International Journal of Engineering & Technology, 4 (1) (2015) 1-11
www.sciencepubco.com/index.php/IJET
©Science Publishing Corporation
doi: 10.14419/ijet.v3i4.3782
Research Paper

Climate change impact on meteorological droughts in watershed scale (case study: southwestern Iran)

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Abstract

Drought is one of the major natural disasters in the world which has a lot of social and economic impacts. There are various factors that affect climate changes; the investigation of this incident is also sensitive. Climate scenarios of future climate change studies and investigation of efficient methods for investigating these events on drought should be assumed. This study intends to investigate climate change impacts on drought in Karoon3 watershed in the future. For this purpose, the atmospheric general circulation models (GCM) data under Intergovernmental Panel on Climate Change (IPCC) scenarios should be investigated. In this study, watershed drought under climate change impacts will be simulated in future periods (2011 to 2099). In this research standard precipitation index (SPI) was calculated using mean monthly precipitation data in Karoon3 watershed. SPI was calculated in 6, 12 and 24 months periods. Statistical analysis on daily precipitation and minimum and maximum daily temperature was performed. To determine the feasibility of future periods meteorological data production of LRAS-WG5 model, calibration and verification was performed for the base year (1980-2007). Meteorological data simulation for future periods under General Circulation Models and climate change IPCC scenarios was performed and then the drought status using SPI under climate change effects analyzed. Results showed that differences between monthly maximum and minimum temperature will decrease under climate change and spring precipitation shall increase while summer and autumn rainfall shall decrease. The most increase of precipitation will take place in winter and in December. Normal and wet SPI category is more frequent in B1 and A2 emissions scenarios than A1B. Wet years increases in the study area during 2011-2030 period and the more continuous drought years gradually increases during 2046-2065 period, the more severe and frequent drought will occur during the 2080-2099 period.

Keywords: *Climate Change Impact; Drought Severity; Drought Frequency; Karoon3 Watershed.*

1. Introduction

Increase greenhouse gases in the Earth's climate have led to imbalance the phenomenon of climate over the past decades defined as Climate Change. Studies show that climate change can have negative effects on water resources, agriculture, environment, health, industry and economy. Drought is one of the major natural disasters in the long-term socioeconomic status. Global warming and climate change is happening and changing weather and climate volatility is associated with greater risk of damage. Since increasing the likelihood of future periods could have devastating consequences for human societies, it is essential to examine the drought situation in the future periods affected by climate change. Climate scenarios of future climate change studies and analysis of efficient methods to study these events in future periods.

For climate change studies on various resources in the future, climatic variables affected by greenhouse gases should be determined. Different techniques are available to simulate the future climatic variables under climate change effects; the most reliable data is atmospheric general circulation models. GCM models are three-dimensional models of the physical relationships that govern the atmosphere, crysphere, biosphere and hydrosphere.

One of the weaknesses of GCM models is large spatial and temporal scales of the climatic variables. Therefore variables regarding hydrological and water resources studies are not sufficiently accurate. It should be downscaled by various techniques. Since different methods are available for downscaling, the uncertainty associated with these methods must be investigated. In this study the effects of climate change on drought was investigated in Karoon3 watershed. The atmospheric general circulation model under a set scenario of climate change in the study area. Then watershed drought status affected by climate change in the future period (2099-2011) was simulated.

Serrat-capdevila et al. (2007) assessed the impact of climate change on water resources in semi-arid basin in southeastern Arizona and northern Sovanara using 17 models of GCM (the region where the downscaling is exponential) were examined to conclude the spatial distribution of flow estimates used in the San Pedro Basin. The results showed that hydrological drought in the basin will take place [1].

Scholz et al. (2008) investigated seasonal variation in rainfall resulting from climate change. Simulation of climate change did not show significant differences in annual rainfall, while seasonal variation in rainfall was considerable [2].

Babaeian et al. (2009) downscaled general circulation climate model outputs ECHO-G with A1 scenario for the period 2010 to 2039. Results were analyzed on the 43 synoptic stations. Results showed that 9 percent of the average annual rainfall will reduce and 0.5 ° C in temperature will increase [3].

Kamal and Massah (2011) simulated average values of temperature and precipitation variables at Gharasou basin in the period 2069-2040 using the model HadCM3-A2 and small-scale statistical simulations. Hundred uncertainties of climate fluctuations time series of temperature and precipitation was also simulated in future periods in the study area. The results showed that the range of uncertainty associated with climate fluctuations during different months of the year are 0.5 to 2 ° C increase in temperature and between 10 to 20 mm of rainfall will change. Ultimately, their findings indicate the uncertainty of hydrological models and less impact on climate fluctuations in the estimated watershed outflow [4].

Zarghami et al. (2011) showed that the pattern of changes in temperature and precipitation have serious effects on the quantity and quality of water resources. LARS-WG model and the atmosphere general circulation model were used. LARS-WG model used for downscaling implementation of six synoptic stations using HADCM3 models and three scenarios A1B, A2 and B1 in the period 2020 to 2090. The results showed that the mean annual temperature and the average annual precipitation decreased about 2.3 and 3 percent, respectively. The artificial neural network model was used to assess the effects of climate change on river flows [5].

Grillaki et al., (2011) investigated climate change impact on hydrology and drought in southern Ontario, Canada under A2 scenario in Creek watershed. Hydrological parameters including climatic variations and seasonal flow regime in the study area has been examined. Precipitation and temperature data were obtained from NARCCAP site for climate simulations in 2069 to 2049. GCM and RCM (HADCM3, CGCM3, GFDL) model was used to generate watershed flow as an input for the hydrological model. All simulations showed that the mean annual rate increases and significant changes in seasonal flow distribution occur. Standardized Precipitation Index for 48 months for the past and future of the watershed was calculated. Results showed that dry conditions in future periods reduced approximately 13.2 percent from the average condition [6].

Abdolhoseini et al. (2011) investigated the minimum and maximum temperature and precipitation changes under scenario A2 models using long-term data on the daily synoptic stations. SDSM was used to downscale with regression method. The drought indices: RDI and SPI were estimated by the 30-year period. Results indicated that a moderate increase in rainfall intensity in all months in the future and increasing of flooding probability. Drought severity analysis stated that duration of the SPI over periods longer than the maximum RDI estimates [7].

Goolmohammadi and Massah (2011) evaluated the effects of the drought situation at GharaSou watershed in future periods using the standardized precipitation index. A geographical information system was applied for calculating the mean areal precipitation time series from 11 meteorological stations, in and out of the area for the hydrological period Jan 1971 to Dec 2000 using Inverse Distance Weighting method. This precipitation time series have been used for the estimation of Standardized Precipitation Index (SPI) for three timescales: 6, 12 and 24 months, for the region. The HadCM3 outputs were downscaled statistically to the region of Gharesou using SDSM software to estimate precipitation time series for a future period 2040-2069. Analysis of drought period has shown that value and frequency of drought would be declined in future in the region [8].

Beheshti et al. (2011) investigated climate change impact on Karun 3 dam and power plant in southwestern Iran in two periods: 2049-2020 and 2099-2070 by atmospheric general circulation models used HADCM3-A2 scenario. SDSM 4.2 was used for statistical downscaling and neural network technique simulated rainfall-runoff model. Results indicated an increase in hydropower with the annual 7 percent in the near future [9].

Moafi et al. (2012) investigated drought situation in Khorasan Razavi province during the period 2030-2011 using LARS-WG5. Statistical downscaling model were simulated under scenario A2. SPI and RDI drought indices were calculated in ten stations. The results showed that these two indicators are fitted with together and drought years will reduce in the next two decades at most studied stations [10].

Verochidou et al. (2013) were examined climate change impacts on meteorological and hydrological drought in watershed scale. HBV, a hydrological model, was used to simulate future periods (2001-2100). The future periods was divided into four periods. Future hydrological parameters will encounter with decreasing rainfall and increasing temperatures [11].

Many researchers have used the Standardized Precipitation Index (SPI) to investigate, predict and evaluate the frequency and duration of droughts [12-21].
The aim of this study is to investigate climate change impacts on drought in Karoon3 watershed in the future using SPI and different scenarios of AOGCM by an stochastic weather generator model known as LARS-WG.

2. Materials and methods

The study area is Karun3 watershed located in southwestern Iran. In first step, observed mean daily rainfall data series in selected watershed stations were calculated and SPIs were estimated for three timescales: 6, 12 and 24 months. Then LARS-WG5 model was used to downscale rainfall data under HadCM3-A1B, HadCM3-A2 and HadCM3-B1 climate change scenarios for future periods. Then the drought index for future periods with respect to the simulated time series is calculated. Finally, the severity, duration and frequency of droughts in future periods evaluated. In the rest of this section, the methods employed in this study to perform the above steps will be explained briefly.

2.1. Study area and data analysis

The study area is located in the Grand River watershed named Karoon. Karoon is the longest and most watery river in Iran. Figure (1) Show the location of study area in Iran. Karoon River is 950 km long and its watershed area is 60,000 square kilometers. One of its sub-watersheds is Karoon3 with 24,000 square kilometers area. Great Karoon watershed is located at longitude 30º to 34º N and latitude 48º to 52º E. There are about 73 rain gauge stations in study area in which the desired station location data from these stations will be used.

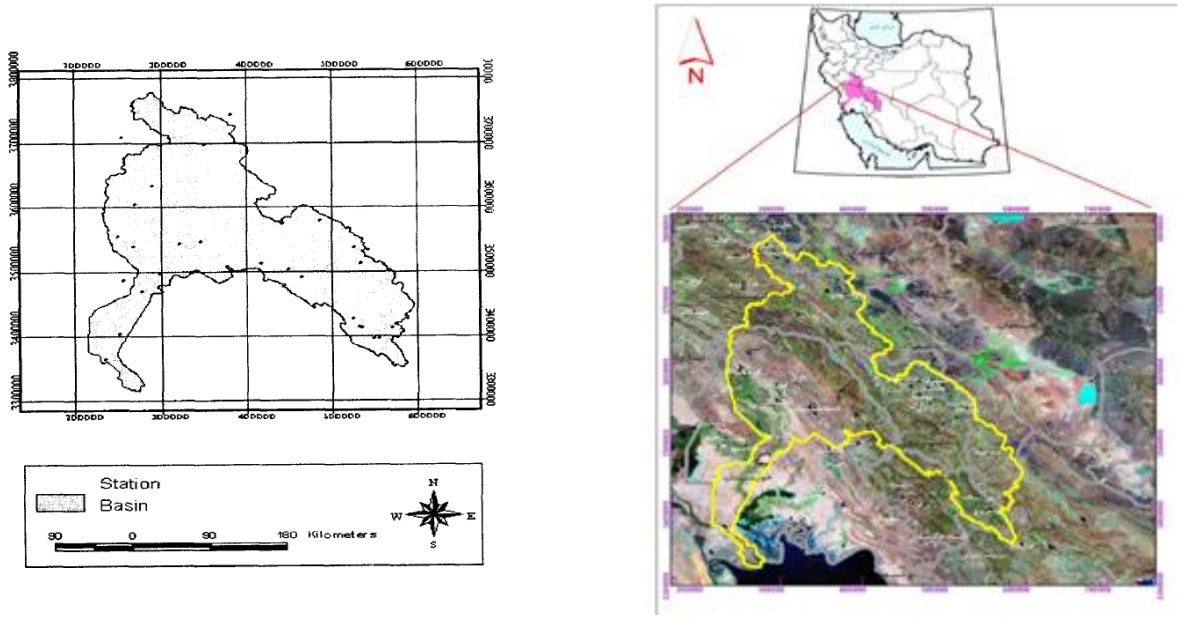


Fig. 1: Weather Stations Position in Karoon Watershed.

Variables used in this study include climatic variables including daily precipitation and daily maximum and minimum temperatures recorded at weather stations, GCM variables, watershed hydrologic characteristics and major river flow. In this study, daily rainfall and daily maximum and minimum temperatures data and from five selected meteorological stations in Karoon3 during 1980 to 2007 were used. The stations were selected according to its data availability and mean altitude of the stations. Various nonparametric tests including Homogeneity test, random test and independence test were used to examine the accuracy of precipitation data for stations.

2.2. Watershed mean precipitation calculation

Regional averaging method can be used to evaluate the severity and magnitude of droughts rather than examining individual rainfall stations separately. Inverse Distance Weighting (IDW) method was assessed to interpolate between rainfall data and derive regional mean precipitations from 1980 to 2007.

2.3. Standard precipitation index (SPI)

SPI was developed by McKee et al. (1993) to assess meteorological drought severity and precipitation deficit. Positive (negative) SPI values indicate greater (less) than median precipitation. As a measure of departure from the median, the

SPI is a probability indication of the severity of the wetness or aridity. McKee et al. (1993) selected the Gamma distribution (Eq. 2) for fitting monthly precipitation data [22], [23]:

$$g(x) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (1)$$

Where:

α : shape parameter

β : scale parameter

x : Precipitation

$\Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y}\, dy$: The gamma function (2)

In calculating SPI, the Gamma distribution (Eq. 1) is then transformed to a Gaussian distribution. The standardized anomaly is then computed with results having an average of zero and a standard deviation of one. All of the above steps make the SPI independent of both the location and the range of values so that different seasons and climate areas are represented on an equal basis. For this purpose, McKee et al. (1993) divided SPI values to seven linguistic drought classes as shown in Table 1.

The SPI was designed to quantify the precipitation deficit for multiple time scales. These time scales reflect the impact of meteorological drought on the availability of water resources. The soil moisture conditions respond to the precipitation anomalies on a relatively short time scale. Groundwater, stream flow, and reservoir storage reflect the longer-term precipitation anomalies. Therefore, McKee et al. (1993) calculated the SPI for 3, 6, 12, 24, 48, and 72 month time scales. In this study, 3, 6, and 9 month time scales have been considered for calculating SPI. In this study, SPIs were calculated using regional mean precipitations for 6 months (short term drought duration), 12 and 24 months (long term drought duration) by MATLAB from 1980 to 2007. Flowchart of SPI deriviation is shown in Figure (2).

Table 1: Linguistic Drought Condition [23].

Linguistic drought condition	Status	SPI
Extremely Wey	EW	more than +2
Very Wet	VW	1.5 to 1.99
Moderately Wet	MW	1 to 1.49
Normal Wet	NW	0 to 0.99
Normal Dry	ND	0 to -0.99
Moderately Dry	MD	-1 to -1.49
Very Dry	VD	-1.5 to -1.99
Extremely Dry	ED	less than -2

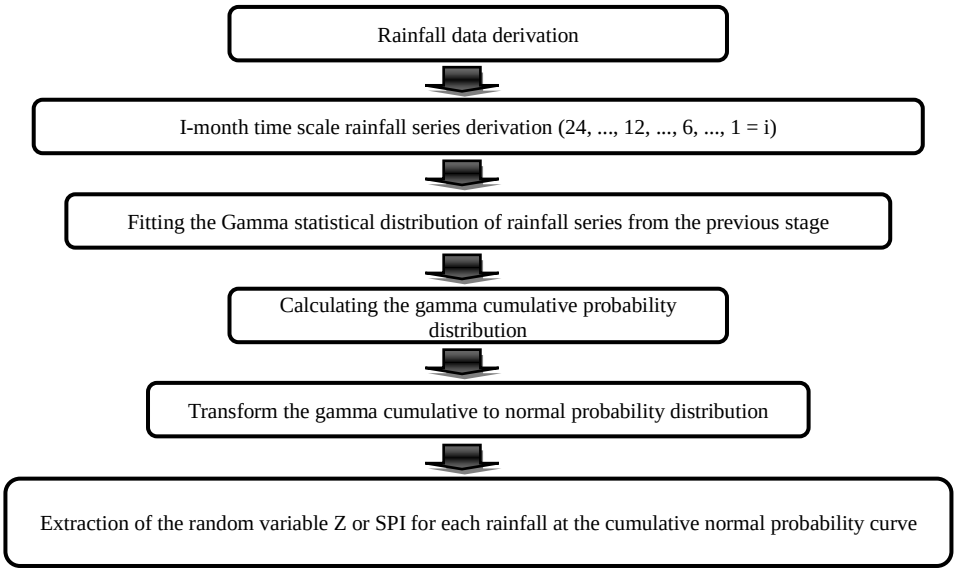


Fig. 2: Standard Precipitation Index Derivation.

2.4. Precipitation data downscaling

In order to investigate past earth climate, observed greenhouse gases, fluctuations in solar radiation and aerosols from volcanic eruptions until 2000 as input data for AOGCM models and climate variables simulate. Then in order to simulate climate variables in future periods, greenhouse gases circulation status is used and climate variable data series will be simulated from 2000 to 2100.

2.5. Downscaling procedure

Climate variables simulated by AOGCM models are geographically large scaled and cannot be used locally or at a watershed scale. Therefore these models cannot be used directly. Due to this problem, modifications to the GCM models and taking into account local conditions, small-scale models or regional models are presented. Regional models follows all physical and mathematical characteristics of atmospheric general circulation models, but they have ability to separate the 0.125 ° (15 km) and Due to this feature, can be predicted local or regional changes in clouds, precipitation, humidity, and temperature. AOGCM data downscaling is used in Iran. In this method, GCM output Reconcile with observed data. Downscaling methods are Proportional Downscaling, Statistical Downscaling, Interpolating Neighbor Cells Information, Dynamic Downscaling and Weather Generator Models.
One of the common methods for downscaling is Weather Generator (WG) model based on relationship between watershed weather data such as recorded precipitation and temperature. The main feature of these models is a comprehensive production of weather data which reflects the location of the study area. Statistical and numerical model is used in this model. In this study, LARS-WG5, one of the WG, was used in order to downscaling daily weather data from HADCM3 [24].

2.6. LARS-WG model

LARS-WG (Long Ashton Research Station Weather Generator) is a stochastic weather generator which can be used for the simulation of weather data at a single site, under both current and future climate conditions. These data are in the form of daily time-series for a suite of climate variables, namely, precipitation (mm), maximum and minimum temperature (°C) and solar radiation (MJm-2day-1). Stochastic weather generators were originally developed for two main purposes:

1) To provide a means of simulating synthetic weather time-series with statistical characteristics corresponding to the observed statistics at a site, but which were long enough to be used in an assessment of risk in hydrological or agricultural applications.
2) To provide a means of extending the simulation of weather time-series to unobserved locations, through the interpolation of the weather generator parameters obtained from running the models at neighboring sites.

It is worth noting that a stochastic weather generator is not a predictive tool that can be used in weather forecasting, but is simply a means of generating time-series of synthetic weather statistically 'identical' to the observations.
New interest in local stochastic weather simulation has arisen as a result of climate change studies. At present, output from global climate models (GCMs) is of insufficient spatial and temporal resolution and reliability to be used directly in impact models. A stochastic weather generator, however, can serve as a computationally inexpensive tool to produce multiple-year climate change scenarios at the daily time scale which incorporate changes in both mean climate and in climate variability. It utilizes semi-empirical distributions for the lengths of wet and dry day series, daily precipitation and daily solar radiation.

3. Results and discussion

The process of generating synthetic weather data can be divided into three distinct steps:

1) Model Calibration: observed weather data are analyzed to determine their statistical characteristics.
2) Model Validation: the statistical characteristics of the observed and synthetic weather data are analyzed to determine if there are any statistically-significant differences.
3) Generation of Synthetic Weather Data: the parameter files derived from observed weather data during the model calibration process are used to generate synthetic weather data having the same statistical characteristics as the original observed data, but differing on a day-to-day basis. Synthetic data corresponding to a particular climate change scenario may also be generated by applying global climate model-derived changes in precipitation, temperature and solar radiation to the LARS-WG parameter files.

In the model calibration, the data consist of daily precipitation, maximum and minimum temperature of the reference weather stations collected for the base period (1980-2007) and input files prepared and the model run for the base period. Since LARS-WG5 is a stochastic model, output files for every run in model verification are different. For this reason, it should be different runs and weight the output values in order to reduce error rate. In this study, number of model run optimized with trial and error which is ten runs for every simulated year.
In model verification regression coefficient (R^2), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to evaluate the model:

$$R^2 = \frac{(n\sum X_p.X_o - \sum X_p \sum X_o)^2}{(n\sum X_p - (\sum X_p)^2)(n\sum X_o - (\sum X_o)^2)} \quad (1)$$

2) $$MAE = \frac{\sum_{1}^{n} |X_p - X_o|}{n}$$

3) $$RMSE = \sqrt{\frac{\sum_{1}^{n} (X_p - X_o)^2}{n}}$$

In which X_p is projected value, X_o is observed value and n is the number of data.

The observed recorded weather data for comparison with simulated values. Weather data from 1980 to 1989 was used for model calibration and weather data from 1990 to 2007 was used for model verification. The calibration results showed that most rainfall will occur in autumn and winter and also air temperature in these seasons will decline substantially. More than 80% probability of dry month will be in summer due to the recorded rainfall.

Figure (3) demonstrate the mean value of weather data in model verification. Total rainfall in model calibration and verification with respect to observed values are shown in Figure (4). There are no significant differences between projected and observed rainfall.

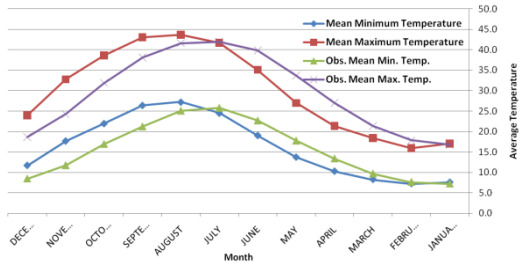


Fig. 3: The Average Daily Minimum Temperature and Maximum Temperature on Different Months (Observed And Projected) in Pooleshalou Station (Model Verification).

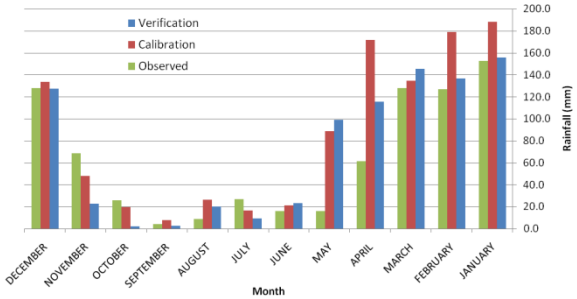


Fig. 4: Average Rainfall in Different Months and Different Model Runs in Model Verification.

IPCC climate change scenarios: A1B, A2 and B1 which are pessimistic, moderate and optimistic respectively. A1B scenario is a description of the world's fastest growing economy and population, so that the maximum population growth occurred in mid-century and then the increase in population, would be reduced. A2 scenario describes a very heterogeneous world with continuously increasing global population and regional economic growth. B1 scenario describes a convergent world's population, but with rapid change in economic structures toward a service and information economy, with reductions in material intensity and the introduction of clean and efficient technologies. Model evaluation results showed that simulated meteorological data could be used for downscaling HADCM3 data and projecting climate data for future periods using IPCC scenarios.

Results from rainfall and drought simulation for different scenarios-periods are in Table 2. Figure 5 shows the projected values versus observed values of SPI calculated from simulated rainfall under A2 emission scenario during 2011 to 2030.

Table 2: Results of Drought Status for Different Emission Scenarios and Future Periods.

Scenarios/Period	A2	A1B	B1
2011-2030	Six-and twelve-month rainfall will decrease and consequently droughts will increase, SPI also indicates that severe droughts will occur.	6 and 12 months rainfall does not show significant changes and severity of droughts will reduce. But, 24-months rainfall will be increased and droughts reduced, indicating an increase in short-term drought period.	Rainfall will increase substantially and wet and normal years will increase, droughts are less frequent and less severe.
2046-2065	In a long term rainfall will decline and droughts will occur at high intensity. The frequency of droughts will increase dramatically during this period. But in the short-term changes in rainfall (6 and 12 months) will not happen.	Total rainfall for six months and twelve months, especially in the early years and the years after 2060 are reduced and more droughts will increase.	Precipitation and drought will Increase, according to the Standardized Precipitation Index will decline substantially and drought frequency will increase.
2080-2099	Rainfall during this period will be reduced and combined with a severe drought.	Precipitation changes indicate of decrease precipitation in the long run, so that in the final years of this period of greatly reduced precipitation, droughts will occur with greater continuity.	Oscillatory changes in rainfall and droughts occur more or less severe would occur.

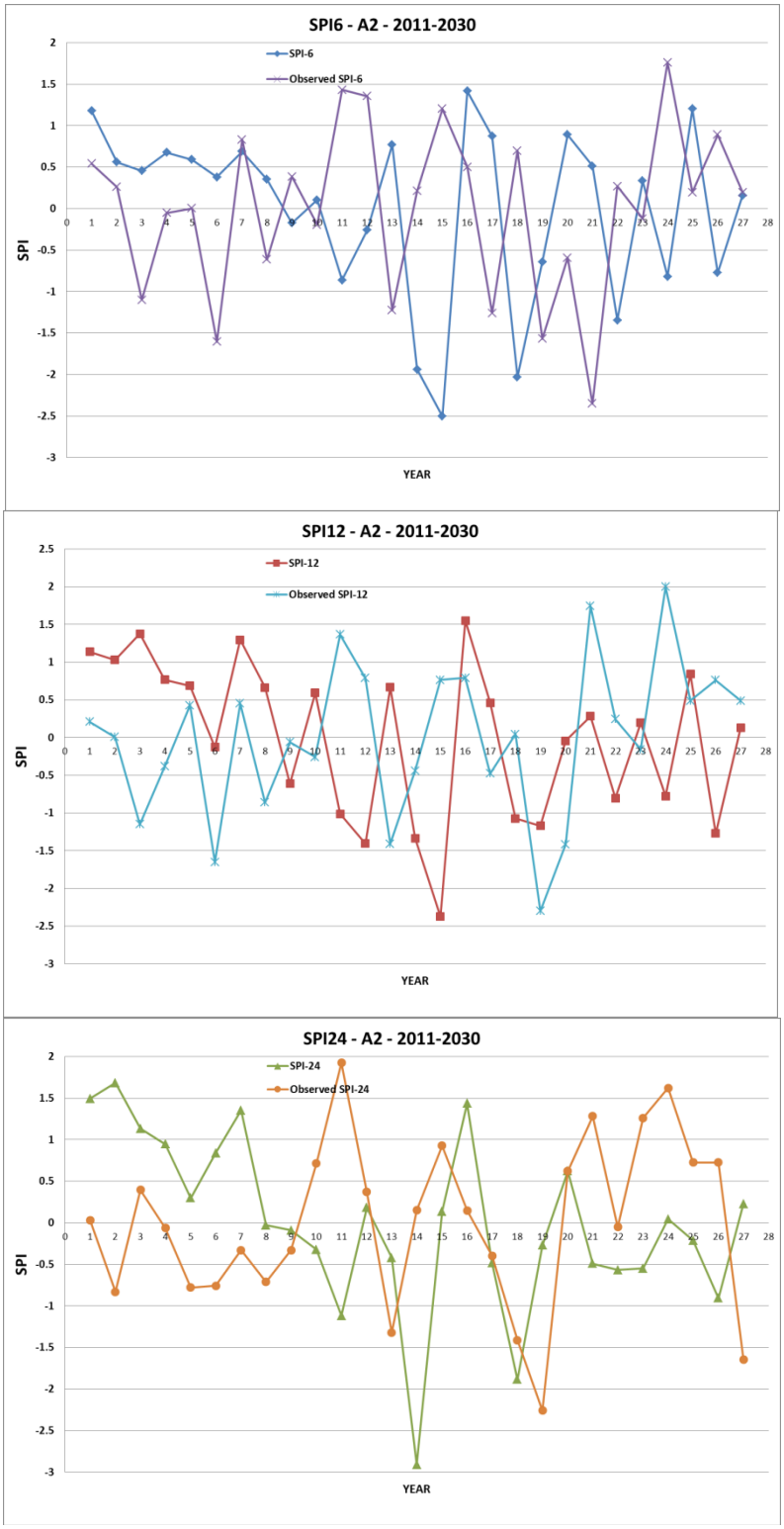


Fig. 5: Standardized Precipitation Index Changes (6, 12, and 24 Months) During 2011-2030 Under A2 Emission Scenario.

The degree of average temperature and precipitation changes in future periods in different months of the year are in Table (3). The difference between the maximum and minimum monthly temperature will decrease and rainfall will decrease in the spring and increase in summer and autumn. The greatest increase in precipitation will happen in December.

Table 3: Average Temperature and Precipitation Changes in Future Periods in Different Months of the Year.

A1B		A2		B1			
Rainfall changes (Percent)	Temperature difference changes (Percent)	Rainfall changes (Percent)	Temperature difference changes (Percent)	Rainfall changes (Percent)	Temperature difference changes (Percent)	Month	Season
1.02	0.98	1.02	1.05	1.02	0.98	JANUARY	
1.05	0.84	1.05	0.93	1.05	0.84	FEBRUARY	Winter
1.08	0.88	1.08	0.93	1.08	0.88	MARCH	
1.01	0.82	1.01	0.85	1.01	0.82	APRIL	
0.9	0.85	0.90	0.87	0.9	0.85	MAY	Spring
0.53	0.95	0.53	0.96	0.53	0.95	JUNE	
0.82	1.06	0.82	1.04	0.82	1.06	JULY	
0.29	0.97	0.29	0.95	0.29	0.97	AUGUST	Summer
0.81	0.98	0.81	0.96	0.81	0.98	SEPTEMBER	
0.98	1.08	0.98	1.07	0.98	1.08	OCTOBER	
0.96	1.17	0.96	1.2	0.96	1.17	NOVEMBER	Autumn
1.04	1.17	1.04	1.22	1.04	1.17	DECEMBER	

Mean daily rainfall intensity for different emission scenarios are shown in Figure (6), (7) and (8). Mean daily rainfall intensity will increase in winter and spring and will partly decrease in summer and autumn under A1B emission scenario. But, mean daily rainfall intensity will decrease in winter and spring and will partly decrease in summer and autumn under A2 emission scenario.

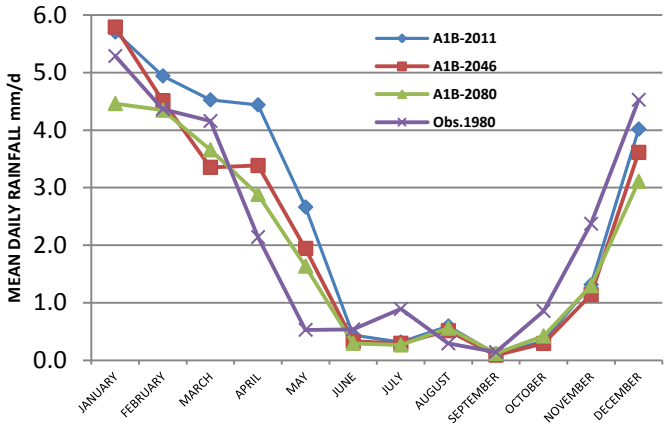


Fig. 6: Mean Daily Rainfall Intensity (Observed and Future Periods) Under A1B Scenario.

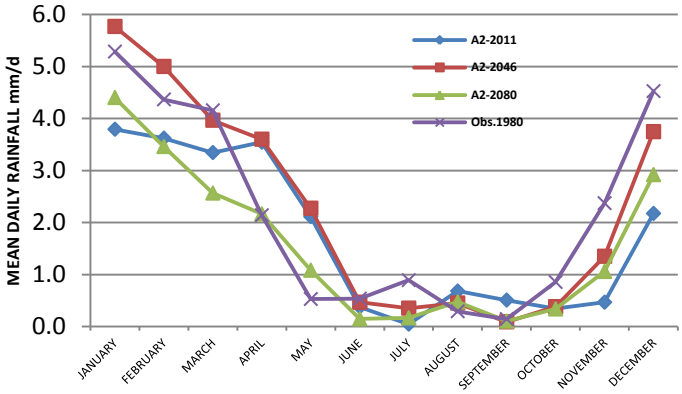


Fig. 7: Mean Daily Rainfall Intensity (Observed and Future Periods) Under A2 Scenario.

Mean daily rainfall intensity will increase in winter and spring and have no significant differences in summer and autumn based on Figure (8). In general the precipitation occurs mainly between January and May in future periods and summer or autumn precipitation decline and lead up to short term drought in the study region.

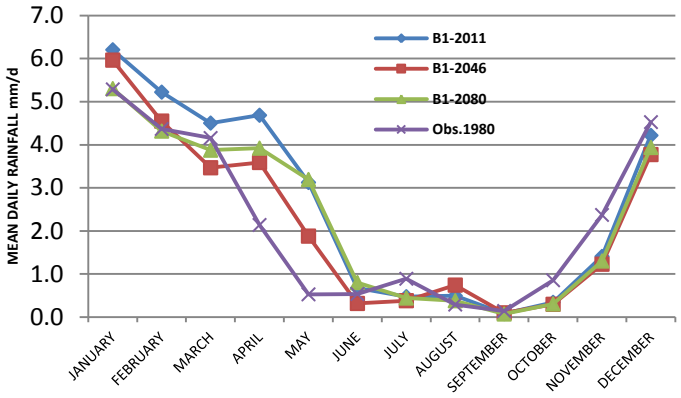


Fig. 8: Mean Daily Rainfall Intensity (Observed and Future Periods) Under B1 Scenario.

Drought severity frequency in future periods for different IPCC emission scenarios are derived in Table (4). Normal drought frequency under A2 and B1 scenarios are more than A1B. Drought years are more frequent under A1B and in 2080-2099 periods.

Table 4: Drought Intensity Frequency in Future Periods under A1B, A2 and B1 Scenarios.

8	7	6	5	4	3	2	1	SPI CLASS		
Extremely Dry	Very Dry	Moderately Dry	Normal Dry	Normal Wet	Moderately Wet	Very Wet	Extremely Wet	Drought Status		Periods
1	2	3	5	12	3	1	0	SPI-6		
1	1	3	7	12	1	1	1	SPI-12	Base	
1	1	2	9	10	3	1	0	SPI-24		
0	0	3	10	9	3	2	0	SPI-6		
1	2	2	7	9	5	1	0	SPI-12	A1B	
3	0	1	9	12	0	2	0	SPI-24		
2	1	1	6	14	3	0	0	SPI-6		2011-2030
1	0	6	5	10	4	1	0	SPI-12	A2	
1	1	1	11	8	4	1	0	SPI-24		
1	2	0	10	9	3	2	0	SPI-6		
1	1	2	8	8	6	1	0	SPI-12	B1	
1	1	2	9	12	0	1	1	SPI-24		
1	2	3	5	12	3	1	0	SPI-6		
1	1	3	7	12	1	1	1	SPI-12	Base	
1	1	2	9	10	3	1	0	SPI-24		
1	1	1	10	9	3	2	0	SPI-6		
1	2	1	9	8	5	1	0	SPI-12	A1B	
0	1	2	8	14	0	2	0	SPI-24		
0	1	2	10	9	3	2	0	SPI-6		2046-2065
1	1	2	9	8	5	1	0	SPI-12	A2	
1	1	2	8	13	0	2	0	SPI-24		
1	1	1	10	10	2	2	0	SPI-6		
1	2	1	9	8	4	2	0	SPI-12	B1	
1	2	2	6	12	2	2	0	SPI-24		
1	2	3	5	12	3	1	0	SPI-6		
1	1	3	7	12	1	1	1	SPI-12	Base	
1	1	2	9	10	3	1	0	SPI-24		
0	0	3	11	8	3	2	0	SPI-6		
0	2	2	9	9	3	2	0	SPI-12	A1B	
1	2	1	8	10	4	1	0	SPI-24		
1	1	1	11	8	3	2	0	SPI-6		2080-2099
0	3	0	11	9	3	1	0	SPI-12	A2	
1	2	0	9	12	1	1	1	SPI-24		
1	2	0	10	9	3	2	0	SPI-6		
1	1	2	6	10	6	1	0	SPI-12	B1	
1	1	2	7	14	0	1	1	SPI-24		

The changes percentage in the of droughts frequency in terms of SPI class over the monitoring period is shown in Table 5. Droughts frequency will increase and therefore wet years will decline under A2 and A1B scenarios during 2011-2030, while 18.5 percent of wet year's frequency will increase. Wet year's frequency under A2 and A1B scenario will decline during 2046-2065. Droughts frequency will increase to 22 percent and wet years decrease to 14.8 percent under A2 and A1B scenario during 2080-2099. Overally Table (5) demonstrates that we will encounter wet years during 2011 to 2030, the duration of possible drought will increase during 2046 to 2065 and more critical and frequent droughts will take place in Karoon3 watershed during 2080 to 2099.

Table 5: Drought Frequency Changes from Observed SPI Class Under A1B, A2 and B1 Scenarios.

	2011-2030								
SPI CLASS	A1B			A2			B1		
	SPI-6	SPI-12	SPI-24	SPI-6	SPI-12	SPI-24	SPI-6	SPI-12	SPI-24
Extremely Wet	0.0	-3.7	-3.7	0.0	-3.7	-3.7	0.0	-3.7	0.0
Very Wet	3.7	0.0	3.7	-3.7	0.0	0.0	3.7	0.0	0.0
Moderately Wet	0.0	14.8	-7.4	0.0	11.1	7.4	0.0	18.5	-7.4
Normal Wet	-11.1	-11.1	7.4	7.4	-7.4	-7.4	-11.1	-14.8	7.4
Normal Dry	18.5	0.0	0.0	3.7	-7.4	7.4	18.5	3.7	0.0
Moderately Dry	0.0	-3.7	-3.7	-7.4	11.1	-3.7	-11.1	-3.7	0.0
Very Dry	-7.4	3.7	-3.7	-3.7	-3.7	0.0	0.0	0.0	0.0
Extremely Dry	-3.7	0.0	7.4	3.7	0.0	0.0	0.0	0.0	0.0
	2046-2065								
SPI CLASS	A1B			A2			B1		
	SPI-6	SPI-12	SPI-24	SPI-6	SPI-12	SPI-24	SPI-6	SPI-12	SPI-24
Extremely Wet	0.0	-3.7	-3.7	0.0	-3.7	-3.7	0.0	-3.7	-3.7
Very Wet	3.7	0.0	3.7	3.7	0.0	3.7	3.7	3.7	3.7
Moderately Wet	0.0	14.8	-7.4	0.0	14.8	-7.4	-3.7	11.1	0.0
Normal Wet	-11.1	-14.8	14.8	-11.1	-14.8	11.1	-7.4	-14.8	7.4
Normal Dry	18.5	7.4	-3.7	18.5	7.4	-3.7	18.5	7.4	-11.1
Moderately Dry	-7.4	-7.4	0.0	-3.7	-3.7	0.0	-7.4	-7.4	0.0
Very Dry	-3.7	3.7	0.0	-3.7	0.0	0.0	-3.7	3.7	3.7
Extremely Dry	0.0	0.0	-3.7	-3.7	0.0	0.0	0.0	0.0	0.0
	2080-2099								
	A1B			A2			B1		
SPI CLASS	SPI-6	SPI-12	SPI-24	SPI-6	SPI-12	SPI-24	SPI-6	SPI-12	SPI-24
Extremely Wet	0.0	-3.7	-3.7	0.0	-3.7	0.0	0.0	-3.7	0.0
Very Wet	3.7	3.7	0.0	3.7	0.0	0.0	3.7	0.0	0.0
Moderately Wet	0.0	7.4	7.4	0.0	7.4	-3.7	0.0	18.5	-7.4
Normal Wet	-14.8	-11.1	0.0	-14.8	-11.1	7.4	-11.1	-7.4	14.8
Normal Dry	22.2	7.4	-3.7	22.2	14.8	0.0	18.5	-3.7	-7.4
Moderately Dry	0.0	-3.7	-3.7	-7.4	-11.1	-7.4	-11.1	-3.7	0.0
Very Dry	-7.4	3.7	3.7	-3.7	7.4	3.7	0.0	0.0	0.0
Extremely Dry	-3.7	-3.7	0.0	0.0	-3.7	0.0	0.0	0.0	0.0

4. Conclusion

In this study, drought status in future periods under climate change in Karoon3 watershed located in southwestern Iran was investigated. For this purpose HadCM3 model output from AOGCM was used under A1B, A2 and B1 emission scenarios to simulate future period precipitation in the study area. Watershed mean rainfall was estimated by IDW method and SPI for 6, 12 and 24 period was calculated in order to evaluate the short-term and long-term possible drought in future periods under SRA1B, SRA2 and SRB1 scenarios.

Results showed that difference between maximum and minimum monthly temperature will decline in spring and summer. Spring rainfall will increase and will decrease in summer and autumn. Maximum increase in rainfall will happen in winter and especially December. Mean daily rainfall intensity will increase in winter and spring and will partly decrease in summer and autumn under A1B emission scenario. But, mean daily rainfall intensity will decrease in winter and spring and will partly decrease in summer and autumn under A2 emission scenario. Mean daily rainfall intensity will increase in winter and spring and have no significant differences in summer and autumn. In general the precipitation occurs mainly between January and May in future periods and summer or autumn precipitation decline and lead up to short term drought in the study region. Drought severity frequency in future periods for different IPCC emission scenarios are derived in Table 4. Normal drought frequency under A2 and B1 scenarios are more than A1B. Drought years are more frequent under A1B and in 2080-2099 periods. Wet years will take place during 2011 to 2030,

the duration of possible drought will increase during 2046 to 2065 and more critical and frequent droughts will take place in Karoon3 watershed during 2080 to 2099.
It is hereby recommended that the other hydrological drought index should be used to investigate the climate change impact on underground and surface water resources for future periods in Karoon3 watershed due to limited water resources. Since in this study results was derived from on of AOGCM model and three emission scenarios, uncertainty of AOGCM and other emission scenarios were not evaluated in this study, it is suggested to investigate uncertainty of using these models in future researches.

Acknowledgements

This study was supported by ahvaz branch of Islamic Azad University. The author also appreciate the editors and reviewers for their comments that lead to improve the quality of the paper.

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