The Impact of Climate Change on Climate Variables and Meteorological Drought Using the climate change Toolkit (CCT) in the Karkheh River Basin, Iran

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Research Article

Keywords: Climate change, Meteorological drought, SPEI, CCT, Karkheh River Basin

Posted Date: November 9th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-976285/v1>

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The impact of climate change on climate variables and meteorological drought using the climate change toolkit (CCT) in the Karkheh River Basin, Iran

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Abstract Drought appears as an environmentally integral part of climate change. This study was conducted to investigate the impact of climate change on climate variables, meteorological drought and pattern recognition for severe weather conditions in the Karkheh River Basin in the near future (2043-2071) and the distant future (2072-2100). The outputs of GFDL-ESM2, HadGEM2-ES, IPSL-CM5A-LR, MIROC and NoerESM1-M models were downscaled under the RCP 2.6 and RCP8.5 scenarios using the Climate Change Toolkit (CCT) at 17 meteorological stations. Then the SPEI index was calculated for the base and future periods and compared with each other. The results showed that the basin annual precipitation will likely increase in both future periods, especially in the near future. The annual maximum and minimum temperatures may also increase especially in the distant future. The rise in the maximum temperature will be possibly greater than the minimum temperature. Seasonal changes in maximum and minimum temperatures and precipitation indicate that the greatest increase in temperature and decrease in precipitation may occur in summer. Hence meteorological drought was also found to increase in the distant future. The application of the CCT model in the region showed that at least once a wet period similar to the flood conditions of 2019 will be observed for the near future. There will also be at least one similar drought in 2014 for the distant future in the region. However, in previous climate studies, future events have not been calculated based on identifying the pattern of those events in the past.

Keywords: Climate change, Meteorological drought, SPEI, CCT, Karkheh River Basin.

1Introduction

Drought is a natural hazard with adverse impacts on the environment, agricultural activities, and water resources. In the literature, it is defined as a long-term dry period affecting different components of the hydrological cycle. As a complex phenomenon, quantitative determination of drought has always been a matter of concern (Vicente-Serrano et al. 2012; Vidal et al. 2010; Dai 2011) owing mainly to its dependence on various components of the water cycle and its development over long-term periods. Climate change is likely to change drought patterns and exacerbate the severity of drought events in the foreseeable future. Therefore, a more comprehensive approach to drought should be considered simultaneously to incorporate: 1. Various

components of the hydrological cycle and their interactions; 2- Drought spatial and temporal characteristics using integrated methods; And 3- Future changes in the components under climate change scenarios. The existing literature mainly looks at one of the mentioned dimensions. Despite the importance of this perspective for the effective management of regional drought, there are limited attempts to consider different aspects of drought using a standard method (Peters 2006). Drought is classified into meteorological, agricultural, hydrological and socio-economic categories. The first three types of drought reflect the physical characteristics of a drought phenomenon (ie, physical drought). Economic drought is related to water scarcity, the impact of which is manifested through socio-economic systems. Although droughts are caused by a lack of rainfall, hydrological drought is usually followed by a meteorological drought because it takes some time for the lack of rainfall to appear in various subsurface components of the hydrological system, such as soil moisture, groundwater and streams (Wilhite and Glantz 2009). The adverse effects of droughts can be mitigated by monitoring their spatio-temporal distribution. A common measurement tool used for this purpose is the application of drought indices, which are mostly used for rainfall or runoff variables to assess the spatio-temporal characteristics of drought. For example, the standardized precipitation-evapotranspiration index (SPEI) has been frequently applied to monitor meteorological droughts. This index was presented by Vicente-Serrano et al. (2010) based on the variables of precipitation, temperature and evapotranspiration. Kim et al. (2020) assessed the risk of drought in the Nakdong River Basin of Korea for the future. They used the meteorological drought index to determine the frequency, severity and likelihood of drought and used IPSL - CM5A - LR, HadGEM2 - AO and CanESM2 models for future studies. The HadGEM2-AO and CanESM2 models predicted that the risk of drought would decrease in the distant future, and the IPSL-CM5A-LR model predicted that the risk of drought would increase in the near and downstream downstream of the Nakdong River Basin. Chhin et al. (2020) examined future changes in temperature, rainfall, and drought characteristics in the Indochina Region (ICR) based (CMIP5). Their results show that the average temperature in (2011-2040) will increase by about 1.1 ° C, in (2041–2070) by about 2.5 ° C and in (2071–2100) by about 4.3 ° C. The average rainfall decreases in the dry season and increases in the wet season. According to SPEI-3, the risk of severe drought in the region is expected to increase in the very distant future period (2071–2100) under both RCP4.5 and RCP8.5 scenarios. Feng et al. (2019) examined meteorological drought changes in the southeastern Australian wheat belt. To analyze the temporal and spatial variations of drought, they used the standardized relative index of precipitation and evapotranspiration (rSPEI) on a seasonal scale (3 months). The results showed that there is a tendency for frequent and severe winter-spring drought in the study area and by the end of the 21st century, more than half of the wheat belt is exposed to winter-spring drought. Kang and Sridhar (2021) briefly assessed drought using climate forecast in the Mekong River Basin. They used the Soil and Water Assessment Tool (SWAT) model to simulate soil moisture, runoff, and evapotranspiration, and used three drought indicators to evaluate historical drought (1953-2016) and seasonal drought forecasting. They concluded that 76.1% of the basin areas will experience reduced rainfall and rising temperatures, resulting in increased drought. Vicente - Serrano et al. (2020) in a study described the world's hydrological and meteorological

droughts under future climate change. Their results show that climatic and hydrological droughts are likely to increase during the 21st century, with approximately 30% of the world's land under water emission scenarios experiencing water shortages. Rodrigues et al. (2019) investigated the effect of climate change under diffusion scenarios on the flow and drought of basins in the Brazilian bio Cerrado. Their results showed that the duration, severity and frequency of meteorological and hydrological droughts will increase in future periods. Ashraf Vaghefi et al. (2017) assessed the California climate change using the Climate Change Toolkit (CCT) software package from 2020 to 2050. Their results showed that wet seasons in the coastal areas of Northern California may be at risk of flooding. Kamali et al. (2017) assessed the risk of drought under some climate change scenarios in the Karkheh River basin, with results indicating that meteorological, hydrological and especially agricultural droughts will increase in the future.

In this work, the Climate Change Toolkit (CCT) was used, which was developed with several objectives in mind. These were i) handling of big data, as it is required by climate change analyses, especially at large scales and long time periods, ii) easy and seamless calculation of necessary steps in climate change studies, such as data reformatting, data interpolation, downscaling and bias correction, and iii) projection of historical extreme events into the future by pattern recognition of past events. CCT is developed to provide an easy-to-use platform for climate change studies. As management of big databases, bias correction and downscaling, and interpolation of climate data to finer resolution are essential processes in climate change studies; Ashraf Vaghefi et al. (2017) developed the software to consider all these vital tasks in one package. In this study, changes in precipitation, minimum temperature, maximum temperature and meteorological drought were investigated in the near future (2043 to 2071) and distant future (2072 to 2100) compared to the base period (1991 to 2019) using the SPEI drought index. Then, using the CCT model capability to calculate critical periods (Critical Consecutive Day Analyzer), dry and wet periods in the future were obtained. Using the flood and drought conditions of previous periods as a critical limit, it is possible to identify the frequency and frequency of floods and drought for the future and apply the right management. In this case, the damage caused by floods and droughts can be reduced. Therefore, in climate studies of the world's major watersheds, such as the Karkheh Basin, the CCT model is a good option for performing micro-scaling processes.

2 Material and methods

2-1 Study area

Karkheh River is the third high-water river in Iran, whose water is controlled by the largest reservoir dam ever built in Iran and the Middle East (Faiznia 2008). The Karkheh river basin spans in the geographical range between 46 °, 6' to 49 °, 10' East longitude and 30 °, 58' to 34 °, 56' North latitude. It is one of the main basins in the west of the country with an area of 51527 km², of which about 33674 km² are located in mountainous areas and 1785.19 km² are plains and foothills (Fig. 1). The vast basin of the Karkheh River has a variety of climatic conditions. The plain of Khuzestan and the southern parts of the basin are semi-arid with mild winters

and hot and long summers. The northern parts and mountainous areas have cold winters and mild summers. The basin temperature varies from - 25 °C to a maximum of 50 °C. The mean annual rainfall in the basin varies from 300 to 800 mm per year, occurring mostly in winter. Climatically, Karkheh watershed belongs to semi-arid areas (Iran Water and Power Resources Development Company 2004).

Fig. 1 Location of the Karkheh river basin in Iran

2-2 Data

In this study, in order to calculate the meteorological drought index, climatic data of 17 stations of the Meteorological Organization were used (Table 1). These data were on a daily time scale and related to the statistical period 1991-2019. Two categories of data were used to extract rainfall, minimum temperature and maximum temperature data for the future, which include: 1- Data of previous climate models (1950 to 2005): These data for easier access in the model They have changed the format from NetCDF to ASCII. These data include precipitation, maximum and minimum temperature. 2- Future Climate Data (2006 to 2100): These data are the same as the data of previous climate models with different time periods.

Table 1 Meteorological stations of Karkheh watershed

Station	North latitude	East longitude	Altitude above sea level (m)
Ahvaz	48.4	31.2	22.5
Aleshtar	48.15	33.49	1567.2
Bostan	48	31.43	7.8
Boroujerd	48.45	33.55	1629
Dezful	48.23	32.24	143
Hamedan	48.32	34.52	1741.5
Ilam	46.26	33.38	1337
Kangavar	47.59	34.3	1468
Kermanshah	47.9	34.21	1318.6
Khorramabad	48.17	33.26	1147.8
Kuhdasht	47.39	33.31	1197.8
Malayer	48.51	34.15	1777.8
Mazo	48.31	32.47	450
Noorabad	48	34.3	1859.1
Poldakhtar	47.43	33.9	713.5
Ravansar	46.39	34.43	1379.7
Safiabad	48.25	32.16	82.9

2-3 Climate change and climate models

Climate is defined as the average, or more precisely, the statistical description of the surface variables of a climatic system, such as precipitation and temperature, over time. Climate change refers to the change in the climatic condition of a region, including change in the mean or other statistical features of surface variables over time (10 years or more). Drought is a recurring, temporary meteorological event that results from a lack of rainfall relative to normal or the expected climatic value that can occur in any climate, but its characteristics vary considerably from region to region. There are different types of droughts; Meteorology, agriculture, hydrology and socio-economic. Different indicators have been developed and applied for drought monitoring in each of these groups. Each drought phenomenon is mainly characterized by three characteristics of severity, duration and frequency of occurrence. The characteristics of drought may not change much over time or may change due to climate change.

The coupled Atmospheric-Ocean General Circulation Models (AOGCMs) are a group of climatic models proposed to promote these models with a more complex structure and show the chemical and biological interactions of the climatic system. On the other hand, the scientific basis, the quality of the observational data, the assessment of extreme events and the models used in the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) have been significantly enhanced than previous reports, thus reducing uncertainty in some aspects of climate change (IPCC 2014).

The new climate models are based on the framework of the Stage 5 Coordinated Climate Models Coordination Working Group Phase 5 (CMIP5) and the Representative Concentration Trajectory (RCP) scenarios which simulate future climate change at regional and global scales. The CMIP5 GCM models and Earth System Models (ESMs) incorporate the interaction of the atmospheric component with land use and vegetation into modeling. The second-generation Canadian Land System Model (CanESM2) is a comprehensive model and the fourth generation of paired general circulation models (CGCM4) and is part of the CMIP5 model series, consisting of atmospheric, ocean and surface components. The historical and future projection periods of the CanESM2 are 1850-2005 and 2006-2100, respectively, and its scenarios include RCP2.6, RCP4.5, RCP6 and RCP8.5. The definitions of these scenarios are given below. Table 2 lists some specifications of CMIP5 models.

Table 2 Specifications of some models in the IPCC database (Rezazadeh et al. 2018)

Model name	Founding group (country)	Atmospheric resolution (degrees)
GFDL-ESM2G	NOAA GFDL)United States of America(	2*2.5
IPSL-CM5A-LR	IPSL)France(	1.9*75.3

NorESM-ME	NCC)Norway(	2.5°9.1
BCC-CSM1.1	BCC) China(	2.8°8.2
CESM1-BGC	NSF-DOE-NCAR)United	1.25°9
	States of America(	
CanESM2	CCCMA)Canada(	2.8°8.2

2-4 The Climate Change Toolkit

The Climate Change Toolkit (CCT) is an effective tool for extraction, interpolation and bias-correction of data obtained from global General Circulation Models (GCM). This model is also used to analyze extreme events such as drought and flood. This model is connected to five global databases of ISI-MIP. It also uses four RCP scenarios. Table 3 lists the names of global databases and emission scenarios in the CCT model. In this study, all five models embedded in CCT were used to project maximum and minimum precipitation and temperature under two scenarios of RCP2.6 and RCP8.5. The required data in this software include: 1) Observational data of precipitation, maximum temperature and minimum temperature obtained from the statistics of 17 meteorological stations of the Karkheh river basin; 2) historical global data (1970 to 2005); These data are available on a scale of 0.5 degrees, which can be used in the absence of observational data; 3) Data from previous climate models (1950 to 2005): This data were reformatted from NetCDF to ASCII for easier access to the model. These data include precipitation, maximum and minimum temperature. 4) Future Climate Data (2006 to 2099).

Table 3 Names of global databases and emission scenarios in the CCT model (Rezazadeh et al. 2018)

Database name in CCT	Model ISI-MIP	Scenario name in CCT	Scenario name in ISI-MIP
GCM1	GFDL-ESM2M	Scenario1	RCP2.6
GCM2	HadGEM2-ES	Scenario2	RCP4.5
GCM3	IPSL-CM5A-LR	Scenario3	RCP6
GCM4	MIROC	Scenario4	RCP8.5
GCM5	NorESM-M		

2-5 Validation of CCT projected data

To validate the models, the coefficient of determination or R^2 (Equation 1) was first calculated to compare the temperature and precipitation simulated by the models based on both emission scenarios and the actual values recorded at the stations. Given that the R^2 coefficient alone is not a suitable criterion for model evaluation, the mean absolute error or MAE and the root mean square error or RMSE (Equations 2 and 3) were also computed and presented.

$$R^2 = \frac{(\sum (P_i - \bar{P})(O_i - \bar{O}))^2}{\sum (P_i - \bar{P})^2 \sum (O_i - \bar{O})^2} \quad (1)$$

$$MAE = \frac{\sum_{i=1}^n |P_i - O_i|}{n} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \quad (3)$$

Where P_i is the predicted values, O_i is the measured values, n is the number of samples used, $\bar{P}$ is the average of the predicted values and $\bar{O}$ is the average of the measured values. In situations where the estimated and observed values are equal, RSME and MAE values are idea, equal to zero and R^2 is 1 (Dawson et al. 2006).

2-6 The CCT uncertainty evaluation

There are several uncertainty sources associated with different stages of climate variables' simulation by AOGCM models such as those related to the simulation of climate models at regional scales, application of various downscaling methods, and emission scenarios (Feng et al. 2011).

One method of analyzing the uncertainty of climate models and emission scenarios is the model parameter weighting in which the selected models are weighed based on the deviation of the simulated meteorological parameter in the base period from the mean observational data according to Equation 4 (Harris and Wilby 2006). According to this method, the models obtaining a high weight in the past modeling are expected to achieve somehow the same weight in predicting the future and, therefore, are selected as the optimum model (Ekstrom and Fowler 2009)

$$W_i = \frac{\left(\frac{1}{\Delta F_i}\right)^2}{\sum_{i=1}^n \left(\frac{1}{\Delta F_i}\right)^2} \quad (4)$$

Where W_i is the weight of each model in the studied month, ΔF_i is the long-term mean deviation of the simulated parameter by each model in the base period from the mean actual or observed data and n is the number of models.

Due to climate change, climatic fluctuations have increased and events such as tornadoes, floods, hail, and droughts are expected to be more intense and occur at shorter intervals. Current estimates indicate that the most significant potential environmental changes across the world are driven by climate change and include those influencing the components of the hydrological cycle such as floods, droughts and storms and challenge the future water resource management for human and ecosystem development. The increasing frequency and

severity of floods and droughts have been confirmed by the latest IPCC report, which discusses the evidence relating to the occurrence and visible effects of climate change in the present (IPCC 2007).

As mentioned, in the CCT model, the length of wet and dry periods can be examined by defining the threshold for wet and dry days. Table 4 is used to define the threshold.

Table 4 Definition of threshold length for dry and wet periods

Region	Dry Period	Wet Period
Tropical Regions	Period Length > 60 days precipitation <2 mm day ⁻¹ .and. max temperature >30° C	Period Length >2 days precipitation >50 mm day ⁻¹
Semi-Arid Regions	Period Length >120 days precipitation <2 mm day ⁻¹ .and. max temperature >35° C	Period Length > 1 day precipitation >20 mm day ⁻¹

2-7 SPEI index

The standard precipitation-evapotranspiration index (SPEI) was presented by Vicente-Serrano et al. (2010). SPEI is a climatic drought index that shows the degree of drought and wetness and is calculated using equations 5 to 8.

$$D_i = P_i - PET_i \quad (5)$$

Where P and PET are the precipitation and potential evapotranspiration, respectively, D is their difference, and i is the month number. There are several equations for calculating PET with no limitation in using SPEI.

After calculating the log-logistic cumulative distribution function according to Equation 6 and its conversion to the standard normal distribution, the SPEI index is computed using Equation 7 (Allen 1998).

$$F(X) = \left[1 + \left(\frac{\alpha}{X - \gamma} \right)^\beta \right]^{-1} \quad (6)$$

$$SPEI = W - \frac{C_0 + C_1 W + C_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3} \quad (7)$$

In Equation 6, α , β and γ are scale, shape and origin and X is the cumulative series of D values in a given time window, respectively. In Equation 7, C_0 , C_1 , C_2 , d_1 , d_2 and d_3 are constants of the SPEI equation and W is obtained from Equations 8 and 9:

$$W = \sqrt{-2 \ln(P)} \text{ For } P \leq 0 \quad (8)$$

$$P = 1 - F(X) \quad (9)$$

If $P > 0.5$, then P is replaced with $1 - P$ in Equation.

This index can be used to monitor dry and wet periods. Drought begins when the index values reach -1e and ends when it becomes positive. The classification of this index is shown in Table 5 (Edwards and McKee 1997). In this study, the programming environment of R software was used to calculate the SPEI index.

Table 5 Moisture classification according to SPEI index (Edwards and McKee 1997)

Drought class	Index value
Extremely wet	2 and more
Moderately wet	1.5 to 1.99
Slightly wet	1 to 1.49
Normal	-0.99 to 0.99
Mild drought	-1.49 to -1
Moderate drought	-1.99 to -1.5
Extreme drought	less than -2

In order to compare the meteorological drought of the base period with the future, the annual weighted mean of the SPEI index of the base and the two future periods was calculated for all studied stations during 29 years statistical period based on the area affected by each station and using the Thiessen method. In this method, we divided the basin into several smaller basins (sub-basins), so that each station was located in a separate sub-basin. Therefore all stations within the basin and the outside areas near basin edges, if any, can be used. This method is used in areas where rain gauges are not distributed evenly across the territory. The advantage of this method is that it determines the position relative to the area represented by each station and, therefore, reduces the effects of the non-uniform distribution of rain gauges.

In the Thiessen method, the location of the basin and its stations are first determined using topographic maps. Stations are then connected spatially using straight lines to form triangles, such that each line does not intersect other lines. By drawing the perpendicular bisector of the line joining the two centers, polygons are obtained that each represents the area covered by a certain station. The weighted mean is calculated using Equation 10.

$$\overline{\text{SPEI}} = \frac{\text{SPEI}_1 A_1 + \text{SPEI}_2 A_2 + \dots + \text{SPEI}_n A_n}{A_1 + A_2 + \dots + A_n} = \frac{\sum_{i=1}^n \text{SPEI}_i A_i}{\sum_{i=1}^n A_i} \quad (10)$$

Where $\overline{SPEI}$ is the weighted mean of the standardized precipitation-evapotranspiration index, $SPEI_i$ is drought index calculated by R and A is the area of each polygon (Albuquerque 2013).

3 Results and Discussion

3-1 Validation of simulated data by CCT implementation

Table 6 shows the validation results of the models used to microscale the GCM models for precipitation data. Tables similar to this table were created for maximum temperature and minimum temperature. These tables are based on the average accuracy of the models used in each of the 17 meteorological stations. Based on the statistical indicators shown in these tables, the model with the highest R2 and the lowest MAE and RMSE was chosen as the best and most reliable model. Hence, as shown in Table 7, the GFDL-ESM2 had the best performance in simulating precipitation in the Karkheh river basin under both RCP8.5 and RCP 2.6 scenarios. Based on the maximum temperature table, the HadGEM2-ES model is more suitable for simulating this data than the other models in both scenarios. The minimum temperature table also shows that the MIROC model is the most efficient in both scenarios for simulating this data. In all three tables, the other models, although having acceptable values of R2, are not recommended due to the relatively high degree of calibration characteristics.

Table 6 Validation of the CCT simulated precipitation in Karkheh River Bains

Scenario	Model	RMSE	MAE	R ²
RCP2.6	GFDL-ESM2	3.2	1.1	0.9989
RCP8.5		4.1	1.5	0.9971
RCP2.6	HadGEM2-ES	4.5	2.3	0.9906
RCP8.5		5.8	3.5	0.9908
RCP2.6	IPSL-CM5A-LR	7.2	5.6	0.9901
RCP8.5		6.7	4.2	0.9902
RCP2.6	MIROC	5.6	3.2	0.8946
RCP8.5		8.1	5.4	0.8934
RCP2.6	NoerESM1-M	5.3	3.4	0.7936
RCP8.5		4.6	2.6	0.8961

3-2 The CCT uncertainty evaluation

Fig. 2 shows the average weight of five GCM models with two scenarios, RCP2.6 and RCP8.5, to estimate future precipitation changes. Similar shapes were created for the maximum temperature and minimum temperature in the future. As given in these tables, the total weight of the variables in different models and scenarios is equal to one per month. The results of weighted GCMs in precipitation prediction show that the weight of all GCMs is less than 0.9. Except for the three summer months, the GFDL-ESM2 model had the highest weight under both scenarios. Based on the maximum temperature results, GCMs weigh less than 0.7. In all months, especially in the three summer months, HadGEM2-ES had the highest weight in estimating the maximum temperature under both scenarios. The minimum temperature results show that GCMs weigh less than 0.45, and the MIROC model, with a slight difference, ranked as the best predictor of minimum temperature.

In general, changes in the weight of GCM models showed that these models differed significantly in estimating maximum temperature and precipitation than minimum temperature. In other words, GCM models have a more similar potency in estimating minimum temperature than maximum temperature and precipitation. Precipitation, maximum temperature and minimum temperature produced using the best-performed models and scenarios were analyzed to investigate the future effect of climate change on temperature and precipitation.

Fig. 2 Weights of different GCMs to predict precipitation

3-3 Precipitation changes

Precipitation was generated using the GFDL-ESM2 model for the near (2071-2043) and distant future (2100-2072) under two scenarios of RCP2.6 and RCP8.5. Fig. 3 shows the changes in the mean monthly precipitation of the next two periods compared to the base period. To calculate these changes, the predicted precipitation for the near and distant future periods was subtracted from the mean of these precipitations in the base period. The vertical lines added to the graphs indicate the standard error rate of mean precipitation at different meteorological stations. The results showed that the highest increase in precipitation in the distant future is projected to occur under the RCP2.6 scenario in January (4.3 mm) which will be about 3.6 mm in the near future in January. The largest precipitation increase under the RCP8.5 scenario was projected to be 3.6 mm for the near future and 1.7 mm for the distant future both in January. As shown in the figure, the amount of precipitation will decrease in agriculturally-important months of May, June, July, August and September during the next two periods as compared to the base period. In general, precipitation is projected to decrease from late spring to early autumn and increase in winter and early spring during both near and distant futures.

To better understand how precipitation changes, seasonal and annual variations of precipitation are shown in Table 7. The results of seasonal precipitation variations show that winter will experience the highest precipitation increase of 2.31 and 2.3 mm in the near future and 2.99 and 0.99 mm in the distant future under RCP2.6 and RCP8.5 scenarios, respectively. Summer is expected to have the highest precipitation reduction of 0.99 and 1.1 mm in the near future and 1.04 and 1.05 mm in the distant future under RCP2.6 and RCP8.5 scenarios, respectively. Annual changes in precipitation also indicate an increase in precipitation between 0.73

to 0.59 mm in the near future and 0.89 to 0.26 mm in the distant future under RCP2.6 and RCP8.5 scenarios, respectively.

Fig. 3 Changes in the average monthly rainfall in future periods for the RCP2.6 and RCP8.5 scenarios compared to the base period

Table 7 Seasonal and annual precipitation changes based on GFDL-ESM2 model under RCP2.6 and RCP8.5 emission scenarios

Emission scenario	Period	Winter	Spring	Summer	Autumn	Annual
RCP2.6	Near future	2.31	0.54	-0.99	1.07	0.73
	Distant future	2.99	0.85	-1.04	0.74	0.89
RCP8.5	Near future	2.3	0.42	-1.1	0.74	0.59
	Distant future	0.99	0.47	-1.05	0.65	0.26

The temperature changes were calculated similarly to the methodology employed for measuring changes in precipitation. The results showed that the highest maximum temperature increase of 1.63 ° C is projected to occur in July of the near future under the RCP2.6 scenario. This amount in July of the distant future is expected to be 1.6°C. Under the RCP8.5 emission scenario, the highest maximum temperature increase was projected to occur in the July of the distant future by 1.76 ° C. In the near future, this amount is expected to be 1.6°C in July. The maximum temperature will also increase under both scenarios as well as in both future periods from March to October. The highest minimum temperature increase of 0.92 ° C will occur in July of the distant future period under the RCP2.6 scenario. This increase in July of the near future is expected to be 0.91° C. The highest minimum temperature increase of 1.1 ° C was found to be in July of the distant future under the RCP8.5 emission scenario. This value July of the near future is projected to be 0.95 ° C. Generally, the minimum temperature increase is projected to occur in April to October of both future periods compared to the base period. Both minimum and maximum temperatures will increase from early spring to early autumn and decrease from late autumn to late winter in both future periods.

The results of seasonal changes indicate that the highest maximum temperature increase of 1.55 and 1.57 ° C in the near future and 1.53 and 1.68 ° C in the distant future, under the RCP2.6 and RCP8.5 scenarios, respectively, will occur in summer. Moreover, winter will experience the highest maximum temperature drop which is projected to be 0.41 and 0.39 ° C in the near future and 0.38 and 0.28 ° C in the distant future under the RCP2.6 and RCP8.5 scenarios, respectively. Annual changes also indicate an increase in maximum temperature between 0.58 to 0.6 ° C in the near future and 0.57 to 0.72 ° C in the distant future under the RCP2.6 and RCP8.5 scenarios, respectively.

Similar to the maximum temperature, summer will experience the highest minimum temperature increase of 0.84 and 0.87 ° C in the near future and 0.84 and 0.98 ° C in the distant future under the RCP2.6 and RCP8.5 scenarios, respectively and winter is expected to have the highest minimum temperature drop of 0.42 ° C in the near future and 0.42 (RCP2.6 scenario) and 0.33 ° C (RCP8.5 scenario) in the distant future. Annual changes also indicate an increase in minimum temperature between 0.21 and 0.22 ° C in the near future and 0.22 to 0.32 ° C in the distant future under the RCP2.6 and RCP8.5 scenarios, respectively.

The results of using the critical period calculation operator in the CCT model showed that in the near future, the average cumulative frequency of wet periods will show a large number of wet periods (between 35 and 42 times) in Karkheh watershed. While in the distant future, the average cumulative frequency of dry periods will show a large number of dry periods (between 28 and 47 times) in this watershed.

3-4 Meteorological drought changes

Using temperature and precipitation parameters, the SPEI index was calculated at a 12-month time scale for the base (1991-2019), near future (2071-2043) and distant future (2100-2072) periods and under RCP2.6 and RCP8.5 scenarios using GFDL-ESM2, HadGEM2-ES, IPSL models -CM5A-LR, MIROC and NoerESM1-M models. Temporal comparison of SPEI was based on the average of the results of the five employed models because similar to uncertainty and validation analysis of the five models for precipitation, minimum precipitation and maximum precipitation, the results showed that all these models performed satisfactorily and similarly in retrieving future SPEI data.

To evaluate the meteorological drought condition of the base and future periods, the weighted mean of the SPEI index of the base and the two future was computed periods at the annual scale for the studied stations during the 29 years statistical period and based on the area affected by each station using the Theissen method. The results of the relationship between the SPEI values of the base period and the two future periods at the 12-month scale are shown in Figures 4(A) and 4(B), respectively. As shown in Fig. 4(A), the SPEI index values under both RCP2.6 and RCP8.5 scenarios, especially under the RCP8.5 scenario in the near future, will be more positive than the base period.

The more positive SPEI value under the RCP8.5 scenario can be attributed to a greater increase in precipitation and a lower increase in temperature in the near future and those of the RCP2.6 scenario. According to Fig. 4(B), the values of this index under both scenarios of RCP2.6 and RCP8.5, especially RCP8.5, are more negative in the distant future than in the base period. The more negative SPEI value under the RCP8.5 scenario can be attributed to a smaller increase in precipitation and a higher temperature increase in the distant future yielded under this scenario than RCP2.6. Spatial changes in meteorological drought in the base period and the two near and distant periods are shown in Figures 5 and 6, respectively. According to Fig. 5, meteorological drought will decrease in the near future under both RCP2.6 and RCP8.5 scenarios. However, according to Fig. 6 and in terms of meteorology, the conditions will be opposite in which the basin will be drier than the base

period. In Figures 5 and 6, concentric circular spots may represent the hypersensitivity of the interpolation method to low-distributed data.

Fig. 4 Mean 12-month SPEI changes in the future under the RCP2.6 and RCP8.5 scenarios compared to the base period (A: near future and B: distant future)

Fig. 5 Spatial distribution of the mean 12-month SPEI in the near future under the RCP2.6 and RCP8.5 scenarios compared to the base period

Fig. 6 Spatial distribution of the mean 12-month SPEI in the distant future under the RCP2.6 and RCP8.5 scenarios compared to the base period

The probability density function (PDF) was used to investigate changes in the drought intensity in the near and distant periods compared to the base period, presented in Figures 7(A) and 7(B), respectively. Fig. 7(A) shows that the severity of the drought in the near future under the RCP2.6 scenario will be the same as the baseline period, except that the probability of its occurrence is almost doubled. However, in this time period under RCP8.5, the probability density function is shifted to the right, meaning that the drought intensity will be less than the base period, but the probability of its occurrence is less than doubled. As shown in Fig. 7(B), the severity of drought in the distant future under RCP2.6 would be the same as the base period, except that the probability of its occurrence is almost doubled. Under RCP8.5, the probability density function is shifted to the left, meaning that the intensity of the drought will be higher than the base period, but the probability of its occurrence is less than double.

Fig. 7 Changes in the probability density function (PDF) used to evaluate the intensity of the 12-month SPEI index in the future compared to the base period (A: near future and B: distant future)

According to Figures 4 to 7, the drought severity is within the normal range in all three time periods, i.e. the intensity between extreme wet and dry years.

To determine the frequency and duration of droughts, drought was considered to occur when the SPEI index was less than zero for at least two months (Kamali et al. 2017). Accordingly, the results of changes in the frequency of meteorological drought in the near and distant future, compared to the base period, are shown in Figures 8(A) and 8(B), respectively. The meteorological drought was occurred 10 times in the base period but is projected to decrease to 8 and 6 times in the near future (Fig. 8(A)) and increase to 14 and 17 times in the distant future (Fig. 8(B)) under the RCP2.6 and RCP8.5 scenarios, respectively. Changes in the duration of meteorological drought in the near and distant future compared to the based period are shown in Figures 9(A) and 9(B), respectively. According to Fig. 9, the mean duration of the meteorological drought of 15 months found in the base period is expected to decrease to 12 and 11 months in the near future and increase to 17 and 24 months under the RCP2.6 and RCP8.5 scenarios, respectively.

Fig. 8 Frequency of 12-month SPEI in the future compared to the base period (A: near future and B: distant future)

Fig. 9 Duration of 12-month SPEI in the future compared to the base period (A: near future and B: distant future)

4 Conclusion

Drought is classified as a natural disaster that has major effects on parts of an ecosystem. Although it is not possible to prevent its occurrence, but its measures can reduce the negative effects. Since the study area has the largest reservoir dam in the Middle East on the Karkheh River, so the study of various droughts, including meteorological drought in the basin is very important.

This study was designed to investigate the effect of climate change on climate variables and meteorological drought in the Karkheh River Basin. For this purpose, precipitation, minimum temperature and maximum daily temperature data were prepared from 17 meteorological stations and the outputs of GFDL-ESM2, HadGEM2-ES, IPSL-CM5A-LR, MIROC and NoerESM1-M models were downscaled under the RCP 2.6 and RCP8.5 scenarios using the Climate Change Toolkit (CCT) at these stations. Then, to check the uncertainty of the models and scenarios, the output of the models in the next two periods was compared by the statistical indices of the coefficient of determination (R^2) the root mean square error (RMSE) and the mean absolute error (MAE) compared to the base period. The best model and scenario were selected to produce precipitation and maximum temperature, minimum temperature and standard precipitation-evapotranspiration index (SPEI) data. The overall results indicate that GCM models perform with different accuracies in estimating future precipitation and temperature that estimated based on model weighting at each station. The results of weighted GCMs in precipitation prediction showed that the GFDL-ESM2 model had the highest weight among other models under both scenarios. Moreover, the highest weight in estimating the maximum temperature was obtained by the HadGEM2-ES model under both scenarios. Finally, the MIROC model, with a slight difference compared to other GCM models, was recognized as the best model in estimating the minimum temperature. GCM models performed somehow similarly in predicting minimum temperature while their performance differed significantly in predicting maximum precipitation and temperature. Annual rainfall will increase in both future periods and especially in the near future. This result contradicts the results of Seidi et al (2011) in the Karkheh watershed, who used only HADCM3 model. The maximum and minimum annual temperatures were found to increase in most cases in the distant future. These results were seen for Karkheh watershed in the studies of Abrishamchi et al (2012) as well as Seidi et al (2011). This result is also consistent with the results of the Kang and Sridhar (2021) study in the Mekong River Basin. Changes in precipitation also indicate that the largest decrease in precipitation would occur in the distant future. The maximum temperature increases higher than the minimum temperature. The seasonal analysis also indicated that the greatest increase in temperature and decrease in precipitation will occur in summer. This result is not consistent with the results of the study of Feng et al. (2019). Furthermore, the severity, duration and frequency of SPEI-based meteorological drought were found to increase in the distant future and cause more water shortage problems compared to the current situation. This result is consistent with the study of Kamali et al. (2017) in the Karkheh watershed. In other watersheds it

is similar to the study of Chhin et al (2020), Vicente-Serrano et al. (2020) and Rodrigues et al. (2019). However, this result is not similar to the study of Kim et al. (2020). The results of using the critical period calculation operator in the CCT model showed that in the near future, the average cumulative frequency of wet periods is higher than dry periods, which may increase the risk of flooding. This result is similar to the study by Ashraf Vaghefi et al. (2017) in California. In the distant future, the situation will be quite the opposite of the near future, and the average cumulative frequency of dry periods is higher than wet periods. Therefore, the need to pay more attention to water resources management in Karkheh basin based on climate scenarios in the future should be on the agenda of managers and researchers. One of the limitations of the CCT program is the use of only 5 climate models. It is suggested that other types of droughts, climate models and scenarios be considered in future studies.

Data availability and material:

The data that support the findings of this study are available from the corresponding author (Afshin Honarbakhsh, afshin.honarbakhsh@gmail.com), upon reasonable request.

Code Availability: Not applicable

Conflict of Interests: Authors declare that they have no conflict of interests.

Consent to participate: Not applicable

Consent for publication: Not applicable

Author's Contribution: Fahimeh Mokhtari, Afshin Honarbakhsh and Saeed Soltani: Writing original draft, modelling, analysis and revising manuscript.

Khodayar Abdolahi and Mehdi Pajoohesh: Review and edit of manuscript.

Ethics approval: Not applicable

Acknowledgement

The authors gratefully acknowledge Sharekord University for the provision of a suitable environment wherein the research was conducted successfully, and they would like to thank Iran Meteorological Organization for permission to use daily meteorological data.

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Figures

Figure 1

Location of the Karkheh river basin in Iran

Figure 2

Weights of different GCMs to predict precipitation

Figure 3

Changes in the average monthly rainfall in future periods for the RCP2.6 and RCP8.5 scenarios compared to the base period

Figure 4

Mean 12-month SPEI changes in the future under the RCP2.6 and RCP8.5 scenarios compared to the base period (A: near future and B: distant future)

Figure 5

Spatial distribution of the mean 12-month SPEI in the near future under the RCP2.6 and RCP8.5 scenarios compared to the base period

Figure 6

Spatial distribution of the mean 12-month SPEI in the distant future under the RCP2.6 and RCP8.5 scenarios compared to the base period

Figure 7

Changes in the probability density function (PDF) used to evaluate the intensity of the 12-month SPEI index in the future compared to the base period (A: near future and B: distant future)

Figure 8

Frequency of 12-month SPEI in the future compared to the base period (A: near future and B: distant future)

Figure 9

Duration of 12-month SPEI in the future compared to the base period (A: near future and B: distant future)