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Evaluation of Changes in Meteorological Parameters in Atrak Basin Considering Climate Change Status

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Abstract

Projection of climate change in basins is very important for determining water capacity, water resources management as well as watershed management studies and environmental hazards. Therefore, in this study, temperature and precipitation changes were projected in Atrak basin, in the northern Khorasan province. For this purpose, the output projection of canESM2 global model were used considering three scenarios of Representative Concentration Pathway (RCP) 2.6, RCP 4.5 and RCP 8.5 using SDSM as downscaling model and temperature and precipitation changes in the period (2021-2050) were compared with the base period (1995-2019). For calibration and validation of SDSM model, station observational data and NCEP/NCAR data were evaluated. MAE, MSE, RMSE and R^2 correlation indices were determined to clarify the performance of the model .The results showed that the SDSM model has a high ability to simulate temperature and precipitation changes in the study area. According to the results of the CanESM2 model, in the future periods, temperature and precipitation would be increased compared to the base period, which might be from 0.9 and 1.0 degree Celsius for minimum and maximum temperatures, respectively. Most of the temperature changes would be related to the eastern parts of the study area while, the amount of precipitation in the basin would be increased from 1.5 up to 11.7 percent, the largest increase of which would be related to the central and northern regions of the basin. The highest and lowest temperature and precipitation changes in the basin are predicted based on RCP 8.5 and RCP 2.6 scenarios.

Keywords: Atrak, Climate change, RCP, SDSM

1. Introduction

Considering that water resources are exposed to the risks of climate change. Human-induced climate change is a serious concern, drawing increasing attention from the media, policy makers and citizens around the world Hardy, J.T. (2003). The study of climate change in the coming years can lead to problems such as drought, flash floods, high evaporation and environmental degradation among climatic elements, temperature and precipitation due to the widespread impact on others. Factors and especially the effects on human activities are of particular importance so that almost the most climatic changes on the surface of the planet are focused on these two parameters (Goodarzi and Hosseini, 2017).

Studying climate change in the coming years can lead to problems such as drought, sudden floods, high evaporation and environmental degradation (Shaemi & Habibi Nokhandan, 2009:34).

Therefore, considering the importance of temperature and precipitation, it is necessary to estimate these parameters in different regions and especially its prediction is very important for areas whose economy is very depended on agriculture. On the other hand, with timely forecasting of temperature and precipitation, it is possible to deal with atmospheric hazards such as floods, droughts, heat waves and reduce the damage caused by it (Goodarzi and Hosseini, 2017).

In recent years, a number of researches has been conducted on the prediction of climate change in different parts of the world. According to the results of climate change studies in the Mediterranean, the relationship between temperature increases and decrease in rainfall and water shortage and increased risk of forest fires in the region has been proved (Panol and Loret, 1998) . Also, according to reports, climate change has caused changes in the hydrological regime in the last few decades globally so that rainfall and surface flows in high and middle latitudes and at low latitudes have decreased and the probability of exposure to maximum climatic events such as flooding and drought has increased (Lane et al., 1999) . Therefore, studying climate change, especially temperature and precipitation changes as one of the most important climatic and hydrological parameters, can pave the way for adopting future strategic policies for water resources management. There are different methods for predicting climate change, the most reliable of which is the use of data from atmospheric oceanic general circulation models or AOGCMs, which are currently the most powerful tools for producing climate scenarios. General Circulation Models (AOGCMs) indicate that rising concentrations of greenhouse gases will have significant implications for climate at global and regional scales. Unfortunately, AOGCMs are restricted in their usefulness for local impact studies by their coarse spatial resolution (typically of the order 50,000 km^2) and inability to resolve important sub–grid scale features such as clouds and topography (Wilby, R.L., & Dawson. W.C. (2007)).

The outputs of these models have low spatial resolution. Therefore, if it is directly used as the input of climatic and hydrological models, it would increase uncertainty. For this reason, downscaling methods are used to increase the spatial resolution of these data, which are including statistical and dynamic methods, and statistical methods are more applicable than other methods because of their quick and easy operation. One of the most widely used statistical downscaling tools is SDSM model, which has many applications in meteorological, hydrological, geographical and environmental studies (Wilby & Harris, 2006) Because in this method, large-scale daily circulation patterns are used on a station scale and when there is a need for rapid and low-cost estimation of climatic changes, it is used and in the case of random meteorological generators and functions methods. The deformed results have provided acceptable results (Samadi and Massah Bavani, 2008).

In this regard, Goodarzi et al. (2011) projected temperature and precipitation changes using SDSM model in Kermanshah. The results showed that SDSM tool is able to show changes in temperature and precipitation and according to statistical methods, its results are acceptable. Cha et al. (2016) predicted summer rainfall changes in Korea using different RCP scenarios. The results showed that in the next period, the amount of precipitation decreases and its intensity increases.

Houshyar, M., Sobhani, B., Hosseini, S. A. (2018). Projected Maximum Temperature in Urmia through Downscaling output of CanESM2 Model. Using SDSM. SDSM model is one of the most widely used statistical microscopic instruments, which has many uses in meteorological, hydrological, geographic and environmental studies. in this method, large-scale daily circulation patterns are used on a stationary scale; and when used for the rapid and cost-effective estimation of climate change, and for randomized meteorological generators and modified functions, have given acceptable results. Given that global models have generally simulated climatic elements until the year 2100, it is possible to use global model data to simulate the desired variables such as precipitation and temperature on a station scale. The variation of the maximum temperatures of the synoptic station of Urmia during the period (2021-2050) of the CanESM2 global model has been used under three scenarios RCP2.6, RCP4.5 and RCP8.5.

Leong Tan et al. (2017) predicted climate change and assessed its effects on water resources in Malaysia. The results showed an increase in rainfall in wet season and a decrease in dry season. Dimri et al. (2018) evaluated possible temperature changes under various RCP scenarios in the Himalayas. According to the results, the minimum and maximum temperatures in this region increase between 0.23-0.54 °C per decade. Nilawar and Waikar (2019) predicted temperature and precipitation changes under two RCP scenarios and its effects on river flow in India. The results showed that temperature and precipitation will increase under both scenarios in future periods. Heydari et al. (2020) predicted temperature and precipitation changes using different RCP scenarios in Urmia Lake basin. The results showed that in the coming periods, the amount of precipitation will decrease and the temperature will increase. Malmir et al. (2016) investigated temperature and precipitation changes in Qarasu watershed using SDSM model. The results show an increase in temperature and a decrease in rainfall in the next period compared to the base period.

Azizi et al. (2019) addressed the prospects of temperature changes in Ilam province based on the models of the fifth report. The results showed an increase in minimum and maximum temperatures in the study area. Kasiri et al. (2020) predicted temperature and precipitation changes in the southern coasts of the Caspian Sea using the Global CanESM2 model and SDSM downscaling model. The results showed that temperature will increase and precipitation will decrease in the study area in the next period.

Therefore, considering the importance of climate change investigation, in this study, climate change prediction in Atrak watershed was investigated using downscale of SDSM model and output of CanESM2 global model under three scenarios of RCP.

The outputs of these models have low resolution accuracy. Therefore, if it is directly located as the input of climatic and hydrological models, it increases uncertainty. For this purpose, downscaling methods are used to increase the spatial resolution of these data which are divided into statistical and dynamic methods (Beecham et al., 2014; Bates et al., 2008). Statistical methods are more applicable than other methods due to their quick and easy operation (Dibike & Coulibaly, 2005; Kilsby et al., 2007) .One of the most widely used statistical downscaling tools is SDSM model, which has many applications in meteorological, hydrological, geographical and environmental studies (Wilby & Harris, 2006).

As in this method, large-scale daily circulation patterns are used on a station-scale and when there is a need for rapid and low-cost estimation of climatic changes, it is used and has provided acceptable results regarding random meteorological generators and deformed functions methods (Samadi and Massah Bavani, 2008).

Naderi et al. (2017) investigated temperature and precipitation changes in Seymareh watershed using SDSM model. The results showed an increase in temperature and a decrease in rainfall in the study area.

Goodarzi et al. (2018) overviewed the future prospects of temperature and precipitation changes using SDSM downscale model in Urmia Lake watershed. Based on the results, the amount of temperature and precipitation will increase in the next period compared to the base period. Therefore, considering the importance of climate change investigation, in this study, climate change prediction in Atrak watershed was investigated using downscale of SDSM model and output of CanESM2 global model under three scenarios of RCP.

2. Materials and Methods

2.1. Study Area

The study area is Atrak basin in northeastern part of Iran. It has an area of 26,430 square kilometers and its main river is Atrak. To investigate climate change in this area, minimum temperature, maximum temperature and precipitation datum of four synoptic stations (with appropriate distribution at the watershed level and long-term and common statistical period (1995-2020)) were used. Geographical location of the study area and meteorological stations are presented in figure 1 as well as the geographical characteristics of meteorological stations in table 1.

Table 1. Geographical characteristics of meteorological stations in the study area

Station	Type	Height	latitude	longitude
Bojnord	synoptic	1065	37.48	57.30
Quchan	synoptic	1287	37.11	58.45
Gonbad Kavus	synoptic	37.2	37.26	55.21
Maraveh Tape	synoptic	460	37.8	55.35

1.1.SDSM

SDSM is a conditional and two-phase re-sampling method for downscaling (Wilby et al., 2007). Here in this method, first scales the predictive variable (such as temperature and precipitation) using combined regression methods and a random meteorological generator method and then is re-produced at the station site (Tatsumi et al., 2013).

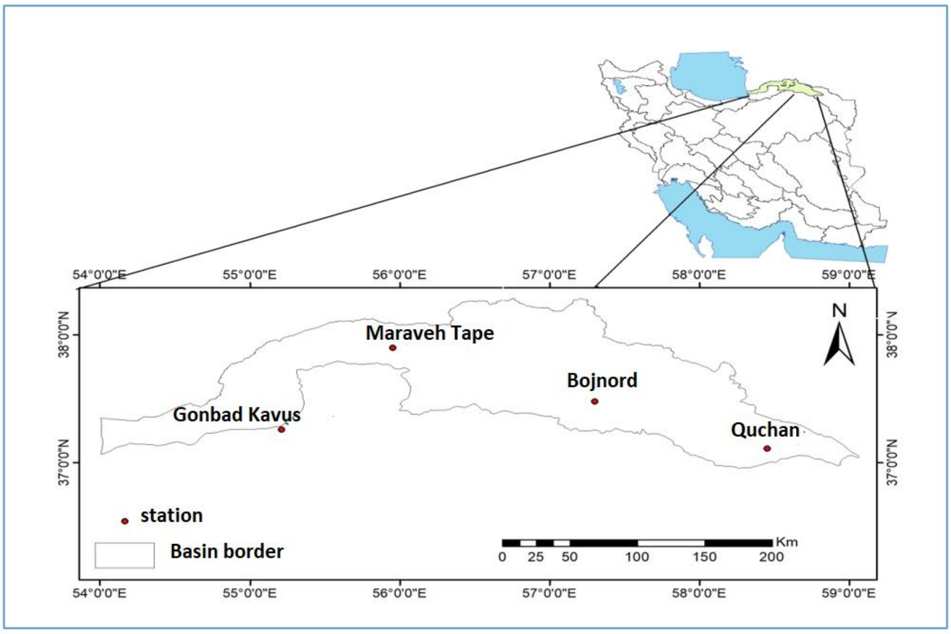

Fig. 1. Geographical location of the study area and meteorological stations

In fact, SDSM combines statistical meteorological productive method and deformed functions. This model was first produced by Wilby et al. in 2002 version 2.1 in the UK, which is based on the use of a combination of regression methods and the production of artificial climatic data for down scaling. In this model, the local climate is represented by the large-scale climate of the region in the form R = F(X), here R represents the local climate variable which is downscaled.

X is a set of large-scale climatic variables, and F is an X-conditional determination function based on the training and validation of historical data (Kamal and Massah Bavani, 2010). In this study, the data of minimum temperature, maximum temperature and precipitation of selected meteorological stations were used daily, data from the National Center for Prediction of Environmental Variables (NCEP) and canesm2 global model data under three scenarios of radiant lattice (RCP 2.6, RCP 4.5, RCP 8.5) were used as networks.

The CanESM2 model is the fourth generation of climate models developed by the Canadian Center for Climate Modeling and Analysis (CCCMA) under the auspices of the Country's Environment Organization. In this model, the whole earth is networked as 64*128 cells with a grid of 1 by 1*1 degree in longitude and latitude. The method is obtaining the data from the Canadian climate change site, this model first scales the station forecasting variables (such as temperature and precipitation) using combined regression methods and a random meteorological generator method and then reproduces the mentioned data.

NCEP variables consist of 26 atmospheric variables among which appropriate variables are selected. This choice is made through correlation coefficient. The data of the mentioned model are anomalies which have been calculated compared to the base period. To evaluate the model in this study, stationary temperature and precipitation data and NCEP data were used in the base period (1995-2019) after selecting the best predictors from the NCEP set of variables, temperature and precipitation forecasting operations for the upcoming period (2021-2050). CanESM2 model was used under three scenarios: RCP2.6, RCP4.5 and RCP8.5. In fact, in order to select the predictors, SDSM software establishes a correlation with the maximum correlation coefficient between the daily observational series of the region and the large scale variables of the observational scale of the region (NCEP) and then, using the parameters obtained from this relationship, by applying the large scale variables derived from the CanESM2 model and different scenarios in the next period, produces the time series of the desired parameter in the region (Goodarzi et al., 2016).

After projecting daily data for the next period, rainfall outputs, minimum temperature and maximum temperature of the model were averaged. Then their variations are calculated relative to the mean values of the baseline period and the diagrams of temperature and precipitation changes related to each station are drawn and analyzed (Karamouz et al., 2006)

1.2.Evaluation of model performance

In order to evaluate and analyze the performance of estimation and prediction models, there are various performance indicators which are briefly explained about the indicators used in this study. The coefficient of determination (R^2) is also a criterion without dimension and the best value is equal to one. The equation (1) shows how to calculate it (Sedaqatkerdar et al., 2008). Mean Square Error (MSE) that can be changed from zero in excellent performance to extreme. Defined as equation (2) Root Mean Squares error (RMSE) is used as an index to show the difference between simulated values from measurement values, this criterion which is defined as equation (3) is used as the most common error index (Lin et al., 2006). Mean Absolute Error (MAE) is used to compare the relative error of simulated values according to the measured values, which is presented as equation (4) (Hu et al., 2001).

$$R^2 = \frac{\sum_{i=1}^{N} X_o X_s}{\sqrt{\sum_{i=1}^{N} X_o^2 \sum X_s^2}} \tag{1}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_o - X_s)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(X_o - X_s)^2}{N}} \tag{3}$$

$$MAE = \frac{\sum_{i=1}^{N}|X_o - X_s|}{N} \tag{4}$$

where in the above equations, the X_o of observational data is the X_s of simulated data and N is the amount of data.

2. Results and Discussion

In the SDSM downscale model before calibration of the model, it is necessary to determine the independent atmospheric variables (NCEP) that have the highest correlation with the observational climatic parameters. Based on the results, the average temperature variables at the height of two meters above ground, geopotential elevation of P500 hectopascal level and average sea level pressure have the highest correlation coefficient with minimum and maximum temperatures and the variables of P850, wind speed at P850 and average temperature at 2 meters have the highest correlation with precipitation in the study area (Table 2).

Then, in order to validate the model, the model parameters were evaluated using NCEP variables and real data for the basic statistical period. The results showed that there is no significant difference between modeled and stations observational values and Pearson correlation values between modeled and actual temperature and precipitation data at the significance level of 0.05 are acceptable. Evaluation of error measurement indices (RMSE, MSE and MAE) also showed that the SDSM model has a high efficiency for downscaling of the studied parameters in the study area.

Based on the results, the accuracy of the model varies in stations and in different parameters so that the model has been more successful than precipitation in the field of temperature modeling and has less accuracy in simulating precipitation, especially in the rainy months of the year.

Table 2. Independent variables used for calibrating the model

Station	Precipitation	Max. Temp.	Min. Temp.
Bojnord	P850 Meridional velocity P850 Zonal Velocity	Mean sea level pressure P500 Geopotential Mean Temperature at 2 m	Mean sea level pressure P500 Geopotential Mean Temperature at 2 m
Quchan	P850 Geopotential P850 Meridional Velocity P850 Convergence	P500 Geopotential P850 Convergence Mean Temperature at 2 m	P500 Geopotential P850 Convergence Mean Temperature at 2 m
Gonbad Kavus	P500 Relative/Specific humidity Mean Temperature at 2 m	Mean sea level pressure P500 Geopotential Mean Temperature at 2 m	Mean sea level pressure P500 Geopotential Mean Temperature at 2 m
Maraveh Tapeh	P500 Geopotential P850 Vorticity Mean Temperature at 2 m	Mean sea level pressure P500 Geopotential Mean Temperature at 2 m	Mean sea level pressure P500 Geopotential Mean Temperature at 2 m

This is due to the complexity of precipitation process and also the structure of climatic and downscaling models. Among the studied stations, the highest model error was related to the precipitation of Gonbad Kavous station with RMSE equal to 6.5 and the lowest error was related to Bojnord station with RMSE equal to 4.7 mm. In the field of temperature modeling in the study area, the model has been more successful in simulating the minimum temperature than the maximum temperature (Table 3).

Table 3. Performance evaluation of SDSM downscaling model using different indicators

Station	parameter	R^2	MSE	MAE	RMSE
Bojnord	Min. Temp.	0.99	0.00	0.02	0.03
	Max. Temp.	0.99	0.00	0.04	0.05
	Precipitation	0.98	21.9	4.2	4.7
Quchan	Min. Temp.	0.99	0.00	0.02	0.03
	Max. Temp.	0.99	0.00	0.03	0.03
	Precipitation	0.97	36.8	5.4	6.1
Gonbad Kavus	Min. Temp.	0.99	0.00	0.03	0.04
	Max. Temp.	0.99	0.00	0.04	0.06
	Precipitation	0.98	42.9	6.3	6.5
Marveh Tapeh	Min. Temp.	0.99	0.00	0.02	0.03
	Max. Temp.	0.99	0.00	0.04	0.04
	Precipitation	0.98	35.1	5.8	5.9

In order to better represent and assure the accuracy of the prediction and also to investigate the uncertainty in the projected parameters, the simulated and observational values were compared monthly during the base period in the study stations using comparative diagrams, in this study, due to the large number of related diagrams, only the results of Bojnord synoptic station were presented as samples .As can be seen, the observed values and simulation of the studied parameters do not differ much from each other, indicating the appropriate performance of the SDSM model for modeling and predicting the changes of the studied parameters (Fig. 2).

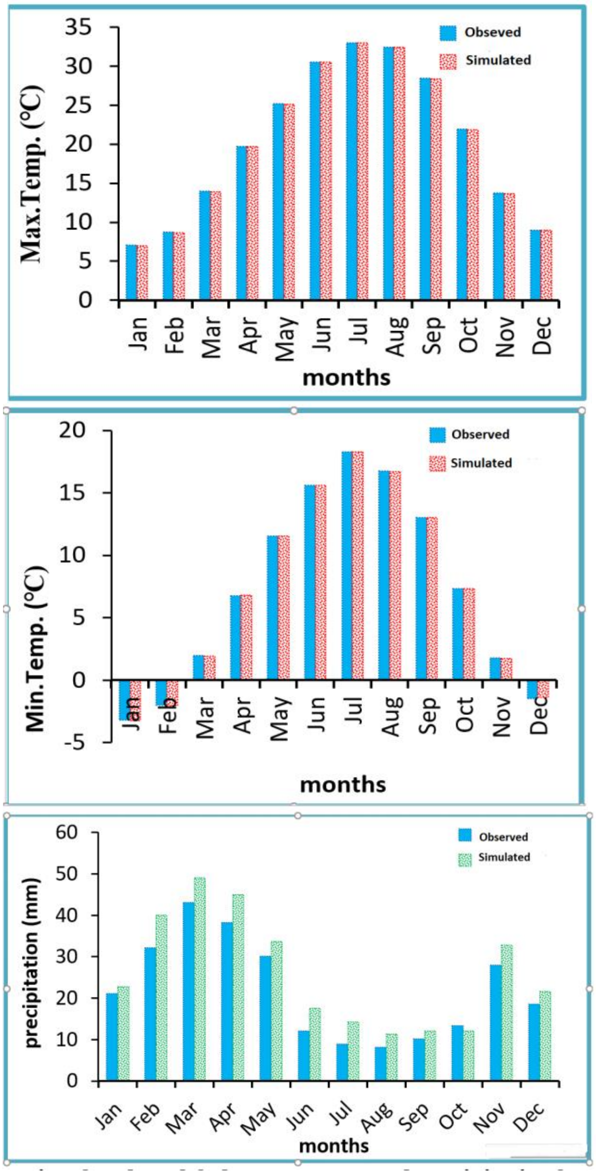

Fig. 2. Observational and projected temperature and precipitation by SDSM in Bojnord

After evaluating the downscale model and ensuring its suitability, the data produced by the CanESM2 model for future periods were investigated under three RCP scenarios. The results of monthly study parameters in the study station show that rainfall in the period (2021-2050) in all studied stations based on RCP 2.6 and RCP 4.5 scenarios in most months of the year will increase compared to the base period, while according to the RCP 8.5 scenario in most months of the year the amount of precipitation has decreased, which is due to the characteristics that this scenario represents. The most decreasing changes based on the mentioned scenario are related to the high rainfall months of the year (Fig. 3).

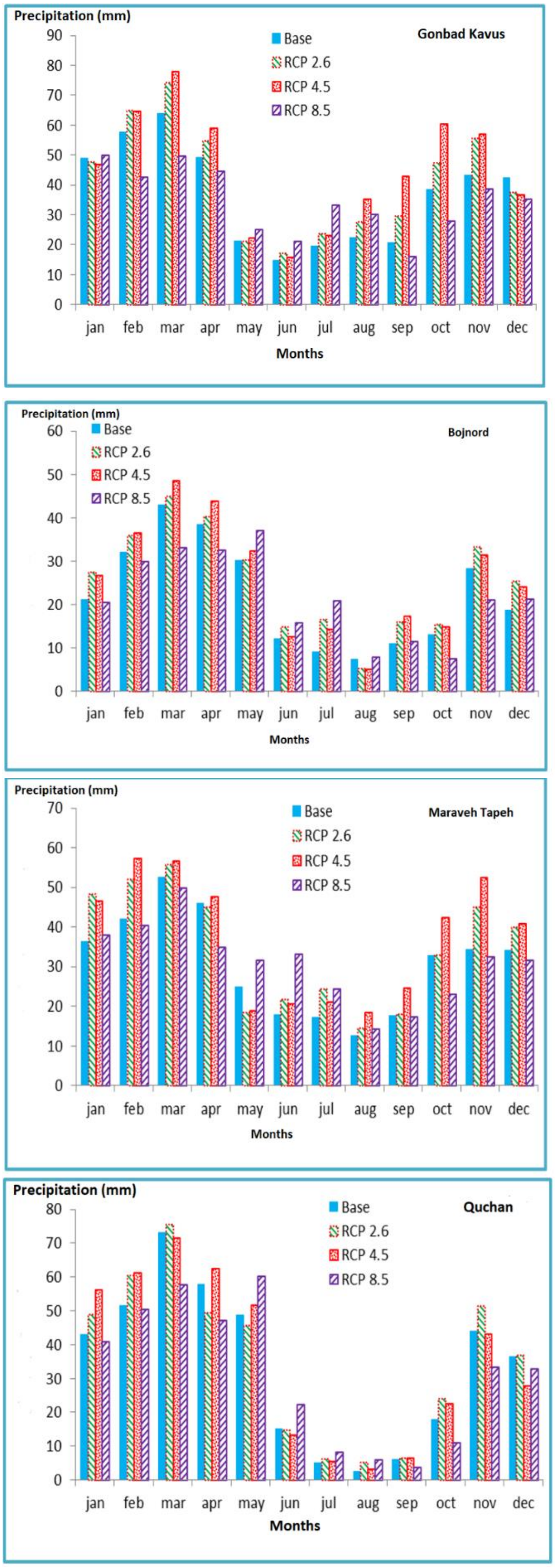

Fig. 3. Monthly precipitation changes compared to the base period within scenarios

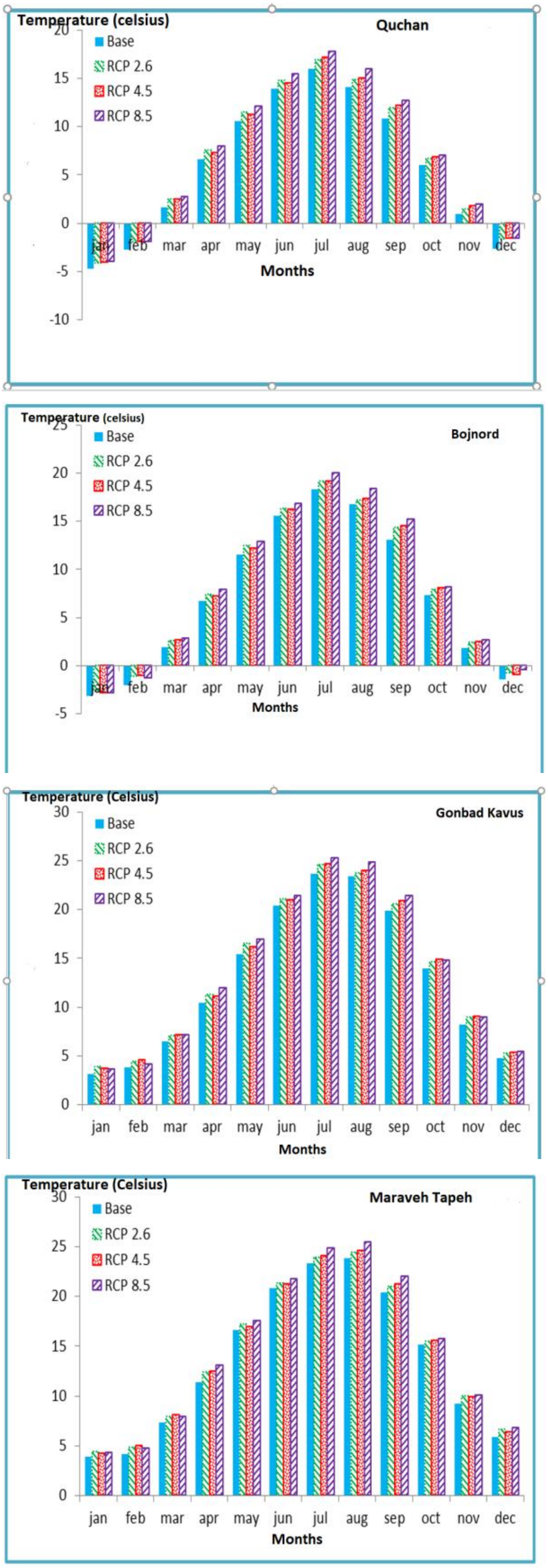

Fig. 4. Minimum temperature changes compared to the base period within scenarios

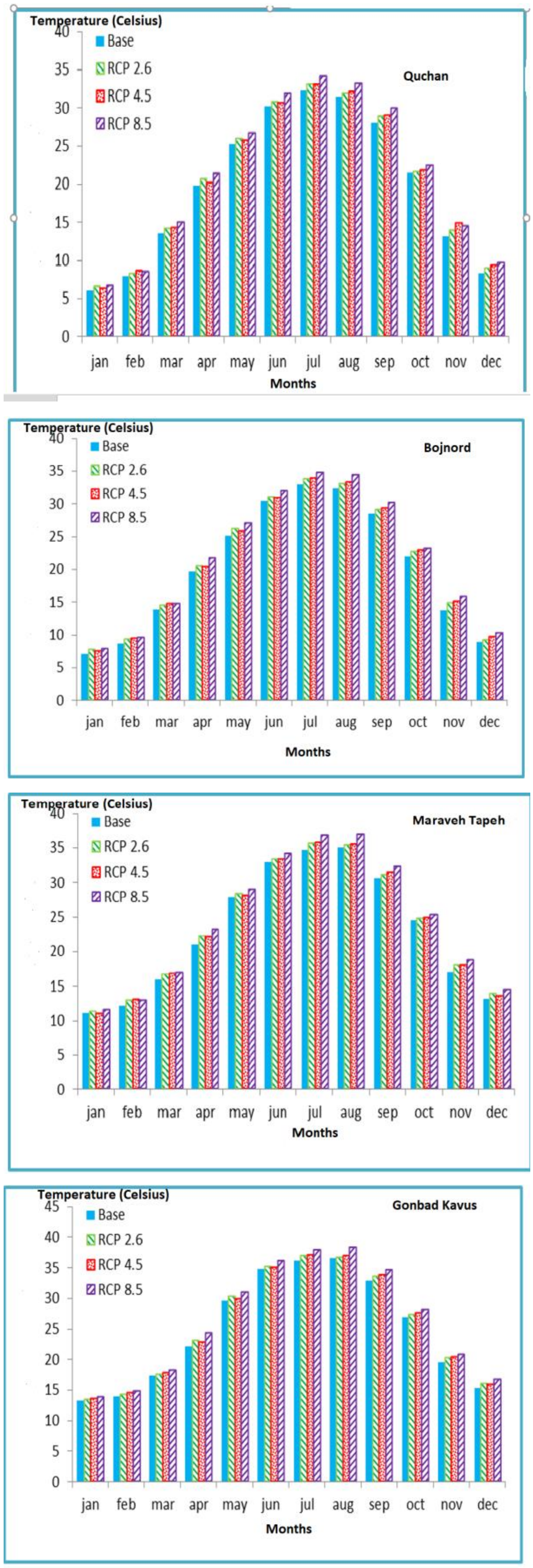

Fig. 5. Maximum temperature changes compared to the base period within the scenarios

Monthly changes of minimum temperature show that temperature will increase based on all three scenarios and in all stations in all months of the year. The most changes were related to the warm months of the year based on the estimated RCP8.5 scenario (Fig. 4). The prediction of monthly changes in maximum temperature also shows that the maximum temperature will increase as well as the minimum temperature based on all three scenarios and in all study stations in all months of the year, and the most changes are estimated based on the RCP8.5 scenario (Fig. 5).

The study of the long-term average of precipitation in the base and future periods by the stations and the studied scenarios shows that the amount of precipitation in the study area will decrease slightly based on the RCP 8.5 scenario, while according to RCP scenarios 2.6 and RCP 4.5 the amount of precipitation will increase . The results of the average scenarios in different stations of the watershed surface showed that the amount of rainfall in all the studied stations in the watershed level will increase compared to the base period. The most changes were related to Maraveh Tapeh station by 11.7% and the lowest changes were related to Quchan station with 1.5% increase compared to the base period, in total, it is expected that precipitation at Atrak basin based on the studied stations will increase by 7.8% compared to the base period (Fig. 6).

In relation to the minimum temperature parameter, the results indicate an increase in the minimum temperature in the studied stations. The highest minimum temperature changes in the study area were related to Quchan stations with 1 degree Celsius and the lowest changes were related to Maraveh Tapeh station with 0.8 degrees Celsius increase in the period (2021-2050) compared to the base period . Based on the results of all three scenarios, the minimum temperatures that occurred in the study area in the base period have not been observed in the next period and the heating trend has shown that its rate varies between 0.7 and 1.2 degrees Celsius, the lowest and highest of which is related to RCP 2.6 and RCP 8.5 scenarios, respectively. In general, the minimum temperature in the study area will increase by an average of 0.9 degrees Celsius. (Fig. 7).

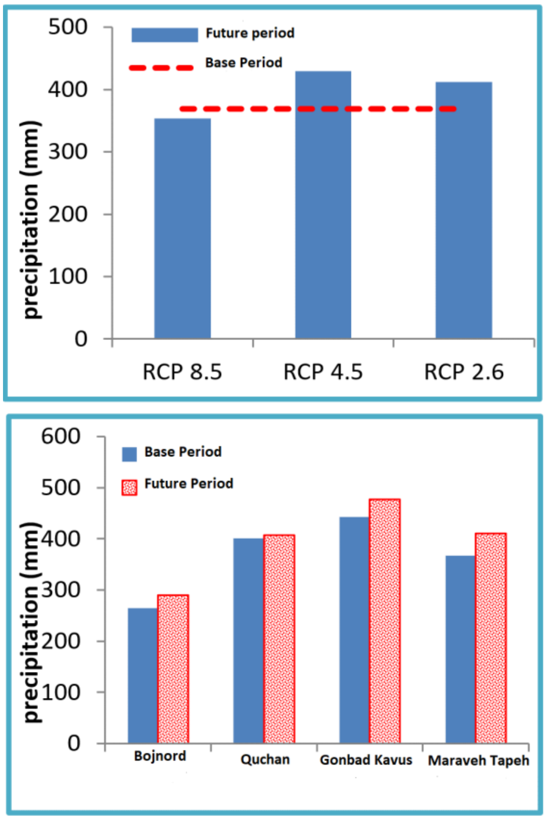

Fig. 6. Precipitation changes compared to the base period within the station and scenario.

The results of the maximum temperature study also show that the maximum temperature will increase like the minimum temperature in the study area, the highest and lowest increases are related to Bojnord station with 1 and Gonbad Kavous station with 0.8 degrees Celsius, respectively. The maximum temperature changes in the study area based on the studied scenarios also show that based on different scenarios, the maximum temperature will increase between 0.6 and 1.4 degrees Celsius. In general, the maximum temperature in the study area is expected to increase by an average of 1 degree Celsius in the next period compared to the baseline period.

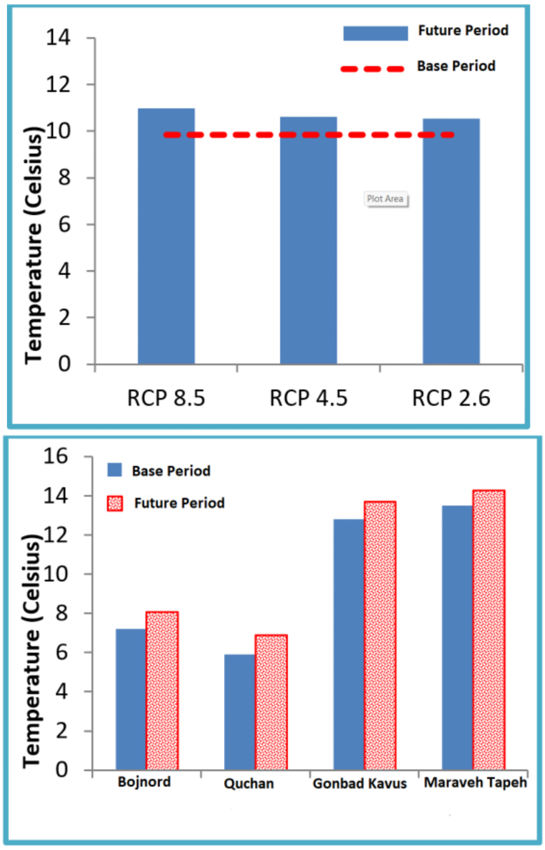

Fig. 7. Minimum temperature changes compared to the base period within the scenarios.

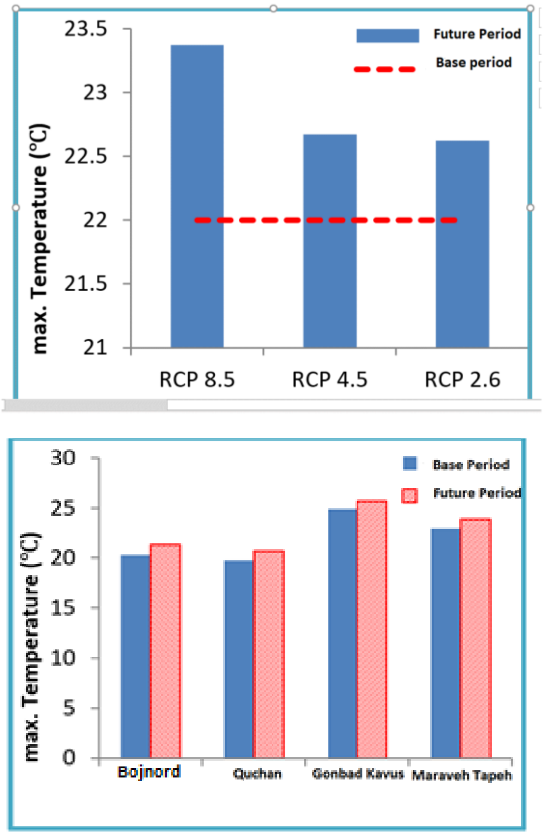

Fig. 8. Maximum temperature changes compared to the base period within scenario

In general, based on the results of rainfall values, minimum temperature and maximum temperature will increase during the forecast period (2021-2050) in Atrak basin. Based on the results, precipitation at the basin level will increase between 1.5 and 11.7 percent, most of which changes are related to the central and northern regions of the basin. Most of the temperature changes are related to the eastern and central regions of the study area. On average, the temperature increase will be between 0.8 and 1 degree Celsius, and the changes in maximum temperature are greater than the minimum temperature.

3. Conclusion

Considering the importance of climate change prediction in this study, climate change prediction was investigated using CanESM2 global model under the influence of three scenarios of radiant retention of RCP2.6, RCP 4.5 and RCP 8.5 and the use of SDSM statistical downscale model in Atrak basin. After the model was evaluated for the baseline period (1995-2019) and based on MAE, MSE, RMSE and R^2 criteria, the accuracy of the model was determined to predict the temperature and precipitation changes in the next period (2021-2050) compared to the base period. The results of the model performance evaluation showed that the SDSM model has a high ability in simulating temperature and precipitation variables in the base period and has less accuracy than temperature in simulating precipitation. This is due to the complexity of precipitation process and the structure of climatic models and also due to statistical downscale methods which are based on multiple linear regression in SDSM model and it is based on the assumption that the relationships obtained with current data are static and usable during future periods, so there are uncertainties in this regard. The results of the model prediction also showed that the amount of precipitation, minimum and maximum temperatures will increase over the next period in all study stations, which will be 7.8% on average at the watershed level for the precipitation variable compared to the base period. Most of the precipitation changes are related to the high rainfall months of the year in the study area. The minimum and maximum temperatures will increase by 0.9 and 1 degree Celsius compared to the base period, respectively. The highest minimum temperature changes were related to Quchan station and the highest maximum temperature changes were related to Bojnord station. Accordingly, the most temperature changes related to the eastern and central regions and the highest rainfall changes are related to the central and northern regions of the study area, the results of this study with Malmir et al. (2016) in Qarasu watershed, Naderi et al. (2017) in Seymareh, Goodarzi et al. watershed (2018) in Urmia and Kasiri et al., (2020) in the southern coasts of the Caspian Sea are the same in conclusion. According to the results of this research, in the study area, temperature and precipitation amounts would be increased compared to the base period. It would increase evapotranspiration, while reducing snowfall but rainfall and flood may be increased. It would decrease growth period which would reduce crop yields. Therefore, it is necessary to concern the necessary strategies to deal with or adapt to the new conditions in Atrak basin.

4. Conflicts of Interest

No potential conflict of interest was reported by the author.

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