DOI:10.28974/idojaras.2022.2.5

IDŐJÁRÁS

Quarterly Journal of the Hungarian Meteorological Service
Vol. 126, No. 2, April – June, 2022, pp. 247–265

Selecting the best general circulation model and historical period to determine the effects of climate change on precipitation

Mostafa Yaghoobzadeh[1, 2]

[1]*Department of Water Engineering, University of Birjand, Birjand, Iran*

[2]*Research Group of Drought and Climate change, University of Birjand, Birjand, Iran*

Author E-mail: M.Yaghoobzadeh@birjand.ac.ir

(Manuscript received in final form March 1, 2022)

Abstract— Assessing the effects of climate change is a key component of the sustainable management of water resources and food security. In this paper, general circulation models (GCM) were evaluated using historical information for Birjand synoptic station, Iran. Modeling was performed using 35 models of the Fifth Climate Change Report for 27 historical periods. The results showed that longer annual periods are the most suitable periods for hydrological simulation when data are available. Therefore, the periods of 1960-1990 may be the most appropriate periods due to the adaptation to the observation data. To estimate rainfall, periods with more years showed a more accurate forecast of the future. Moreover, the results showed more changes in the RCP 8.5 scenario than in the RCP 4.5 scenario. According to the comparison of models, the NorESM1-M model with a root mean square error (RMSE) of 0.091 and the GISS-E2-R model with a low percent bias (PBIAS) can be an appropriate model for estimating rainfall.

Key-words: climate change, CIMP5, historical period, precipitation

1. Introduction

The practical activities for considering the climate change and drought effects on agriculture and water resources are recently increasing in the world (*Karasakal et al.,* 2020a, 2020b; *Tao et al.,* 2021; *Wang et al.,* 2021; *Xu et al.,* 2021; *Zhang et al.,* 2021). Climate change can affect various aspects of communities, including sustainable water management (*Huang et al.,* 2021), environmental protection

(*Rjoub et al.,* 2021; *Oladipupo et al*., 2022), energy supply (*Odugbesan* and *Rjoub*, 2020; *Hou et al*., 2021; *Adebayo et al.,* 2021a, 2021b, 2022), economic growth (*Lin et al.,* 2021), ecological footprint (*Ahmed et al.*, 2021), and food security (*Gholamin* and *Khayatnezhad*, 2020, 2021).

As the Middle East is located in the arid region of the world, it has a lot of problems to deal with due to the limitation of the water resources in the region, the increasing demand for water due to the increase of urbanization, and the intensifying global warming (*Li et al.*, 2021b; *Ma et al.*, 2021; *Sun* and *Khayatnezhad*, 2021; *Zhu et al.,* 2021). Global warming, changes in spatial and temporal precipitation patterns, as well as changes in the prediction of these changes are likely to occur in the next century (*Godage et al.,* 2021). Temperatures, which have risen about 0.6 °C since 1860, are projected to rise from 2 to 4 °C until 2100 compared to the period from 1850 to 1950 (IPCC, 2007; *Zhang et al.,* 2019; *Zhao et al.,* 2021; *Chen et al.*, 2022).

Climate change effects on natural ecosystems are one of the most critical consequences (*Wang et al*., 2022). It causes a change in the production and services of these resources and, ultimately, the benefits derived from them. Changes in the quality and quantity of water resources, the condition of forests and pastures, green space, wildlife, aquatic animals, etc. can be mentioned (*Ren* and *Khayatnezhad*, 2021).

Regarding the requirement for this vital substance in all human activities, one of the main concerns of experts in different science fields due to climate change is the effects on water resources (*Fung et al*., 2010). Any change in these variables can affect natural ecosystems' yield rate and structure since the variables of precipitation, temperature, and solar radiation are the most critical inputs of natural ecosystems, especially watersheds (*Tangonyire*, 2019; *Mahmood et al*., 2019; *Li et al.,* 2021a; *Yin et al*., 2022a). Undoubtedly, the available water in a watershed is the most sensitive and vital factor in the economic, social, environmental processes, which is affected by climate change. Therefore, investigating climate change effect on this vital substance has particular importance.

Atmospheric general circulation models (AOGCM) simulate the climatic system of Earth's evolution at any given time, including atmospheric, ocean, ice, sea, land, and atmospheric conditions (*D'Agata et al.,* 2020; *Rahman* and *Islam,* 2020; *Kong*, 2020; *Yin et al.*, 2022b; *Quan et al.*, 2022). To create and modify complex terrestrial climate variables, atmospheric circulation models describe how these components interact with each model. Therefore, they are known as a vital instrument to stimulate climate change and estimate the future (*Mogano* and *Mokoele*, 2019; *Nourani et al*., 2019; *Afshar et al*., 2021; *Guo et al*., 2021; *Sun et al.,* 2021).

Due to comparing climate change models, *Gregory et al.* (2001) compared ten models of the Third Climate Change Report, and *Samadi et al.* (2010) compared 11 models of the Fourth Climate Change Report. *Kamal* and *Massah*

Boani (2012) compared the impact of uncertainties of seven TAR models (Third Climate Change Report) including the CCSR, CGCM2, CSIRO-MK2, ECHAM4, GFDL-R30, HadCM3, NCAR-DOE PCM models and nine selected models from AR4 (Fourth Climate Change Report) including the CCSM3, CGCM3, CSIRO Mk3, GFDL CM2.1, GISS ER, HadCM3, ECHAM5, MIROC-med, PCM models under A2 release scenario on the runoff of Qarah su Basin in 2040–2069. Their results showed that using AR4 models with more management of uncertainty leads to more practical results than using TAR models.

The choice of the appropriate historical period affects climate change results and the importance of the type of selected GCM model. In the Fourth Climate Change Report, historical and future period data were presented simultaneously (*Yaghoobzadeh et al.*, 2017). For this reason, researchers such as *Mousavi et al.* (2016) used the 1980–2010 period to determine climate change effects by presenting the data of the Fifth Climate Change report. Based on their results, the separation of historical periods from future ones, the elective historical period should preferably be chosen by the 2005 year period. Choosing a historical period and the future one is very essential for climate change research. Choosing a historical period is very essential in choosing a future period. Despite global warming and rising temperatures, the historical period closer to the present shows more temperature changes than in the years before 2000, and these effects of temperature changes affect the goal of each researcher. On the other hand, in downscaling methods such as LARS-WG, and in particular the coefficient of variation of the coefficient of change factor, the number of historical and future periods should be as uniform as possible, which makes the need to consider periods with the appropriate number of years more obvious.

No specific research has been done so far on choosing a suitable historical period for assessing the future climate change effects. Hence, for the stations with more extended metering periods, it is always essential to choose a suitable historical period that responds well to future changes. Due to the Fourth Climate Change Report, the 1960–1990 period was selected as an appropriate period by the Intergovernmental Panel on Climate Change (IPCC), and the 1970–2000 period after the 1960–1990 period can be selected as an appropriate period (IPCC, 2007). According to the Fourth Climate Change Report, some researchers have chosen these periods as the appropriate historical period in their research. For example, the 1961-1990 period was used as a suitable period for many researchers to evaluate the variables of precipitation, and minimum and maximum temperature (*Alvankar et al.,* 2016; *Parracho et al.,* 2016; *Nourani et al*., 2020; *Oseke et al.,* 2021; *Nabipour et al*., 2020; *Sibuea et al*., 2021). Considering the fifth report, the 1986–2005 period was also discussed, and future changes compared to this period were examined. However, the 1970–2000 period was used as a training period (IPCC, 2013).

Each researcher has used a specific historical period in his research so that no suitable answer can be found for why he chose this period. *Shen et al.* (2018)

used the 1971–2000 historical period, and *Zhang et al*. (2018) used the 1961–1990 period to evaluate the effect of climate change effect on hydrological characteristics in future periods. Selecting the appropriate historical period also depends on appropriate data availability from the synoptic stations, which may be forced to use shorter periods due to a lack of data. Due to the synoptic data existence since 1992, *Weinberger et al.* (2017) used the 1992–2002 period to estimate temperatures in ten regions of the United States. However, in case of available data, choosing a 30-year-long period is better than other elective periods. *Sobhani et al.* (2017) used the 1970–1999 and the 1961–1990 periods to estimate precipitation and temperature variables in the future, respectively. Given the availability of the Fifth Reporting Period for all models up to 2005, choosing the post-2005 historical period for the Fifth Report data is fraught with errors, and researchers should use the early years of the future for the years after 2005. *Kouhestani et al.* (2016) used the long period of 1948–2014 as a historical period.

Selecting the AOGCM model and the appropriate historical period can express the results with -ranging changes. We tried to select the appropriate model from almost all CMIP5 models (Fifth Climate Change Report) to estimate precipitation parameters in the future period, and limit values, relative error percentages and meteorological parameters' uncertainty were calculated for all models and periods as well.

2. Material and methods

Precipitation values for 35 GCM models of the fifth report and 27 selected historical periods of Birjand synoptic station data were evaluated to select appropriate GCM models and historical periods for climate change research. The city of Birjand is located in eastern Iran and has an arid and semi-arid climate with an average rainfall of 170 mm per year (*Fig. 1*).

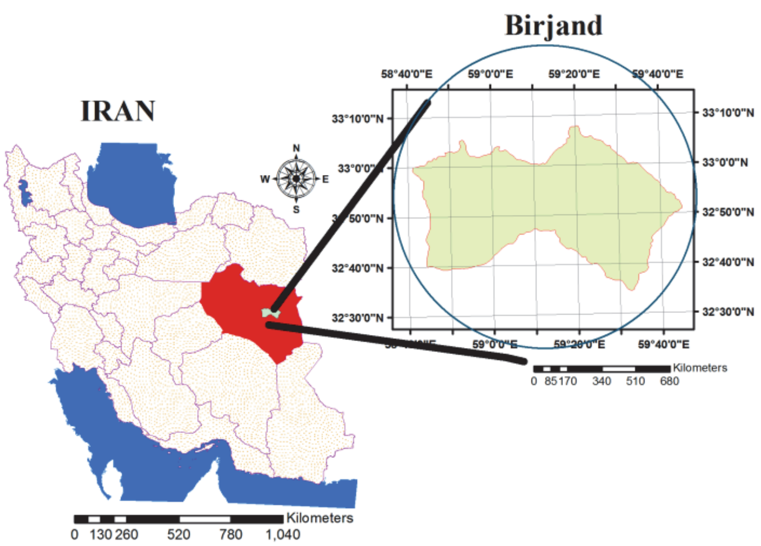


Fig. 1. Location of the study area.

In order to conduct this research, historical precipitation data of GCM models were first obtained from the IPCC site in the Fifth Climate Change Report. After collecting report data on meteorological variables resulting from GCM models that are monthly for Birjand, the selected periods were determined using the estimated months and years of the models and compared with the results of observation station periods using error estimation methods. *Tables 1* and *2* present the Fifth Climate Change Report's models and the selected periods used in this study, respectively.

Table 1. The models of the fifth climate change report presented in this research

ACCESS1	1.25° ×1.87°	Commonwealth Scientific and Industrial Research Organization, Australia
ACCESS1.3	1.25° ×1.87°	Commonwealth Scientific and Industrial Research Organization, Australia
BCC-CSM1.1	2.8° × 2.8°	Beijing Climate Center, China Meteorological Administration, China
BCC-CSM1-M	2.8° × 2.8°	Beijing Climate Center, China Meteorological Administration, China
BNU-ESM	2.8° × 2.8°	College of Global Change and Earth System Science, Beijing Normal University, China
CanESM2	2.8° × 2.8°	Canadian Centre for Climate Modeling and Analysis, Canada
CCSM4	1°× 1°	NCAR, University Corporation for Atmospheric Research, United States
CESM1-BGC	1°× 1°	National Science Foundation, United States
CESM1-CAM5	0.94° ×1.25°	National Science Foundation, United States
CMCC-CMS	3.71° ×3.75°	Centro Euro-Mediterraneo per I Cambiamenti Clamatici, Italy
CNRM-CM5	1.4° × 1.4°	Centre National de Recherches Météorologiques and Centre Européen de Recherché et Formation Avancées en Calcul Scientifique, France
CSIRO Mk3.6	1.8° × 1.8°	Commonwealth Scientific and Industrial Research Organization with Queensland Climate Change Center of Excellence, Australia
EC-EARTH	1.121° ×1.125°	EC-EARTH Consortium, Europe
FGOALS	2.8° × 2.8°	
FIO-ESM	2.8° × 2.8°	First Institute of Oceanography, China
GFDL-ESM2M		
GFDL CM3	2°× 2.5°	NOAA/Geophysical Fluid Dynamic Laboratory, United States
GFDL-ESM2G	2°× 2°	NOAA/Geophysical Fluid Dynamic Laboratory, United States
GISS-E2-H-CC	2°× 2.5°	NASA Goddard Institute for Space Studies, United States
GISS-ES-R	2°× 2.5°	NASA Goddard Institute for Space Studies, United States
GISS-E2-R-CC	2°× 2.5°	NASA Goddard Institute for Space Studies, United States
HadGEM2-ES	1.25°× 1.875°	Met Office Hadley Centre, United Kingdom
HADGEM2-CC	1.25°× 1.875°	Met Office Hadley Centre, United Kingdom
INM-CM4.0	1.5° × 2°	Institute of Numerical Mathematics, Russian Academy of Sciences, Russia
IPSL-CM5A-LR	2°× 4°	Laboratoire de Météorologie Dynamique and L'Institut Pierre-Simon Laplace, France
IPSL-CM5A-MR		Laboratoire de Météorologie Dynamique and L'Institut Pierre-Simon Laplace, France
IPSL-CM5B-LR		Laboratoire de Météorologie Dynamique and L'Institut Pierre-Simon Laplace, France

Table 1. Continued

MIROC5	1.4° × 1.4°	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan
MIROC-ESM	3°× 3°	Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan
MIROC-ESM-CHEM		Atmosphere and Ocean Research Institute, National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology, Japan
MPI-ESM-LR	1.8° × 1.8°	Max Planck Institute for Meteorology, Germany
MPI-ESM-MR		Max Planck Institute for Meteorology, Germany
MRI-CGCM3	1°× 1°	Meteorological Research Institute, Japan Meteorological Agency, Japan
NorESM1-M	2°× 2°	Norwegian Climate Centre, Norway

3. Downscaling

In this research, using bias correction and spatial disaggregation (BCSD) method, downscaling process is performed. In the BCSD technique, biases are removed using the quantitative mapping method. This kind of method is compared the simulated climate values and observed values at specific points in the statistical distribution. It can adjust the simulated values to match the observed values well. The adjustment amount is recorded and applied well to future simulations. Then, adjusted simulations are downscaled to a finer-resolution spatial scale utilizing a linear interpolation method. The downscaling method calculates the values among adjusted data points to match smaller-scale resolution using surrounding data point values and linear relationships on the distance among large- and small-scale historical data point locations (*Jafarzadeh et al*., 2018). The monthly precipitation value of GCMs were obtained for historical periods from 1960 to 2005 and future periods from 2020 to 2100 from the CMIP5 Climate and Hydrology Projections website downscaled by the BCSD approach (*Schwalm et al.,* 2013). The monthly precipitation values were extracted for 4 points surrounding the studied station.

4. Performance criteria

By testing the downscaled outputs of GCM against historical precipitation, the best GCMs performance among historical periods for a study area was identified. To evaluate the accuracy of methods, the following seven criteria were used root mean square error (RMSE, Eq.(1)), mean absolute error (MAE, Eq.(2)), relative error percentage (RD, Eq.(3)), average relative error of months of the year (MRDM, Eq.(4)), relative average error of month per year (RDMM, Eq.(5)), percent of bias (PBIAS, Eq.(6)), RMSE-observations standard deviation ratio

(PSR, Eq.(7)), and Nash–Sutcliffe formula(NS, Eq.(8)) (*Lalehzari* and *Boroomand-Nasab*, 2017; *Fang et al.,* 2021; *Chen et al.,* 2021*; Miao et al.,* 2022; *Xu et al.,* 2022).

The seven criteria are formulated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i^{obs} - x_i^{sim})^2}{n}}, \tag{1}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|x_i^{obs} - x_i^{sim}\right|}{n}, \tag{2}$$

$$RD = \left|\frac{x_i^{obs} - x_i^{sim}}{x_i^{obs}}\right|, \tag{3}$$

$$MRDM = \frac{\sum_{i=1}^{n}\left|\frac{x_{i-mean}^{obs} - x_{i-mean}^{sim}}{x_{i-mean}^{obs}}\right|}{n}, \tag{4}$$

$$RDMM = \frac{\sum_{i=1}^{n}\left(\sum_{J=1}^{12} RD_J\right)_i}{n}, \tag{5}$$

$$PBIAS = \frac{\sum_{i=1}^{n} 100(X_i^{obs} - X_i^{sim})}{\sum_{i=1}^{n} X_i^{obs}}, \tag{6}$$

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^{n}(X_i^{obs} - X_i^{sim})^2}}{\sqrt{\sum_{i=1}^{n}(X_i^{obs} - X_{i-mean}^{obs})^2}}. \tag{7}$$

$$NS = 1 - \frac{\sum_{i=1}^{n}(x_i - x_{obs})^2}{\sum_{i=1}^{n}(x_{obs} - \overline{x_{obs}})^2} \tag{8}$$

where x_i^{sim} are the predicted values by GCM models, x_i^{obs} are the measured values at the synoptic station, x_{i-mean}^{sim} is the average of predicted values by GCM models among the months of year, X_{i-mean}^{obs} is the average of measured values at the synoptic station among the months of year, RD_J is the relative error of the month in question, n is the number of models used in the research, and J is the number of the months of year.

5. Results

Since the selection of the future period in research strongly depends on the choice of the historical period, as in the methods of dynamic downscaling, the number of years of the historical period and the future period must be the same. Therefore, the requirement for choosing the right period is even more important for the historical period. Thus, 27 historical periods were selected for each of the 35 GCM models from long-term periods such as 1960–2005 to short-term ones such as 1995–2005. According to *Table 2*, the long-term historical periods such as 1960–2005 and 1960–2000 have a lower percentage of RMSE and MAE error compared to other periods, and the 1965–1990 historical period is among the periods with less than 30 years being in a good agreement with the precipitation data from the synoptic station. According to the PBIAS coefficient, which indicates the overestimation or underestimation of the observed value, the periods with less years produced higher overestimation. However, the period 1960–1990 that had lower PBIAS coefficient and RSR could be used as a suitable period. Also, in the Fifth Climate Change Report, the IPCC has selected the period 1985–2005 as the appropriate historical period. The period 1985–2005 can be a very good period to choose as a historical period due to the low relative error rate and PBIAS. Since the two periods of 1960–1985 and 1990–2005 have a lower PBIAS coefficient due to underestimation and overestimation compared to observed data, using only one error coefficient cannot indicate good results from that period and these periods had higher RSR coefficient compared to other periods. Table 3 shows more data matching the model and synoptic station in a longer historical period. Shorter historical periods such as 1970–1990 compared to 1975–2005 period had a lower error. The 1960–1995, 1960–2005 and 1960–2000 periods had lower relative error rates. There were periods such as 1960–1980, which had a lower average relative error of month (4.131), but they had a higher average of relative error (142.334). Therefore, both percentages of relative error must be considered.

Table 2. Percentage of error of different selected historical periods compared to the observation period

period	Years number	RSR	PBIAS	RDMM	MRDM	MAE	RMSE
1960–1999	40	0.032	4.104	34.233	4.306	-0.019	0.064
1965–2004	40	0.035	3.202	36.768	3.488	-0.015	0.068
1960–1989	30	0.058	2.548	33.969	4.021	-0.012	0.087
1970–1999	30	0.101	8.462	43.137	8.381	-0.033	0.113
1975–2004	30	0.086	6.393	40.973	6.673	-0.017	0.136
1965–1989	25	0.056	3.803	37.914	3.855	-0.018	0.085
1975–1999	25	0.118	9.686	44.445	9.188	-0.011	0.049
1980–2004	25	0.135	3.766	44.820	4.348	-0.048	0.171
1970–1989	20	0.086	5.135	41.639	6.638	-0.025	0.107
1980–1999	20	0.199	9.93	48.213	9.640	-0.036	0.162
1985–2004	20	0.195	2.034	47.682	3.877	-0.030	0.201

The results of climate change effects could be different due to multiple kinds of models. *Table 3* presents the models which bear the most similarity to the historical period or the lowest error percentage to daily precipitation data from the synoptic stations. According to this table, the NorESM1-M model was more consistent with the observational data than to other AOGCM models with the lowest RMSE value (RMSE = 0.091) and PBIAS value (PBIAS = 1.401). The GISS-E2-R model with low PBIAS value can be suitable model for precipitation research. The appropriate model can be selected based on the purpose and importance of research topic in the future.

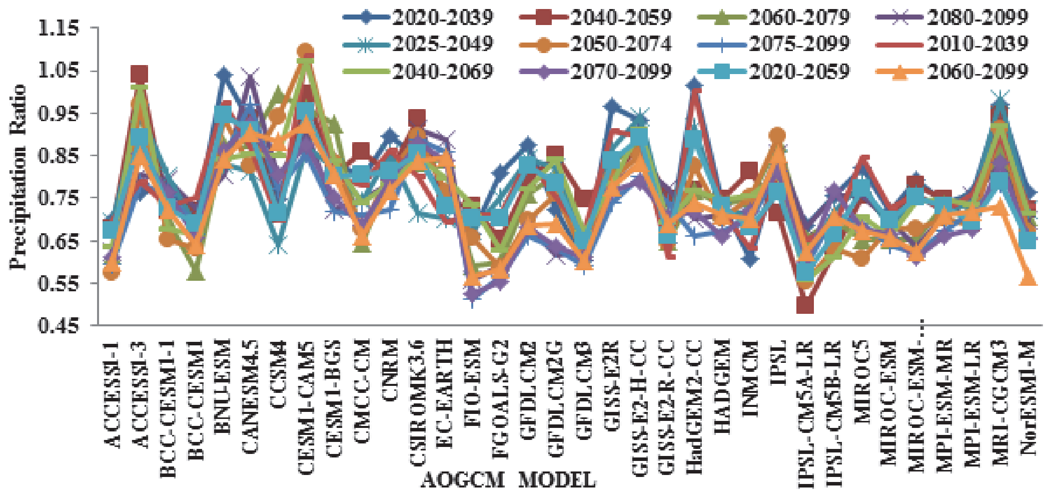
Table 3. Determining the best model of the fifth report from comparing Birjand station data with precipitation data of climate change models

number	Model	R^2	NS	MAE	RMSE
1	NorESM1-M	0.971	0.959	0.007	0.091
2	HADGEM2-CC	0.981	0950	0.023	0.095
3	GFDL-ESM2G	0.974	0.941	0.015	0.098
4	GFDL-ESM2M	0.962	0.937	0.015	0.102
5	GISS-E2-R	0.955	0.937	0.008	0.106
6	MPI-ESM-LR	0.962	0.931	0.014	0.106
7	CANESM2	0.968	0.933	0.017	0.107
8	BNU-ESM	0.966	0.928	0.009	0.108
9	CSIROMK3.6	0.974	0.925	0.025	0.109
10	IPSL-CM5A	0.955	0.921	0.005	0.139
11	CANESM2	0.961	0.923	-0.024	0.140
12	MPI-ESM-LR	0.955	0.921	-0.016	0.140
13	CMCC-CM	0.973	0.922	-0.056	0.141
14	CNRM-CM5	0.966	0.916	-0.016	0.142
15	MRI-CGCM3	0.940	0.918	-0.024	0.143
16	GISS-E2-R-CC	0.951	0.913	-0.016	0.147
17	CESM1-CAM5	0.961	0.899	-0.054	0.156
18	inmcm4	0.959	0.904	-0.013	0.156
19	GISS-E2-H-CC	0.939	0.903	-0.035	0.157
20	BCC-CSM1-M	0.966	0.899	-0.040	0.159
21	CESM1-BGC	0.947	0.896	-0.007	0.160
22	MIROC5	0.958	0.895	-0.043	0.163
23	IPSL-CM5B	0.954	0.891	-0.031	0.164
24	GFDL-CM3-PR	0.942	0.882	-0.038	0.170
25	MIROC-ESM	0.934	0.867	-0.057	0.172
26	FGOALS	0.948	0.883	-0.038	0.172

Table 3. Continued

number	Model	R^2	NS	MAE	RMSE
27	FIO-ESM	0.920	0.872	-0.005	0.174
28	CCSM4	0.963	0.883	-0.078	0.174
29	IPSL	0.949	0.878	-0.050	0.176
30	ACCESS1	0.932	0.874	-0.009	0.176
31	MIROC-ESM-CHEM	0.952	0.878	-0.025	0.182
32	HADCM3	0.905	0.964	-0.018	0.183
33	BCC-CSM1-1	0.911	0.838	-0.037	0.198
34	HADGEM2	0.910	0.837	-0.007	0.201
31	MIROC-ESM-CHEM	0.952	0.878	-0.025	0.182
32	HADCM3	0.905	0.964	-0.018	0.183
33	BCC-CSM1-1	0.911	0.838	-0.037	0.198
34	HADGEM2	0.910	0.837	-0.007	0.201

Fig. 2 shows the growth ratio from the future periods to the historical period for two scenarios of RCP 4.5 and RCP 8.5 in different AOGCM models. This figure shows that different models had different precipitation estimations in future periods than to the historical period. For the RCP 4.5 scenario, CESM1-CAM5 and ACCESS1-3 models showed the largest changes, and the IPSL model the lowest changes in the estimation of the precipitation changes for the next period. For the RCP 8.5 scenario, CANEM2 and CESM1-CAM5 models showed the most changes, and IPSL-CM5A-LR and FGOALS-S2 models showed the lowest changes. Model changes for future periods in the RCP 4.5 scenario reached a maximum of 1.1 in the value of the growth ratio in the historical period, while these changes in the RCP 8.5 scenario in some models reached 1.45 in the historical period in some models.



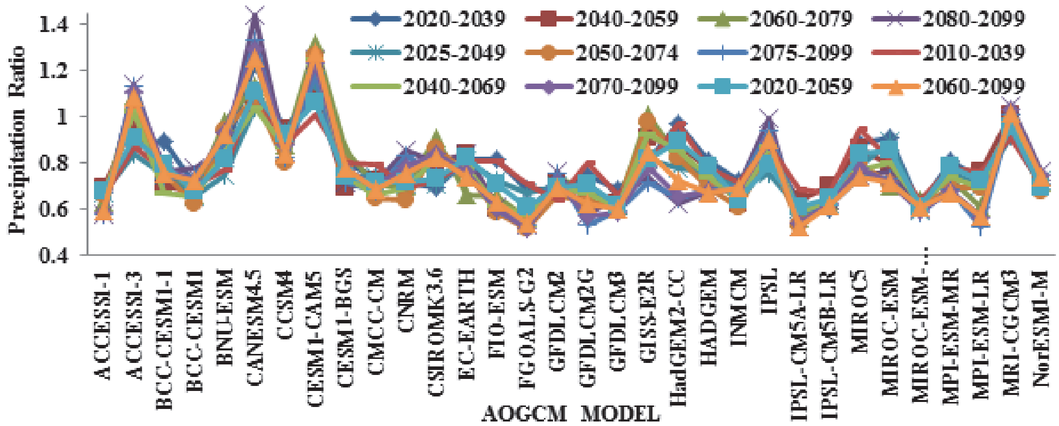


Fig. 2. Precipitation ratios of future periods to historical period for the RCP 4.5 (upper panel) and RCP 8.5 (lower panel) scenarios for different AOGCM models.

There are many differences between historical periods with different time intervals. There was a significant difference due to rainfall by choosing different historical periods with several time series in the future. Considering a historical period with more number of years leads to a decrease in the annual rainfall over time. Until 2100 AD, the annual amount of precipitation values for different historical periods vary from 165 mm for 20-year-long periods to 158 mm for the 25- and 30-year-long periods (*Fig. 3*). These changes in the RCP 8.5 scenario ranged from 163 to 151 mm. More accurate forecast in the future will be expected with lower historical periods by several years. For example, the historical period with 25 and 30 years easily indicate changes in the precipitation up to 2100 AD. The overall results showed more changes in the RCP 8.5 scenario than in the RCP 4.5 scenario. Scenario RCP 8.5 showed changes of about 153 mm, while scenario RCP 4.5 showed 158 mm. *Farzaneh et al.* (2012) and *Singh et al.* (2019) showed that in the 1951–2100 period, there was a high variation in precipitation.

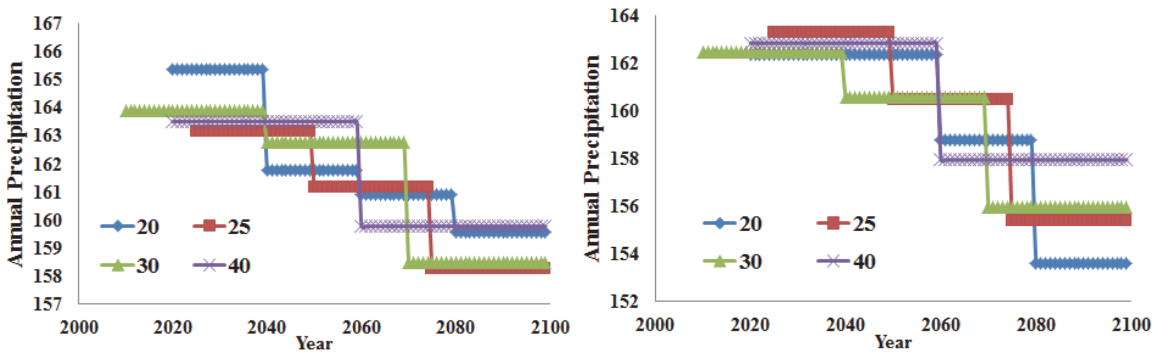


Fig. 3. The effect of the length of the historical period on annual precipitation changes 2100 AD for the RCP 4.5 (left) and RCP 8.5 (right) scenarios.

Fig. 4 shows the changes in future periods compared to the historical periods. These graphs show the effect of selecting incorrect of the historical period on changes in future periods. According to the *Fig. 4*, the historical periods 1980–2000 and 1985–2005 have the lowest changes in RCP 4.5 and RCP 8.5 scenarios compared to periods with the other 20 years. In the case of the 25-year-long historical periods and the RCP 4.5 scenario, the changes in the future period of precipitation value compared to the historical period 1975–2000 periods was lower than other historical periods, while the RCP 8.5 scenario for the 1980–2005 period had the lowest changes in precipitation value than other periods. For precipitation changes in the future periods with 30 years, the changes in the historical period 1975–2005 were lower than the other two periods (30 years) for RCP 4.5 and RCP 8.5 scenarios. The changes of RCP 4.5 scenario were also less than the RCP 8.5 scenario which shows more certainty of the results of this scenario. Regarding changes in the next 40-year-long periods, the 1960–2000 historical period had a smaller range of changes than the 1965–2005 period, and it might be due to the increased rainfall in the period of 2005 compared to the period of 2000. Also, these graphs show that the range of changes distant future years for all graphs has been less than in near future. It shows a decrease in precipitation in the late 21st century for the studied region.

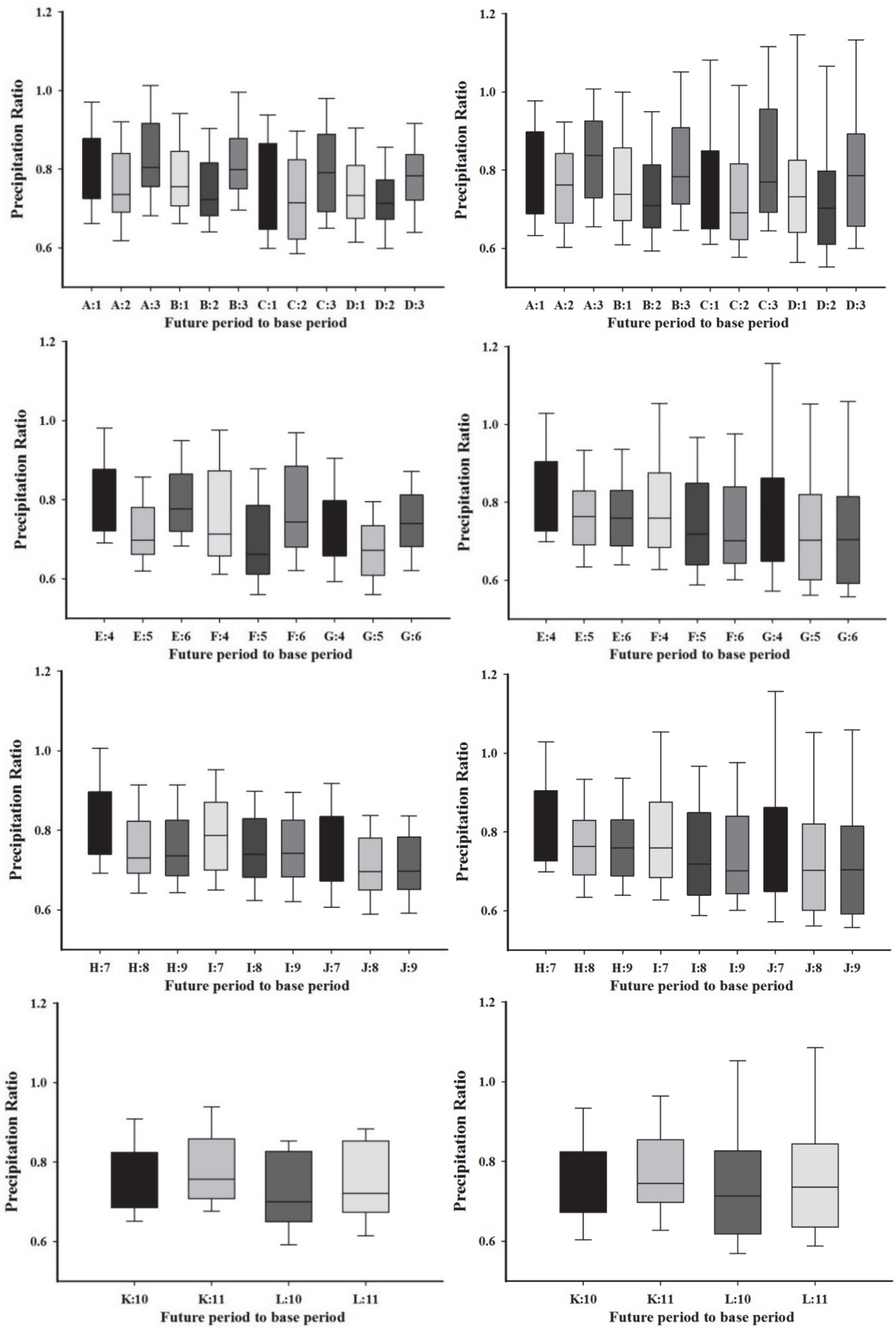


Fig. 4 Changes in the ratio of the annual rainfall in the future periods (2020-2039: A, 2040-2059: B, 2060-2079: C, 2080-2099: D, 2025-2049: E, 2050-2074: F, 2075-2099: G, 2010-2039: H, 2040-2069: I, 2070-2099: J, 2020-2059: K, 2060-2099: L) to the historical period (1970-1990: 1, 1980-2000: 2, 1985-2005: 3,1965-1990: 4, 1975-2000: 5, 1980-2005: 6, 1960-1990: 7, 1970-2000: 8, 1975-2005: 9, 1960-2000: 10, 1965-2005) for the scenario RCP4.5 (left) and RCP8.5 (right).

Fig. 5 shows the range of annual rainfall changes in different GCM models from 2020 to 2100 AD for the two scenarios (RCP 4.5 and RCP 8.5). The results of scenario RCP 4.5 showed that MPI-ESM-MR and HADGEM models had the lowest range of precipitation changes by 2100. Both models had estimated precipitation about 160 mm by 2100. Most models had rainfall estimation of about 170 mm. Among the models, FIO-ESM, FGOALS-G2, and MIROC-ESM-CHEM models had a rainfall estimation of about 130 mm, and BNU-ESM and MRI-CGCM3 models estimated a rainfall from 190 to 200 mm for the studied station by 2100. The results of scenario 8.5 showed that IPSL-CM5B-LR and CANESM2 models would have the lowest and highest precipitation changes by 2100, respectively. CANESM2 and FGOALS-G2 models had the highest (about 265 mm) and the lowest (85 mm per year) annual rainfall estimations, respectively. The results of rainfall changes in scenario RCP 8.5 showed that all models estimated an average of about 150 mm from rainfall per year up to 2100 AD.

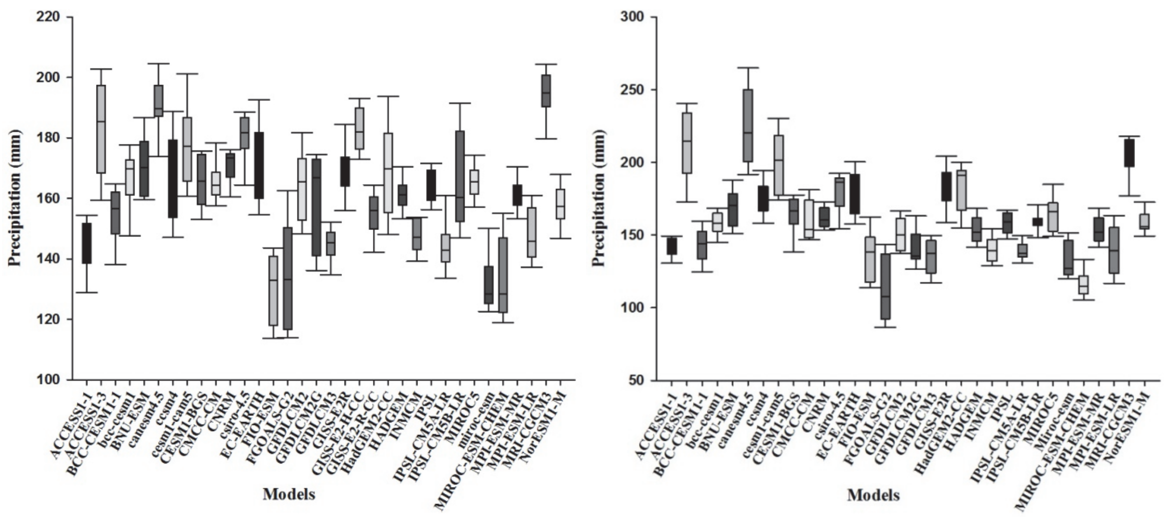


Fig. 5. Box diagrams of precipitation changes of GCM models during the years 2020 to 2100 AD for the scenario RCP4.5 (left) and RCP8.5 (right).

6. Conclusion

Selecting the suitable climate models and historical periods for predicting the future rainfall variations compared to the previous periods could be an important analysis technique. This may be due to different GCM models and historical periods and their impact on research results. Therefore, a comparison was made between 35 GCM models and 27 selected historical periods from long-term period's like1960–2005 to short-term ones like the 1995–2005 period. The results showed that long-term historical periods such as 1960–2005 and 1960–2000 have lower RMSE and MAE error rates than other periods. Furthermore, the historical period 1965–1990 was among periods under 30 years and it was in good agreement with the precipitation data from the synoptic stations. Periods with less years were overestimated. Nevertheless, the 1960–1990 period had lower PBIAS and RSR coefficients than that could be used as a suitable period. The proposed period of 1985–2005 from the IPCC can also be a suitable period to choose as a historical period considering the low relative error rate and PBIAS. The results showed that with longer historical period, there was more agreement between model precipitation data and synoptic stations. The results of climate change effects could be varied based on the different models. The NorESM1-M model was more consistent with the observational data than other AOGCM models with the lowest RMSE and PBIAS values. The GISS-E2-R model with low PBIAS value can be a suitable model for rainfall estimation. Depending on the purpose and importance of research topic in the future, a suitable model should be selected. Different models had several estimates of precipitation in the future periods compared to the historical period. In the RCP 4.5 scenario, CESM1-CAM5 and ACCESS1-3 models had the biggest changes and IPSL models had the lowest estimate for precipitation changes for the future periods. For the RCP 8.5 scenario, CANEM2 and CESM1-CAM5 models had the biggest changes, and IPSL-CM5A-LR and FGOALS-S2 models had the smallest changes. Model changes for the future periods in the RCP 4.5 scenario have reached a maximum of 1/1 of the historical periods, while these ratios have reached 1.45 in the RCP 8.5 scenario in some models.

References

Adebayo, T.S., Awosusi, A.A., Odugbesan, J.A., Akinsola, G.D., Wong, W.K., and *Rjoub, H.,* 2021a: Sustainability of energy-induced growth nexus in Brazil: do carbon emissions and urbanization matter? *Sustainability 13*(8), 4371. https://doi.org/10.3390/su13084371

Adebayo, T.S., Coelho, M.F., Onbaşıoğlu, D.Ç., Rjoub, H., Mata, M.N., Carvalho, P.V., and *Adeshola, I.* 2021b: Modeling the dynamic linkage between renewable energy consumption, globalization, and environmental degradation in South Korea: does technological innovation matter?. *Energies 14*(14), 4265. https://doi.org/10.3390/en14144265

Adebayo, T.S., Rjoub, H., Akinsola, G.D., and *Oladipupo, S.D.,* 2022: The asymmetric effects of renewable energy consumption and trade openness on carbon emissions in Sweden: new evidence from quantile-on-quantile regression approach. *Environ. Sci. Pollut. Res. 29*, 1875–1886. https://doi.org/10.1007/s11356-021-15706-4

Afshar, A., Khosravi, M., and *Molajou, A.,* 2021: Assessing adaptability of cyclic and non-cyclic approach to conjunctive use of groundwater and surface water for sustainable management plans under climate change. *Water Resour. Manage. 35*, 3463–3479. https://doi.org/10.1007/s11269-021-02887-3

Ahmed, Z., Ahmad, M., Rjoub, H., Kalugina, O.A., and *Hussain, N.,* 2021: Economic growth, renewable energy consumption, and ecological footprint: Exploring the role of environmental regulations and democracy in sustainable development. *Sust. Develop*. https://doi.org/10.1002/sd.2251

Alvankar, S.R., Nazari, F., and *Fattahi, E.* 2016: The Intensity and Return Periods of Drought under Future Climate Change Scenarios in Iran. *J. Spatial Anal. Environ. 3*, 99–120. https://doi.org/10.18869/acadpub.jsaeh.3.2.99

Chen, X., Quan, Q., Zhang, K., and *Wei, J.,* 2021: Spatiotemporal characteristics and attribution of dry/wet conditions in the Weihe River Basin within a typical monsoon transition zone of East Asia over the recent 547 years. *Environ. Model. Software. 143,* 105116. https://doi.org/10.1016/j.envsoft.2021.105116

Chen, Z., Liu, Z., Yin, L., and *Zheng, W.,* 2022: Statistical analysis of regional air temperature characteristics before and after dam construction. *Urban Climate 41*. https://doi.org/10.1016/j.uclim.2022.101085

D'Agata, C., Diolaiuti, G., Maragno, D., Smiraglia, C., and *Pelfini, M.,* 2020:) Climate change effects on landscape and environment in glacier zed Alpine areas: retreating glaciers and enlarging forelands in the Bernina group (Italy) in the period 1954–2007. *Geol. Ecol. Landscapes 4*, 71–86. https://doi.org/10.1080/24749508.2019.1585658

Fang, X., Wang, Q., Wang, J., Xiang, Y., Wu, Y., and *Zhang, Y.,* 2021: Employing extreme value theory to establish nutrient criteria in bay waters: A case study of Xiangshan Bay. *J. Hydrol. 603*, 127146. https://doi.org/10.1016/j.jhydrol.2021.127146

Farzaneh, M.R., Eslamian, E., Samadi, S.Z., and *Akbarpour, A.,* 2012: An appropriate general circulation model (GCM) to investigate climate change impact. *Int. J. Hydrol. Sci. Technol. 2,* 34–47. https://doi.org/10.1504/IJHST.2012.045938

F*ung, C.F., Lopez, A.,* and *New, M.,* 2011: Modelling the impact of climate change on water resources. John Wiley & Sons. https://doi.org/10.1002/9781444324921

Gholamin, R. and *Khayatnezhad, M.,* 2021: Impacts of PEG-6000-induced drought stress on Chlorophyll content, relative water content (RWC), and RNA content of peanut (Arachis hypogaea L.) roots and leaves. *Biosci. Res. 18*, 393–402.

Gholamin, R. and *Khayatnezhad, M.,* 2020: The Effect of Dry Season Stretch on Chlorophyll Content and RWC of Wheat Genotypes (Triticum Durum L.). *Biosci. Biotech. Res. Comm. 13*(4).

Godage, R.S.W., Gajanayake, B., and *Jayasinghe-Mudalige, U.K.,* 2021: Coconut Growers Knowledge, Perception and Adoption on Impacts of Climate Change in Gampaha and Puttalam Districts in Sri Lanka: An Index-Based Approach. Current Research in Agricultural Sciences, 8(2), 97–109.

Gregory, J.M., Church, J.A., Boer, G.J., Dixon, K.W., Flato, G.M., Jackett, D.R., Lowe, J.A., Farrell, S.P., Roeckner, E., Russell, G.L., Stouffer, R.J., and *Winton, M.,* 2001: Comparison of results from several AOGCMs for global and regional sea-level change 1900–2100. *Climate Dynam. 18,* 225–240. https://doi.org/10.1007/s003820100180

Guo, L.N., She, C., Kong, D.B., Yan, S.L., Xu, Y.P., Khayatnezhad, M., and *Gholinia, F.,* 2021: Prediction of the effects of climate change on hydroelectric generation, electricity demand, and emissions of greenhouse gases under climatic scenarios and optimized ANN model. *Energy Rep. 7*, 5431–5445.

Hou, R., Li, S., Wu, M., Ren, G., Gao, W., Khayatnezhad, M., and *Gholinia, F*., 2021: Assessing of impact climate parameters on the gap between hydropower supply and electricity demand by RCPs scenarios and optimized ANN by the improved Pathfinder (IPF) algorithm. *Energy 237*, 121621.

Huang, D., Wang, J., and *Khayatnezhad, M.* 2021: Estimation of actual evapotranspiration using soil moisture balance and remote sensing. *Iranian J. Sci. Technol. Transact. Civil Engin. 45,* 2779–2786. https://doi.org/10.1007/s40996-020-00575-7

IPCC, 2007: The physical science basis. In: (Eds. *Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K., Tignor, M., Miller, H.*), Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK.

IPCC, 2013: The physical science basis. In: (Eds. *Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M.*), Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

Jafarzadeh, A., Pourreza-Bilondi, M., Aghakhani Afshar, A.H., Khashei-Siuki, A., and *Yaghoobzadeh, M.,* 2018: Estimating the reliability of a rainwater catchment system using the output data of general circulation models for the future period (case study: Birjand City, Iran). *Theor. Appl. Climatol. 137*, 1975-1986. https://doi.org/10.1007/s00704-018-2714-z.

Kamal, A. and *Massah Bavani, A.*, 2012: Comparison of future uncertainty of AOGCM-TAR and AOGCM-AR4 models in the projection of runoff basin. *J. Earth Space Phys. 38*,175–188.

Karasakal, A., Khayatnezhad, M., and *Gholamin, R.,* 2020a: The durum wheat gene sequence response assessment of Triticum durum for dehydration situations utilizing different indicators of water deficiency. *Biosc. Biotech. Res. Comm. 13*, 2050–2057. https://doi.org/10.21786/bbrc/13.4/62

Karasakal, A., Khayatnezhad, M., and *Gholamin, R.,* 2020b: The effect of saline, drought, and Presowing Salt Stress on Nitrate Reductase Activity in Varieties of Eleusine coracana (Gaertn). *Biosc. Biotech. Res. Comm. 13,* 2087–2091. https://doi.org/10.21786/bbrc/13.4/68

Kong, Q., 2020: The dilemma and way of fighting climate change in coastal areas in China in the view of ecological justice. *J. Coastal Res., 103(sp1)*, 500–505. https://doi.org/10.2112/SI103-101.1

Kouhestani, S.H., Eslamian, S.S., Abedi-Koupai, J., and *Besalatpour, A.A.,* 2016: Projection of climate change impacts on precipitation using soft-computing techniques: A case study in Zayandeh-rud Basin, Iran. *Glob. Planet. Change 144*:158–170. https://doi.org/10.1016/j.gloplacha.2016.07.013

Lalehzari, R. and *Boroomand-Nasab, S.* 2017: Improved volume balance using upstream flow depth for advance time estimation. *Agric. Water Manage. 186,* 120–126. https://doi.org/10.1016/j.agwat.2017.03.005

Li, A., Mu, X., Zhao, X., Xu, J., Khayatnezhad, M., and *Lalehzari, R.,* 2021a: Developing the non-dimensional framework for water distribution formulation to evaluate sprinkler irrigation. *Irrigat. Drainage 70,* 659–667. https://doi.org/10.1002/ird.2568 https://doi.org/10.1002/ird.2568

Li, X, Zhang, K., Gu, P., Feng, H., Yin, Y., Chen, W., and *Cheng, B.,* 2021b: Changes in precipitation extremes in the Yangtze River Basin during 1960–2019 and the association with global warming, ENSO, and local effects. *Sci. Total Environ. 760*, 144244. https://doi.org/10.1016/j.scitotenv.2020.144244

Lin, X., Zhao, Y., Ahmad, M., Ahmed, Z., Rjoub, H., and *Adebayo, T.S.,* 2021: Linking innovative human capital, economic growth, and CO2 emissions: an empirical study based on Chinese provincial panel data. *Int. J. Environ. Res. Public Health 18*(16), 8503. https://doi.org/10.3390/ijerph18168503

Ma, A., Ji, J., and *Khayatnezhad, M.,* 2021: Risk-constrained non-probabilistic scheduling of coordinated power-to-gas conversion facility and natural gas storage in power and gas based energy systems. *Sust. Energy, Grids Networks 26*:100478. https://doi.org/10.1016/j.segan.2021.100478

Mahmood, G.G., Rashid, H., Anwar, S., and *Nasir, A.* 2019: Evaluation of climate change impacts on rainfall patterns in Pothohar region of Pakistan. *Water Conservat. Manage. 3*, 1–6. https://doi.org/10.26480/wcm.01.2019.01.06

Miao, R., Liu, Y., Wu, L., Wang, D., Liu, Y., Miao, Y., and *Ma, J.,* 2022: Effects of long-term grazing exclusion on plant and soil properties vary with position in dune systems in the Horqin Sandy Land. *Catena* (IF5.198). https://doi.org/10.1016/j.catena.2021.105860

Mogano, P. and *Mokoele, N.,* 2019: South African Climate Change Adaptation Politics: Urban Governance Prospects *Int. J. Social Sci. Humanity Studies 11*, 68–83.

Mousavi, S.S., Karandish, F., and *Tabari, H.,* 2016: Temporal and spatial variation of rainfall in Iran under climate changes until 2100. *Irrig. Water Engin. J. 25*,152–165.

Nabipour, N., Mosavi, A., Hajnal, E., Nadai, L., Shamshirband, S., and *Chau, K.W.* 2020: Modeling climate change impact on wind power resources using adaptive neuro-fuzzy inference system. *Engineer. Appl. Computat. Fluid Mech. 14*, 491–506. https://doi.org/10.1080/19942060.2020.1722241

Nourani, V., Razzaghzadeh, Z., Baghanam, A.H., and *Molajou, A.,* 2019: ANN-based statistical downscaling of climatic parameters using decision tree predictor screening method. *Theor. Appl. Climatol. 137*, 1729–1746. https://doi.org/10.1007/s00704-018-2686-z

Nourani, V., Rouzegari, N., Molajou, A., and *Baghanam, A.H.,* 2020: An integrated simulation-optimization framework to optimize the reservoir operation adapted to climate change scenarios. *J. Hydrol. 587*, 125018. https://doi.org/10.1016/j.jhydrol.2020.125018

Odugbesan, J.A. and *Rjoub, H.,* 2020: Relationship among economic growth, energy consumption, CO2 emission, and urbanization: evidence from MINT countries. *Sage Open 10*(2), 2158244020914648. https://doi.org/10.1177/2158244020914648

Oladipupo, S.D,, Rjoub, H., Kirikkaleli, D., and *Adebayo, T.S.* 2022: Impact of Globalization and Renewable Energy Consumption on Environmental Degradation: A Lesson for South Africa. International *J. Renew. Energy Develop. 11*, 145–155. https://doi.org/10.14710/ijred.2022.40452

Oseke, F.I.E., Anornu, G.K., Adjei, K.A., and *Eduvie, M.O.,* 2021: Predicting the impact of climate change and the hydrological response within the Gurara reservoir catchment, Nigeria. *J. Water Land Develop. 51*, 129–143.

Parracho, A.C., Melo-Gonçalves, P., and *Rocha, A*., 2016: Regionalization of precipitation for the Iberian Peninsula and climate change. *Phys. Chem. Earth, Parts A/B/C 94*,146–154. https://doi.org/10.1016/j.pce.2015.07.004

Quan, Q., Liang, W., Yan, D., and *Lei, J.,* 2022: Influences of joint action of natural and social factors on atmospheric process of hydrological cycle in Inner Mongolia, China. *Urban Climate 41*, 101043. doi: 10.1016/j.uclim.2021.101043

Rahman, M.M. and *Islam, I.* 2020: Exposure of urban infrastructure because of climate change-induced flood: lesson from municipal level planning in Bangladesh. *Ecofeminism Climate Change* 1(3), 107–125. https://doi.org/10.1108/EFCC-05-2020-0011

Ren, J. and *Khayatnezhad, M.,* 2021: Evaluating the storm water management model to improve urban water allocation system in drought conditions. *Water Supply 21,* 1514–1524. https://doi.org/10.2166/ws.2021.027

Rjoub, H., Odugbesan, J.A., Adebayo. T.S., Wong, W.K. 2021: Sustainability of the moderating role of financial development in the determinants of environmental degradation: evidence from Turkey. *Sustainability 13*(4), 1844.

Samadi, S.Z., Sagareswar, G., and *Tajiki, M.,* 2010: Comparison of General Circulation Models: methodology for selecting the best GCM in Kermanshah Synoptic Station, Iran. *Int. J. Global Warming 2*, 347–365. https://doi.org/10.1504/IJGW.2010.037590

Schwalm, C.R., Huntinzger, D.N., Michalak, A.M., Fisher, J.B., Kimball, J.S., Mueller, B., and *Zhang, Y.,* 2013: Sensitivity of inferred climate model skill to evaluation decisions: a case study using CMIP5 evapotranspiration. *Environ. Res. Lett. 8*(2), 24028. doi: 10.1088/1748-9326/8/2/024028

Shen, M., Chen, J., Zhuan, M., Hua Chen, H., Xu, C.H., and *Xiong, L.,* 2018: Estimating uncertainty and its temporal variation related to global climate models in quantifying climate change impacts on hydrology. *J. Hydrol. 556*, 10–24.

Sibuea, M.B., Sibuea, S.R., and *Pratama, I.,* 2021: The impact of renewable energy and economic development on environmental quality of ASEAN countries. *AgBioForum 23*(1), 12–21.

Singh, V., Jain, S.K., and *Singh, P.K.,* 2019: Inter-comparisons and applicability of CMIP5 GCMs, RCMs and statistically downscaled NEX-GDDP based preci134-pitation in India. *Sci. Total Environ. 697,*134–163.

Sobhani, B., Eslahi, M., and *Babaeian, I.,* 2017: Comparison of statistical downscaling in climate change models to simulate climate elements in Northwest Iran. *Phys. Geograp. Res. 49*, 301–325.

Sun, Q., Lin, D., Khayatnezhad, M., Taghavi, M., 2021: Investigation of phosphoric acid fuel cell, linear Fresnel solar reflector and organic ranking cycle polygene ration energy system in different climatic conditions. *Proc. Safety Environ. Protect. 147*, 993–1008.

Sun, X. and *Khayatnezhad, M.* 2021: Fuzzy-probabilistic modeling the flood characteristics using bivariate frequency analysis and α-cut decomposition. *Water Supply 21*, 4391–4403. https://doi.org/10.2166/ws.2021.186

Tangonyire, D.F., 2019: Impact of climate change on farmers in the Talensi District of the upper east region of Ghana. *Malaysian J. Sustain. Agricult. 3*(2), 35–45.

Tao, Z., Cui, Z., Yu, J., and *Khayatnezhad, M.,* 2022: Finite difference modeling of groundwater flow for constructing artificial recharge structures. *Iranian J. Sci. Technol. Transact. Civil Engin*. 46, 1503-1514. https://doi.org/10.1007/s40996-021-00698-5

Wang, C., Shang, Y., and *Khayatnezhad, M.,* 2021: Fuzzy stress-based modeling for probabilistic irrigation planning using Copula-NSPSO. *Water Res. Manage.* 35, 4943–4959. https://doi.org/10.1007/s11269-021-02981-6

Wang, H., Khayatnezhad, M., and *Youssefi, N.,* 2022: Using an optimized soil and water assessment tool by deep belief networks to evaluate the impact of land use and climate change on water resources. *Concur. Comput. 34*, e6807. https://doi.org/10.1002/cpe.6807

Weinberger, K.R., Haykin, L., Eliot, M.N., Schwartz, J.D., Gasparrini, A., and *Wellenius, G.A.,* 2017: Projected temperature-related deaths in ten large U.S metropolitan areas under different climate change scenarios. *Environ. Int. 107*,196–204. https://doi.org/10.1016/j.envint.2017.07.006

Xu, J., Zhou, L., Hu, K., Li, Y., Zhou, X., and *Wang, S.,* 2022: Influence of wet-dry cycles on uniaxial compression behavior of fissured loess disturbed by vibratory loads. *KSCE J. Civil Engineer. 26*, 2139–2152. https://doi.org/10.1007/s12205-022-1593-0

Xu, Y.P., Ouyang, P., Xing, S.M., Qi, L.Y., Khayatnezhad, M., and *Jafari, H.,* 2021: Optimal structure design of a PV/FC HRES using amended Water Strider Algorithm. *Energy Rep. 7*, 2057–2067. https://doi.org/10.1016/j.egyr.2021.04.016

Yaghoobzadeh, M., Ahmadi, M., Seyyed Kaboli, H., Zamani, Gh.R., and *Amirabadizadeh, M.,* 2017*:* The Evaluation Of Effect Of Climate Change On Agricultural Drought Using ETDI And SPI Indexes. *J. Water Soil Convers. 24*(4), 43–61.

Yin, L., Wang, L., Keim, B.D., Konsoer, K., and *Zheng, W.,* 2022a: Wavelet analysis of dam injection and discharge in three gorges dam and reservoir with precipitation and river discharge. *Water 14*(4), 567. https://doi.org/10.3390/w14040567

Yin, L., Wang, L., Zheng, W., Ge, L., Tian, J., Liu, Y., and *Liu, S.* 2022b: Evaluation of empirical atmospheric models using swarm-C satellite data. *Atmosphere 13*(2), 294. https://doi.org/10.3390/atmos13020294

Zhang, H., Khayatnezhad, M., and *Davarpanah, A.,* 2021: Experimental investigation on the application of carbon dioxide adsorption for a shale reservoir. *Energ. Sci. Engin. 9*, 2165–2176. https://doi.org/10.1002/ese3.938

Zhang, L., Nan, Z., Yud, W., Zhao, Y., and *Xu. Y. 2018:* Comparison of baseline period choices for separating climate and land use/land cover change impacts on watershed hydrology using distributed hydrological models. *Sci. Total Environ*. 622–623, 1016–1028.

Zhang, K., Wang, S., Bao, H., and *Zhao, X.,* 2019: Characteristics and influencing factors of rainfall-induced landslide and debris flow hazards in Shaanxi Province, China. *Nat. Hazards Earth Syst. Sci. 19*(1), 93–105. https://doi.org/10.5194/nhess-19-93-2019

Zhao, X., Xia, H., Pan, L., Song, H., Niu, W., Wang, R., and *Qin, Y.,* 2021: Drought monitoring over Yellow River Basin from 2003–2019 using reconstructed MODIS Land Surface Temperature in google earth engine. *Remote sens. 13*(18), 3748. https://doi.org/10.1002/ese3.938

Zhu, P., Saadat,i H., Khayatnezhad, M., 2021: Application of probability decision system and particle swarm optimization for improving soil moisture content. *Water Supply. 21*, 4145–4152. https://doi.org/10.2166/ws.2021.169