12	16	13	20	87	14	11	6	8	13	10	62
M9	7	14	21	9	14	16	81	1	16	11	3	15	14	60	21	6	5	4	11	13	60
M10	6	11	1	2	13	17	50	20	12	7	20	14	21	94	4	13	13	1	19	3	53
M11	1	3	2	1	9	8	24	3	19	14	2	5	4	47	1	8	9	5	6	7	36
M12	4	9	11	11	18	19	72	9	13	3	1	3	15	44	2	10	2	7	8	6	35
M13	16	4	16	3	4	11	54	10	15	2	4	7	13	51	10	14	10	2	16	4	56
M14	2	5	6	7	6	14	40	5	18	5	6	10	17	61	11	15	11	3	17	5	62
M15	3	12	14	8	10	15	62	2	10	1	15	11	16	55	8	12	8	10	14	12	64
M16	10	15	15	13	3	6	62	18	3	4	10	17	2	54	5	20	17	19	2	14	77
M17	14	18	10	16	7	4	69	15	11	17	19	18	1	81	17	16	18	20	9	16	96
M18	15	16	5	17	8	5	66	11	6	18	13	20	10	78	19	19	21	14	5	21	99
M19	20	17	12	18	2	3	72	17	5	10	12	21	8	73	13	17	19	21	4	19	93
M20	17	20	19	15	1	2	74	12	8	8	14	16	5	63	9	18	16	13	7	15	78
M21	11	19	17	10	5	1	63	13	14	16	17	19	3	82	20	21	20	17	1	20	99

Color	Key	Color	Key	Color	Key	Color	Key	Color	Key
	1st Rank		2nd Rank		3rd Rank		4th Rank		5th Rank

For Ho Chi Minh City, CC has the highest importance value or weightage (43.5%) which means that its effect on ranking of RCMs is significant. The total contribution of NRMSD, ANRMSD and AARD are 16.3%, 24.7% and 15.6% respectively. RCMs: M9, M15, M11, M1, and M14 with the weightage average value of 0.927, 0.923, 0.914, 0.802, and 0.783 occupies 1st, 2nd, 3rd, 4th, and 5th positions respectively, whereas M3 with the weightage average value of 0.270 occupies 21st position.

For Kathmandu valley, CC has the highest importance value or weightage (52.2%) which means that its effect on ranking of RCMs is significant. The total contribution of NRMSD, ANRMSD and AARD are 15.4%, 16.1% and 16.2% respectively. RCMs: M11, M12, M6, M10, and M16 with the weighted average value of 0.875, 0.779, 0.743, 0.713, and 0.704 occupies 1st, 2nd, 3rd, 4th, and 5th positions respectively, whereas M3 with the weighted average value of 0.028 occupies 21st position.

Similar kind of analysis was conducted for all other 5 climate indices (SDII, R50mm, Rx1day, TX mean, and TN mean) (Supplementary Tables 1-10). The weighted average value of all 21 RCMs for six climate indices and three Asian cities; Bangkok and its vicinity, Ho Chi Minh city and Kathmandu Valley are shown in supplementary Figs. 4-6, respectively.

3.3. Final selection of RCMs

The above analysis indicates that each performance indicator responds differently for various RCMs and climate indices. We also found out that the best model for one climate index is not the same best model for other climate indices. In the present study, an effort was made to explore all 4 performance indicators simultaneously to assess their applicability (and their relative contribution) while ranking the RCMs for each climate index in three Asian cities. For the final selection of the RCMs in each Asian cities, the rank of each RCMs for all climate indices are summed up to obtain the rank score and the RCMs with least rank score is the better performing RCMs (Table 5). We found out that, RCMs; *WAS44_SMHI_RCA4_IPSL_CM5A_MR (M11), WAS44_SMHI_RCA4_NCC_NorESM1_M (M14), WAS44_SMHI_RCA4_CCCma_CanESM2 (M7), WAS44_SMHI_RCA4_ICHE_EC_EARTH (M10) and, WAS44_SMHI_RCA4_MPI_ESM_LR (M13) are the top five best performing RCMs in Bangkok and its vicinity, Thailand, respectively. Likewise, RCMs; WAS44_SMHI_RCA4_MIROC5 (M12), WAS44_SMHI_RCA4_CCCma_CanESM2 (M7), WAS44_IITM_REGCM4-4_MPI_ESM_MR (M6), WAS44_SMHI_RCA4_IPSL_CM5A_MR (M11), and WAS44_SMHI_RCA4_MPI_ESM_LR (M13) are top five best performing RCMs for Ho Chi Minh city, Vietnam, respectively. Similarly, RCMs; WAS44_IITM_REGCM4-4_CSIRO_MK3-6-0 (M3), WAS44_SMHI_RCA4_MIROC5 (M12), WAS44_SMHI_RCA4_IPSL_CM5A_MR (M11), WAS44_SMHI_RCA4_CCCma_CanESM2 (M7), and WAS44_IITM_REGCM4-4_MPI_ESM_MR (M6) are top five RCMs for Kathmandu valley, Nepal, respectively.*

The result reveals that RCMs; *WAS44_SMHI_RCA4_CCCma_CanESM2 (M7) and WAS44_SMHI_RCA4_IPSL_CM5A_MR (11)* are common in top five position in all 3 Asian cities.

The comparison between observed vs historical RCMs for mean monthly rainfall (1976–2005), mean monthly maximum, and mean minimum temperature (1976–2005) of all RCMs in three Asian cities is shown in supplementary Figs. 1-3.

3.4. Climate model ensemble to reproduce observed indices

To check the ability of climate model ensembles to reproduce the observed climate indices, the ensembles of three RCMs: RegCM4-4, RCA4 and CSIRO-CCAM driven by different GCMs (Table 1) were first calculated and were evaluated for six climate indices; Consecutive Dry Days (CDD), Simple Daily Intensity Index (SDII), Number of extremely heavy precipitation days (R50mm), Maximum 1-day precipitation amount (RX1day), Mean of daily maximum temperature (TX mean) and Mean of daily minimum temperature (TN mean) using four performance indicators. The performance indicators used were correlation coefficient, normalized root mean square deviation, absolute normalized root mean square deviation and average absolute relative deviation.

Table 6 shows the value obtained for the four performance indicators (CC, NRMSD, ANRMSD and AARD) for three model ensembles in 3 Asian cities (Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley) for Consecutive Dry Days (CDD). Minimum or zero error is desirable in case of NRMSD, ANRMSD and AARD whereas an ideal value of 1 is desirable for CC.

The result shows that, model ensembles of RCA4 perform better for climate indices Consecutive Dry Days (CDD) in both Asian cities: Bangkok and its vicinity and Ho Chi Minh city with the value of 0.269, 0.496, 0.230 and 0.352 for CC, NRMSD, ANRMSD and AARD respectively in Bangkok and its vicinity and 0.214, 0.475, 0.230 and 0.389 for CC, NRMSD, ANRMSD and AARD respectively in Ho Chi Minh city. Similarly, for Kathmandu valley RCA4 model ensembles is correlated well with observed data with a value of 0.235, whereas in case of NRMSD, ANRMSD and AARD, CSIRO-CCAM model ensembles is the preferred RCMs with value of 0.746, 0.519 and 0.487, respectively.

Similar analysis was performed for all other climate indices (SDII, R50mm, Rx1day, TX mean, and TN mean) and summarized in Supplementary Table 12.

4. Conclusions

For the rational catchment management and climate change impact assessment studies, there is an urgent need for the reliable future climate change projection. Regional Climate Models (RCMs) are the most modern tools for simulating the future climate conditions. However, inherent uncertainties, along with other factor such as time limitations, human resource availability, or computational constraints make it imperative to sort out the most appropriate set of RCMs for the assessment of climate change impacts in the region.

In this study, four performance indicators (CC, NRMSD, ANRMSD and AARD) were applied to rank 21 RCMs in three Asian cities (Bangkok and its vicinity, Ho Chi Minh city and Kathmandu Valley) for six different climate indices; Consecutive Dry Days (CDD), Simple Daily Intensity Index (SDII), Number of extremely heavy precipitation days (R50mm), Maximum 1-day precipitation amount (RX1day), Mean of daily maximum temperature (TX mean) and Mean of daily minimum temperature (TN mean). Entropy method was endorsed to acquire weights of these 4 indicators and weightage average techniques was used for ranking of 21 RCMs.

Table 6
Rectangular matrix of four performance indicators (Correlation coefficient (CC), Normalized root mean square deviation (NRMSD), Absolute normalized root mean square deviation (ANRMSD) and Average absolute relative deviation (AARD)) obtained for three model ensembles for consecutive dry days (CDD) in three Asian cities; Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley.

Consecutive Dry Days (CDD)				
Bangkok and its vicinity				
Model ensemble	CC	NRMSD	ANRMSD	AARD
RegCM4-4	0.108	0.584	0.308	0.669
RCA4	0.269	0.496	0.230	0.352
CSIRO-CCAM	-0.013	0.617	0.395	0.434
Ho Chi Minh city				
RegCM4-4	0.060	0.544	0.287	0.629
RCA4	0.214	0.475	0.230	0.389
CSIRO-CCAM	-0.164	0.748	0.625	0.602
Kathmandu valley				
RegCM4-4	0.181	0.806	0.609	0.552
RCA4	0.235	0.799	0.551	0.877
CSIRO-CCAM	-0.053	0.748	0.519	0.487

The result highlighted that each indicator responds differently for various RCMs and climate indices and the best model for one climate index is not the same best model for other climate indices. Among the 21 RCMs, the study reveals that, WAS44_SMHI_RCA4_IPSL_CM5A_MR (M11), WAS44_SMHI_RCA4_MIROC5 (M12), and WAS44_IITM_REGCM4-4_CSIRO_MK3-6-0 (M3) are the best performing RCMs in Bangkok and its vicinity, Ho Chi Minh city and Kathmandu valley, respectively. The result discloses that RCMs; WAS44_SMHI_RCA4_CCCma_CanESM2 (M7) and WAS44_SMHI_RCA4_IPSL_CM5A_MR (11) are common in top five position in all 3 Asian cities.

The results of this study provide insight into the performance of different RCMs in simulating the past climate over the three Asian cities, which advances our knowledge of the applicability of RCMs in assessing climate change in this region. In the future, more RCM simulations at higher resolution should be conducted and ensembled to examine the climate dynamics of the Asian cities.

CRediT authorship contribution statement

The first author collected data, conducted modelling experiments. The second author conceptualized the research. All other authors contributed in terms of comments and suggestions to improve the research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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References

Anagnostopoulos, G.G., Koutsoyiannis, D., Christofides, A., Efstratiadis, A., Mamassis, N., 2010. A comparison of local and aggregated climate model outputs with observed data. Hydrol. Sci. J. 55, 1094–1110.

Beran, A., Hanel, M., Nesladkova, M., Vizina, A., 2016. Increasing water resources availability under climate change. Procedia Eng. 162, 448–454.

Chai, T., Draxler, R.R., 2014. Root mean square error (RMSE) or mean absolute error (MAE)? –arguments against avoiding RMSE in the literature. Geosci. Model Dev. 7 (3), 1247–1250. https://doi.org/10.5194/gmd-7-1247-2014.

Endris, H.S., 2013. Assessment of the performance of CORDEX regional climate models in simulating east african rainfall. J. Clim. 26, 8453–8475. https://doi.org/10.1175/JCLI-D-12-00708.1.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C., Rummukainen, M., 2013. Evaluation of climate models. In: Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Fordham, D.A., Wigley, T.M.L., Brook, B.W., 2011. Multi-model climate projections for biodiversity risk assessments. Ecol. Appl. 21 (8), 3317–3331. https://doi.org/10.1890/11-0314.1.

Gbobaniyi, E., 2014. Climatology, annual cycle and interannual variability of precipitation and temperature in CORDEX simulations over West Africa. Int. J. Climatol. 34, 2241–2257. https://doi.org/10.1002/joc.3834.

Giorgi, F., Hewitson, B., Christensen, J., Hulme, M., Von Storch, H., Whetton, P., Jones, R., Mearns, L., Fu, C., 2001. Regional climate information—evaluation and projections. In: Houghton, J.T. (Ed.), Climate Change 2001: The Scientific Basis. Contribution of Working Group I to the Third Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, USA, pp. 583–638.

Giorgi, F., Jones, C., Asrar, G.R., 2009. Addressing climate information needs at the regional level: the CORDEX framework. WMO Bull. 58 (3), 175–183.

Gosling, S.N., Arnell, N.W., 2016. A global assessment of the impact of climate change on water scarcity. Clim. Chang. 134, 371–385.

IPCC, 2013. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Cambridge, United Kingdom and New York.

Khan, A.J., Koch, M., 2018. Selecting and downscaling a set of climate models for projecting climate change for impact assessment in the upper Indus Basin (UIB). J. Clim. 6, 18. https://doi.org/10.3390/cli6040089.

Koutsoyiannis, D., Efstratiadis, A., Georgakakos, K.P., 2007. Uncertainty assessment of future hydroclimatic predictions: a comparison of probabilistic and scenario-based approaches. J. Hydrometeorol. 8, 261–281.

Kowalczyk, E.A., Garratt, J.R., Krummel, P.B., 1994. Implementation of a Soil-canopy Scheme Into the CSIRO GCM—Regional Aspects of the Model Response. Melbourne.

Li, X., Wang, K., Liu, L., Xin, J., Yang, H., Gao, C., 2011. Application of the entropy weight and TOPSIS method in safety evaluation of coal mines. Procedia Eng. 26, 2085–2091.

Mariotti, L., Bacer, S., Coppola, E., Giorgi, F., 2014. A new regional climate simulation using RegCM4 over the CORDEX South Asia domain. InEGU General Assembly Conference Abstracts 16, 5449.

Ojha, R., Kumar, D.N., Sharma, A., Mehrotra, R., 2014. Assessing GCM convergence for India using the variable convergence score. J. Hydrol. Eng. 19 (6), 1237–1246. https://doi.org/10.1061/(asce)he.1943-5584.0000888.

Oleson, K.W., Niu, G.Y., Yang, Z.L., Lawrence, D.M., Thornton, P.E., Lawrence, P.J., Stockli, R., Dickinson, R.E., Bonan, G.B., Levis, S., Dai, A., Qian, T., 2008. Improvements to the community land model and their impact on the hydrological cycle. J. Geophys. Res. 113, 1021–1026.

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. J. Clim. 20 (17), 4356–4376. https://doi.org/10.1175/jcli4253.1.

Pomerol, J.C.H., Romero, S.B., 2000. Multi-criterion decision in management: principles and practice. Kluwer Academic, Dordrecht.

Raju, K.S., Nagesh, D.K., 2010. Multi-criterion Analysis in Engineering and Management. Prentice Hall of India, New Delhi.

Raju, K.S., Kumar, D.N., 2014. Ranking of global climate models for India using multi-criterion analysis. Clim. Res. 60 (2), 103–117. https://doi.org/10.3354/cr01222.

Rummukainen, M., 2010. State-of-the-art with regional climate models. Wiley Interdiscip. Rev. Clim. Chang. 1, 82–96.

Samuelsson, P., Gollvik, S., Ullerstig, A., 2006. The land-surface scheme of the rossby Centre regional atmospheric climate model (RCA3). SMHI. http://www.diva-portal.org/smash/record.jsf?pid=diva2%3A947542&dswid=7665.

Sharifi, E., Steinacker, R., Saghafian, B., 2016. Assessment of GPM-IMERG and other precipitation products against gauge data under different topographic and climatic conditions in Iran: preliminary results. Remote Sens. 8 (2), 135. https://doi.org/10.3390/rs8020135.

Shrestha, S., Neupane, S., Shanmugam, M., Pandey, V.P., 2020. Mapping groundwater resiliency under climate change scenarios: a case study of Kathmandu Valley. Nepal. Environ. Res. 183 (2020), 109149. https://doi.org/10.1016/j.envres.2020.109149.

Southeast Asia Regional Climate Downscaling Project (SEACLID). APN E-Lib. https://www.apn-gcr.org/resources/items/show/1886. (Accessed 3 April 2020).

Stefanidis, S., Dafis, S., Stathis, D., 2020. Evaluation of regional climate models (RCMs) performance in simulating seasonal precipitation over mountainous central pindus (Greece). Water 12, 2750. https://doi.org/10.3390/w12102750.

Vijaya, V.R.S., Sanjairaj, I., Goic, R., 2012. A review of climate change, mitigation and adaptation. Renew. Sust. Energ. Rev. 16 (1), 878–897.

Wilcke, R.A.L., Barring, L., 2016. Selecting regional climate scenarios for impact modelling studies. Environ. Model. Softw. 78, 191–201. https://doi.org/10.1016/j.envsoft.2016.01.002.

Willmott, C., Matsuura, K., 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Clim. Res. 30, 79–82. https://doi.org/10.3354/cr030079.

Wu, J., Sun, J., Liang, L., Zha, Y., 2011. Determination of weights for ultimate cross efficiency using Shannon entropy. Expert Syst. Appl. 38 (5), 5162–5165.

Xue, Y., Janjic, Z., Dudhia, J., Vasic, R., De Sales, F., 2014. A review on regional dynamical downscaling in intra-seasonal to seasonal simulation/prediction and major factors that affect downscaling ability. Atmos. Res. 147, 68–85.

Zanis, P., Katragkou, E., Ntogras, C., Marougianni, G., Tsikerdekis, A., Feidas, H., Anadranistakis, E., Melas, D., 2015. Transient high-resolution regional climate simulation for Greece over the period 1960–2100: evaluation and future projections. Clim. Res. 64, 123–140.

Zhang, X., Alexander, L.V., Hegerl, G.C., Klein-Tank, A., Peterson, T.C., Trewin, B., Zwiers, F.W., 2011. Indices for monitoring changes in extremes based on daily temperature and precipitation data. WIREs Clim. Change 2011 (2), 851–870.