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Downscaling diurnal temperature over west and southwest Iran: A comparison of statistical downscaling approaches

Mohammad Reza Poodineh

Department of Physical Geography
University of Sistan and Baluchestan, Zahedan, Iran
mrpoodineh@yahoo.com

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Abstract— This study aimed to forecast temperature variations in the western and southwestern part of Iran using a general circulation model and artificial neural networks (ANN). The data included mean diurnal temperatures from synoptic stations, National Centers for Environmental Prediction/ National Center for Atmospheric Research (NCEP/NCAR) reanalysis data, and outputs of a third-generation global climate model, the Hadley Centre Coupled Model version 3 (HadCM3), under A2 and B2 scenarios for the baseline period (1961–1990). The data of the first (1961–1975) and second 15 years (1976–1990) of the baseline period were used for model calibration and validation, respectively. Both models, however, produced reliable estimates at the plain stations with neither outperforming the other due to their negligible errors. However, the neural network results of mountain synoptic stations showed a lower error rate than the statistical downscaling model (SDSM) outputs. All in all, we can say that there was a larger amount of error in the outputs of the atmospheric general circulation models (AGCMs) in the mountainous regions. According to the outputs of the neural network and the AGCMs, temperatures at the studied stations were on the rise. In fact, this increase was more noticeable at the plain stations. This can be attributed to their proximity to the sea, to their latitude, and to the more intensive industrial activities (especially, extraction of petroleum and production of petroleum products) taking place near the plain stations.

Key-words: diurnal temperature, AGCMs, SDSM, HadCM3

1. Introduction

A general circulation model (GCM) indicates whether increasing concentrations of greenhouse gases will have considerable climate outcomes on global and regional scales. It is still debatable how much increasing greenhouse gases will affect meteorological processes; however, it is evident that increased concentrations of greenhouse gases have directly and indirectly affected climatic elements both spatially and temporally (*Smith et al.*, 2010). Sea level rise and changes in temperature threshold and rainfall are among the outcomes of climate change. Changes in precipitation distribution patterns and the 1 °C change in the temperature of the water resources of a region are some of the other events resulting from climate change. Long-term forecasts of climate variables to be aware of the extent of variations, and hence, to take necessary actions to alleviate the adverse effects of climate change have attracted the specialists in climatology and agriculture, and even in social sciences and economics (*Maraun et al,* 2015). More frequent heat waves can be pointed out as the direct effects, while the increased heat island intensity and the decrease in boundary layer height as indirect outcomes of the climate change. Evaluation of climate change with the help of AGCMs has attracted in Iran and abroad in the past 10 years. Only a few of such evaluations are mentioned here to save space. For instance, Harpham and Wilby conducted a study in England by using different models such as the outputs of the HadCM3 model, a radial basis function network, and a multi-layer perceptron artificial neutral network (MLP) ANN to predict precipitation for different regions. The results showed that each of those methods was able to forecast precipitation, although they had different capabilities in different regions. In fact, the (MLP) ANN yielded better results (*Harpham* and *Wilby*, 2005). In another study, *Meshkati et al.* (2010) analyzed and evaluated the least-angle regression (LARS) model in simulating the meteorological data in Golestan Province. Their results indicated that the performance of LARS in modeling the meteorological variables of the surveyed stations was generally acceptable and could be employed to reconstruct the data of the stations for past periods. In the same relation, *Ababaei et al.* (2011) used downscaling the data of the AGCM to evaluate climate change in Iran for 2010–2039.

GCMs can never be used directly for regional or local predictions. They require downscaling to improve their predictions on local scales by applying local behaviors. All of these operations are known as downscaling, which is a term used to describe the process related to data for evaluating the effects of climate change at temporal or spatial scales (*Ashraf*, 2011a, 2011b). Nevertheless, the results of a study conducted on GCMs show increased concentrations of greenhouse gases that have considerable outcomes for climate on global and regional scales at different temporal and spatial scales (*Sahai et al*, 2003). Prediction of future weather conditions and their outcomes for regional hydrology are very important in identifying appropriate strategies for reducing the effects of climate change and adapting to weather conditions (*Kug et al.*, 2008). GCMs are troublesome in studies on the effects of climate change due to lack of accurate regional data. Therefore, to determine climate change in the western and southwestern parts of Iran, the SDSM and a neural network were employed to predict temperature changes.

Samadi et al. (2013) reviewed the statistical downscaling of river runoff in a semi-arid catchment. According to the SDSM and ANN projections, daily temperature will increase up to +0.58 °C (+3.90%) and +0.48 °C (+3.48%), and daily precipitation will decrease up to −0.1 mm (−2.56%) and −0.4 mm (−2.82%), respectively. The results suggest a significant reduction of stream flow in both downscaling projections, particularly in winter. The discussion considers the performance of each statistical method for downscaling future flow at catchment scale as well as the relationship between atmospheric processes and flow variability and changes.

Dorji et al. (2017) reviewed the statistical downscaling of river runoff in a semi-arid catchment using a statistical downscaling model (SDSM) and a time delay neutral network (TDNN). The results from this study will augment other investigation and research for improving the prediction of rainfall. IPCC AR5 reports gaps in understanding the climate impacts on precipitation at the catchment scales. Further work to downscale variability and extreme indices are important for impact studies. Within the stated limitations, the results of the reviewed study provide daily values of temperature and rainfall for applications, like driving a hydrology model for the Colombo area. It also provides a scientific guideline for impact assessment studies, framing policies and long-term adaptation planning. The projected annual increase for the representative concentration pathway (RCP) is 8.5; the average temperature is 2.83 °C (SDSM) and 3.03 °C (TDNN), and the rainfall is 33% (SDSM) and 63% (TDNN) for the 2080s.

2. Data and methodology

This study aimed to compare and simulate temperatures of the western and southwestern parts of Iran by using a neural network and downscaling of AGCMs. The research data included mean diurnal temperatures from synoptic stations in plain (Ahwaz, Abadan, and Dezful) and mountainous regions (Shahr-e Kord, Khorramabad, and Hamadan), NCEP analysis data, and outputs of HadCM3 third-generation global climate model under A2 and B2 scenarios for the baseline period (1961–1990). The temperatures for three periods (2010–2039, 2040–2069, and 2070–2099) were predicted and compared with those of the baseline period. The data of the first 15 years (1961–1975) and those of the second 15 years (1976–1990) of the baseline period were used for model calibration and validation, respectively. *Fig. 1* shows the distribution of the studied stations.

GCMs can never be used directly for regional or local predictions, because they need downscaling to improve their predictions on local scales by applying local behaviors. Therefore, the data should be downscaled before they are used. The Hadley Coupled Atmosphere-Ocean General Circulation Model (HadCM3) is a coupled atmospheric-ocean general circulation model (AOGCM) designed and developed at the Met Office Hadley Center for Climate Change in England. This model, which was described by *Pope et al.* (2000), consists of an atmospheric component named HadAM3 and an ocean component named HadOM3, which has a sea ice component. HadAM3 has a horizontal resolution of $2.5° \times 3.75°$ latitude × longitude), 96 × 73 grid points on the scalar grid on the entire planet Earth. Its spectral resolution is T42, which corresponds to a horizontal grid spacing with the dimensions of 417 km × 78 km (at the equator).

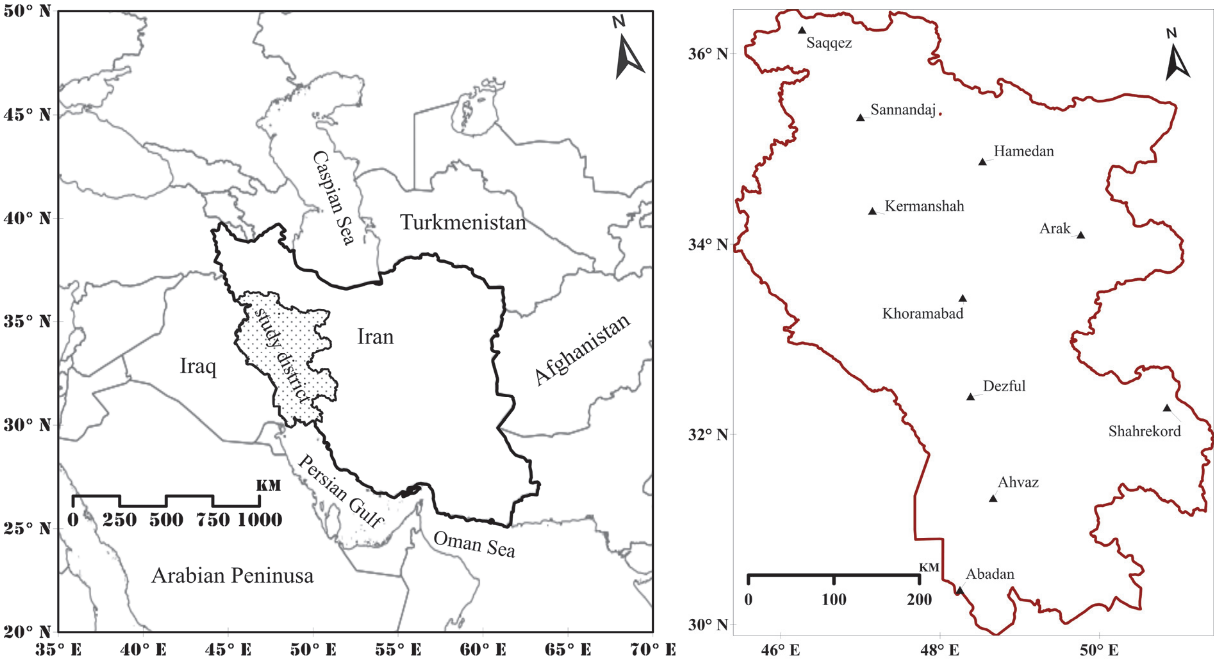

Fig. 1. Key map of study area (left) and spatial distribution of the weather stations (right).

The ocean model (HadOM3) has 20 levels with a resolution of 1.5°×1.5°. The high resolution power of the ocean component is the most important advantage of this model (*Pope et al.*, 2000). HadOM3 has a resolution of 1.25 × 1.25 degrees and 20 levels. The high resolution of HadOM3 is the most important advantage of this model (*Pope et al.*, 2000). Climate scenarios use the data from emission scenarios for future predictions. In simpler terms, climate scenarios are the outputs of dynamical models for climate change in future decades. Downscaling refers actually to the process of moving from large-scale predictors towards observed local scale predictions. After verification, these equations can be used in downscaling future predictions through employing emission scenarios (here, A2a and B2a scenarios). Climate scenarios use the data from emission scenarios to predict the future. Put more simply, climate scenarios are the outputs of statistical climate models for future decades. In this study, data quality had to be controlled first for downscaling. The results indicated that the best way of using the simulation data was to use the raw data (without data transformation). The independent variables that were able to make a good estimate of the actual data were selected to estimate the temperature. Some of the independent variables had an average correlation but did not make an accurate estimate of the actual data when they were entered into the model, and hence they were omitted. However, as the model was an AGCM, and this kind of model is based on the assumption that climate change is influenced both by local and macro factors on the scale of the atmosphere, it was attempted to include more independent variables as long as the computational error was smaller than 0.05. Some variables, such as special humidity, zonal component, and meridian component sometimes had fairly good correlation, but greatly increased the estimation error when they were entered into the model. Therefore, such variables were not included in the model to evaluate temperature variations at the studied stations. In this stage, in addition to the mentioned items, special attention was paid to the degree of overlap (collinearity or variance inflation factor (VIF)) between the independent variables and the dependent variable (the temperature of interest). After the independent variables were selected at each station to estimate the temperature, the degree of overlap between the independent variables and the dependent variable was calculated for each station and taken into account to estimate the changes in temperature. The following method was used to calculate the degree of overlap between temperature and each of the predictor variables (*Pan* and *Jackson*, 2008):

$$VIF = \frac{1}{1-r^2}\,, \tag{1}$$

where *VIF* is the variance inflation factor and r^2 is the coefficient of determination.

Moreover, the entire process of controlling data and evaluating variables in each step was performed outside the SDSM to better control the prediction process. Therefore, all of these steps were performed in MATLAB using programming possibilities before the prediction process was carried out to have full control over the trend in data. The entire process of controlling the data and evaluating the variables is an other item that must be paid attention to in statistical downscaling. For this purpose, the number of ensemble effects was selected by considering descriptive characteristics, probability distributions, and differentiation test and fluctuation analysis. Hence, these steps were trained by increasing and decreasing the ensemble effects through considering the independent variables, the *VIF*, and the bias rate under evaluation to obtain the best results.

An artificial neural network (ANN) was used to study and compare the variations in estimates through SDSM. An ANN is a computational method that tries to present a mapping from the input space (the input layer) to the desired space (the output layer) by identifying the intrinsic relationships between the data with the help of the learning process and through utilization of processors called neurons. The hidden layer(s) process the information received from the input layer and send it to the output layer. Each network is trained by receiving examples. Training is a process that eventually results in learning. Network learning takes place when communication weights between the layers change so much that there is an acceptable difference between the predicted and calculated values. When this happens, the learning process is completed. These weights express the network memory and knowledge. The larger the number of hidden layers is the more complicated the probability of network convergence will become. After selecting and analyzing the variables based on the A2a and B2a scenarios, temperatures of the southern and southwestern regions in Iran were predicted for up to 2099. However, most researchers believe that prediction results are reliable for up to one fourth of the statistical period. Therefore, this principle was taken into account in making predictions by using the neural network. Finally, the model was implemented for each of the studied stations, and a database with the dimension of 32040×10 was studied and analyzed for the future climate change for the statistical period 2011–2099. In the next stage, regression methods were utilized to study variations in the trend. Spectral analysis was used to study and analyze the fluctuations and cycles of temperature at the studied stations.

3. Results and discussion

The SDSM and a neural network were employed to study changes in temperature and to predict the future temperatures for the southern and southwestern parts of Iran. One of the most important steps in SDSM is the selection of dominant variables, because the independent variables directly influence the characteristics of the model and the results obtained from it (*Santer*, 1996). The SDSM evaluates the statistical relationships between the observed (or predicted) variables and the large-scale (or predictor) variables based on correlation and partial correlation. Five variables having the highest correlation (p-value = 0) with the observed data on temperature were selected from the 26 tested variables based on the coefficients of correlation between the observed data and the diurnal predictor variables using the SDSM software. *Table 1* shows the correlation coefficients of the variables. According to this table, compared to the other predictor variables, the average temperature at the stations in southwest Iran (Ahwaz, Dezful, Abadan, Shahrekord, Khorramabad, and Hamadan) had very significant correlations with the sea level pressure, the 500 hPa geopotential level, the relative humidity (%) at the 850-hPa level and close to ground surface and the average temperature at the 2 m height. Among the mentioned variables, the sea level pressure and the average 2 m height temperature had the most common diffraction surface with the mean temperatures at the southwestern stations. Pressure has an undeniable role in the governing atmospheric situation and conditions in a region by affecting most of the climate variables (*Mohammadi*, 2014). Some researchers believe that pressure abnormalities have greater effects at higher latitudes than at lower latitudes (*Blasing*, 1981). This element is so effective that it is always analyzed as the first element in the identification and studies of climatic conditions of a region (*Broccoli* and *Harnack*, 1981). Nonetheless, the sea level pressure and its relationships with temperature differ both temporally and spatially. For instance, more temperature abnormalities in distribution are observed in tropical regions than in extratropical ones (*Whetton*, 1990).

Table 1. Results of evaluating the HadCM3 and neural network outcomes

			General Circulation Models					Neural Network	
		Parameter	**orrelation**	**Partitional correlation**	**Mean square error**	**Ensemble effects**	**VIF**	**Weight**	**MSE**
Plain stations	**Ahwaz**	Seal level pressure	-0.837	-0.710	0.86	25	9	0.58	0.93
		Altitude of 500 hPa	0.837	0.661					
		Altitude of 850 hPa	-0.573	-0.456					
		Ground level relative humidity	-0.845	-0.419					
		Ground level average temperature	0.951	0.909					
	Abadan	Seal level pressure	-0.825	-0.611	0.91	30	8	0.61	0.58
		Altitude of 500 hPa	0.784	0.511					
		Altitude of 850 hPa	-0696	-0.523					
		Ground level relative humidity	-0.743	-0.341					
		Ground level average temperature	0.896	0.832					
	Dezful	Seal level pressure	-0.850	-0.260	1.1	20	10	0.36	0.65
		Altitude of 500 hPa	0.875	0.632					
		Altitude of 850 hPa	-0.814	-0.231					
		Ground level relative humidity	-0.852	-0.341					
		Ground level average temperature	0.961	0.360					

Continue *Table 1*. Results of evaluating the HadCM3 and neural network outcomes

			General Circulation Models					Neural Network	
Mountain stations	Shahrekord	Sea level pressure	-0.888	-0.410	0.96	30	7	0.654	1.73
		Altitude of 500 hPa	0.875	0.456					
		Altitude of 850 hPa	-0.812	-0.330					
		Ground level average temperature	0.960	0.354					
	Khorramabad	Seal level pressure	-0.858	-0.413	1.42	20	8	0.741	1.72
		Altitude of 500 hPa	0.872	0.411					
		Altitude of 850 hPa	-0.807	-0.312					
		Ground level relative humidity	-0.841	-0.461					
		Ground level average temperature	0.948	0.623					
	Hamadan	Seal level pressure	-0.789	-0.352	2.14	35	7	0.80	0.65
		Altitude of 500 hPa	0.874	0.412					
		Altitude of 850 hPa	-0.707	-0.248					
		Ground level relative humidity	-0.659	-0.514					
		Ground level average temperature	0.955	0.647					

Although results of the SDSM in estimating and predicting temperatures in some areas of the regions were acceptable, its accuracy was lower than that of the neural network in some other stations including those in Hamadan and Khorramabad. However, *Sahai et al.* (2010) obtained similar results in the analysis of weather variations in India. Despite these differences in SDSM results, in some stations such as Ahwaz, Dezful, and Abadan, both the neural network and HadCM3 yielded suitable results in predicting temperature. Therefore, as mentioned earlier, we can say that the error rates of both methods at some stations are not so considerable as to conclude definitely that the neural network produced better results. On the scale of global research, although most SDSM predictions exhibited lower accuracy than other methods (*Ojha*, 2010), it produces acceptable results compared to the neural network in some cases at different times and locations (*Chen et al.*, 2012; *Hassan et al.*, 2012).

Results of the analysis showed that the VIF values for the southern stations were 6–9%, indicating that these stations exhibited the lowest error rate. In downscaling, VIF is added to or deducted from the regression model to regulate the variance of diurnal weather variables (*Khan et al.,* 2006). Nevertheless, *Fiseha et al.* (2012) studied changes in extreme temperature profiles in the US using five predictor variables and reported VIF values ranging from 8 to 10%). However, some researchers believe that VIF values should take into account the trend and fluctuations in variables in addition to the extent of overlap with the predictor variables in estimating the data for future (*McGuffie et al.*, 1999). For most stations, 20–35 ensemble effects produced more acceptable results so that the means, variances, and minimum and maximum values exhibited the least differences (*Figs. 2* and *3*). Many of the researchers obtained similar results in the downscaling of temperature prediction. According to some researchers, increasing ensemble effects have no significant impacts on the model results for some climate elements having very low coefficients of changes. In addition, identifying the spatial and temporal distribution of data has a key role in selecting the number of ensemble effects.

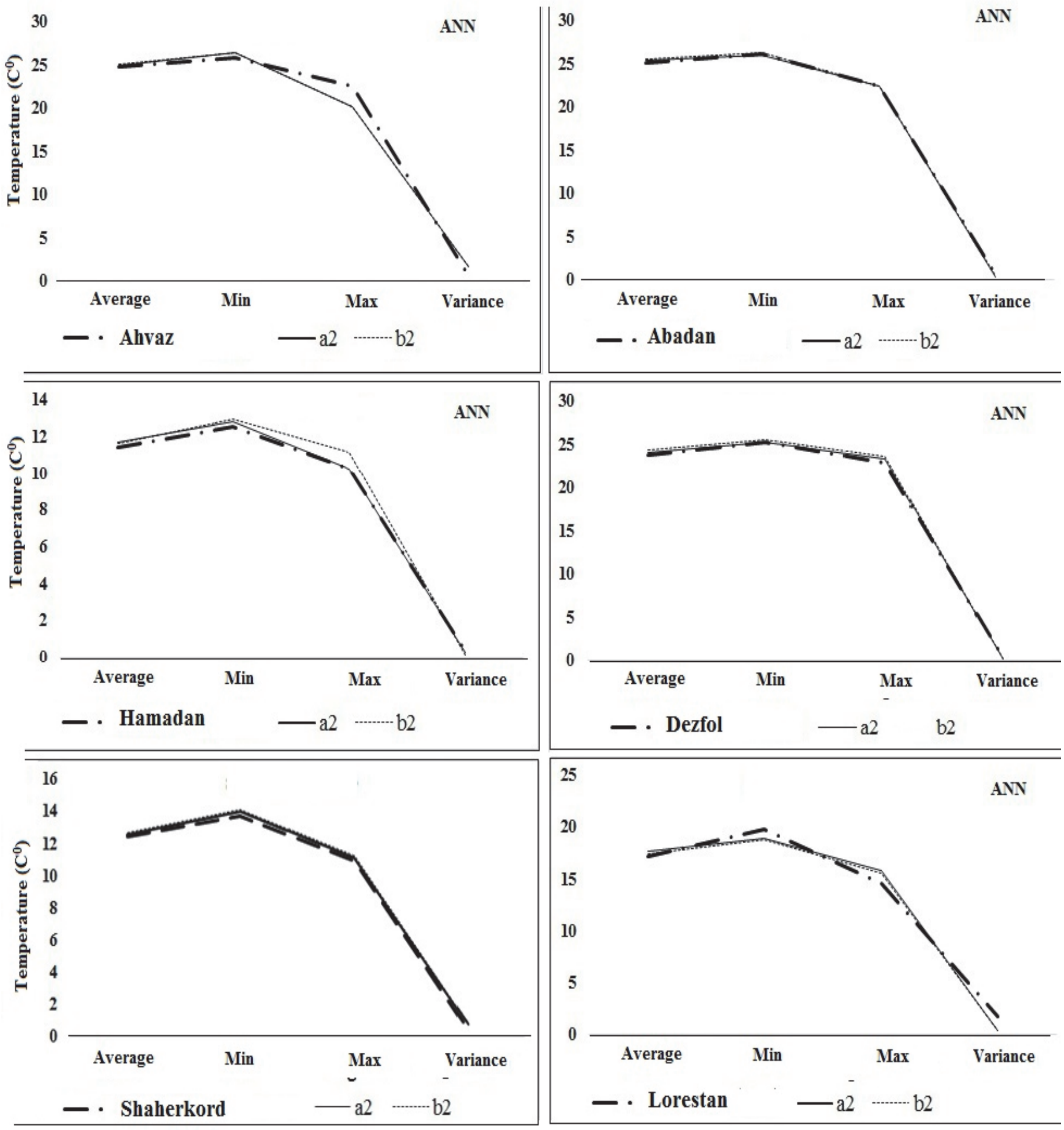

Fig. 2. Evaluation of the predicted changes in temperature based of the neural network for 1961–1990.

Regarding the evaluation of climate change, estimation of increases and decreases has a basic role in predicting future climate change. In fact, researchers pay close attention to the values of the minimums and maximums in selecting the superior models of climate change in addition to the general trend in climatic norms (*Chen et al.*, 2012). In this approach, the model is considered optimal if it can estimate the climatic trend well and produce acceptable results in predicting the fluctuations.

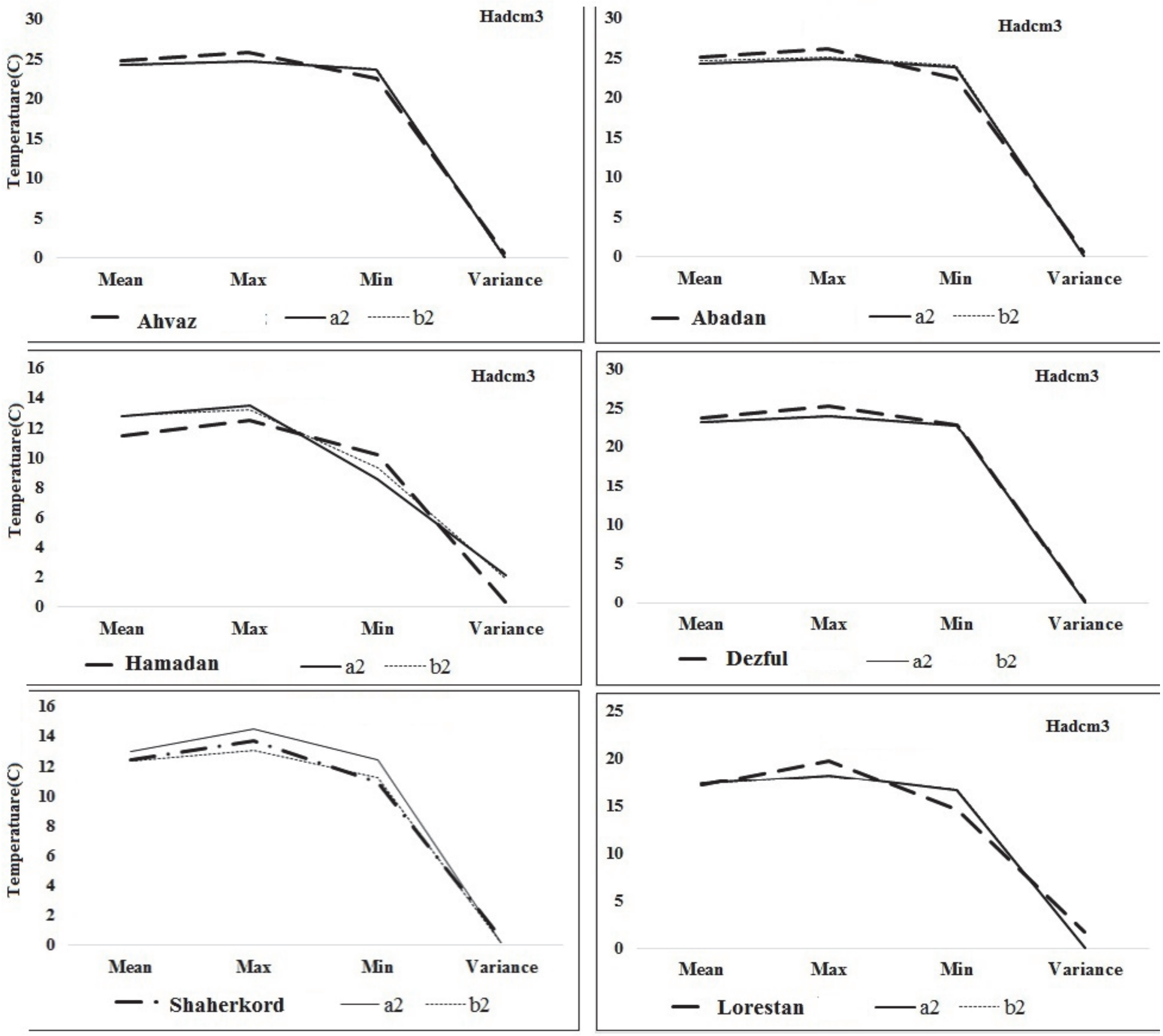

Fig. 3. Predicted mean variations based on the output of HadCM3 during 1961–1990 evaluating future temperature variations in the southwestern part of Iran.

Since the values of the minimums and maximums are very important in predicting climate elements (in other words, the time series), these values as well as the frequency distributions were determined in this research. According to the results, although the stations at Ahwaz, Abadan, and Dezful measured the target values well, the resultant amount of error in the output of the GCM for the mentioned stations does not allow us to say definitely that the neural network yielded acceptable results. Therefore, the amounts of error at these stations were not statistically significant at a 95% confidence level in evaluating climate change. The conditions were slightly different at the other stations. For instance, the outputs of the HadCM3 model showed a better evaluation than the neural network in estimating temperature variations at the Shahrekord station. However, neural network outputs were more acceptable at the Shahrekord and Khorramabad stations. The reason for this superiority, as discussed earlier, is based on the principle that a model is more appropriate for predicting future change if it can express the observed temperature variations well.

Table 2 shows the spatial characteristics of temperature at the stations in southwest Iran based on the outputs of the downscaling of HadCM3 and the neural network for the A2a and B2a scenarios. In the first column of each index, spatial characteristics of the measured data are listed for comparison with the simulated data for the scenarios. According to this table, there were considerable increases in the average temperatures at the studied stations based on the HadCM3 and neural network outputs for the A2a and B2a scenarios. The outputs of the HadCM3 model for the A2a scenario show that the average temperature increased by 2.5 degrees at the plain stations (Abadan, Ahwaz, and Dezful) but, based on the B2a scenario, the temperatures at these stations increased by 2 degrees. Therefore, the increases and decreases in temperature for the A2a and B2a scenarios were much higher than the observed increases and decreases in temperature. Differences in the central indices indicate the diurnal increases and decreases in temperature. This can be backed by the closeness of the values for the mean and the median (50th percentile) and the low value of the mode in all of the research periods. However, the Khorramabad station showed higher diurnal decreases and increases than other stations so that temperature prediction at this station based on the neural network exhibits a similar situation. This can indicate that there will be more heat and cold waves in the future based on the outputs of the GCMs for the A2 and B2 scenarios. Accordingly, the descriptive characteristics of temperature for future years based on the neural network for the A2a and B2a scenarios exhibited increases of 1 and 1.5 °C, respectively. Nevertheless, unlike the AGCMs, the neural network outputs for the central indices (mean, median, and mode) are more consistent with the actual data. Therefore, we can infer that the mean temperature in the future will exhibit increases and decreases and display high spatial diversity. The high coefficients of change based on both methods show the high changeability of temperature in the studied stations. This may be due to the higher concentration of highlands in west Iran because of the effects of temperature modifiability at high altitudes. The skewness was positive for spatial characteristics but negative for the different scenarios. This indicates that the number of areas with averages higher than total mean of the region is larger than the number of areas with averages lower than the total mean of the region. The value of the diffraction (variance) shows how the observations are dispersed around the mean. It had its highest value, which was another confirmation of the increases and decreases in diurnal temperature in the future. The values obtained from analyzing the 25th, 50th, and 75th percentiles show that the temperature will experience larger values based on the A2a scenario.

Table 2. Spatial characteristics of temperature at the studied stations based on the A2a and B2a scenarios during 2015–2025

	Scenario		Abadan	Ahwaz	Dezful	Hamadan	Khorramabad	ShahreKord
Mean	Station		25.5	25.3	23.6	11.6	11.08	12.1
	Neural network	A2	26.4	26.1	24.4	12.5	17.9	13.0
		B2	26.1	25.8	24.1	12.2	17.6	12.7
	HADCM3	A2	27.8	28.6	27.6	13.7	19.7	14.9
		B2	27.1	27.8	26.8	13.6	19.1	14.9
Median	Station		25.4	25.3	24.0	11.7	17.2	11.9
	Neural network	A2	26.2	62.2	24.8	12.5	18.1	12.8
		B2	25.9	25.9	24.5	12.2	17.8	12.5
	HADCM3	A2	27.7	28.6	27.5	13.1	19.8	15.0
		B2	26.9	27.7	26.7	13.0	19.1	15.0
Coefficient of changes	Station		3.7	3.7	15.2	5.3	6.9	5.8
	Neural network	A2	3.6	3.6	7.1	4.9	6.6	5.5
		B2	3.6	3.6	14.9	5.0	6.7	5.6
	HADCM3	A2	2.5	2.4	2.5	9.3	2.6	2.8
		B2	2.5	5.5	2.6	9.4	1.7	2.8
Skewness	Station		-0.3	-0.5	-6.3	-0.3	-0.2	-0.1
	Neural network	A2	-0.3	-0.5	-6.3	-0.3	-0.2	-0.1
		B2	-0.3	-0.5	-6.3	-0.3	-0.2	-0.1
	HADCM3	A2	0.0	0.0	0.0	0.5	-0.3	0.4
		B2	0.0	0.0	0.0	0.5	-0.4	0.4
Max.	Station		28.2	27.1	26.2	13.1	19.8	13.7
	Neural network	A2	29.0	27.9	27.0	13.8	20.6	14.5
		B2	28.7	27.6	26.7	13.5	20.3	14.2
	HADCM3	A2	29.0	29.8	28.8	16.0	20.7	16.1
		B2	28.2	29.0	28.0	15.9	19.7	16.1
Min.	Station		22.5	22.5	0	10.2	14.4	10.2
	Neural network	A2	23.3	23.3	0.8	11.0	15.2	11.0
		B2	23.0	23.0	0.5	10.7	14.9	10.7
	HADCM3	A2	26.5	27.3	26.3	11.6	18.6	14.2
		B2	25.7	26.5	25.4	11.5	18.4	14.2
Quarter1	Station		25.0	24.8	23.6	11.2	16.3	11.7
	Neural network	A2	25.8	25.6	24.4	12.0	17.1	12.5
		B2	25.5	25.3	24.1	11.7	16.8	12.2
	HADCM3	A2	26.5	27.3	26.3	11.6	18.6	14.2
		B2	26.6	27.4	26.4	12.6	18.9	14.5
Quarter2	Station		25.4	25.4	24.0	11.7	17.3	12.0
	Neural network	A2	26.2	26.2	24.8	12.5	18.1	12.8
		B2	25.9	25.9	24.5	12.2	17.8	12.5
	HADCM3	A2	27.4	28.2	27.2	12.8	19.4	14.5
		B2	26.9	27.7	26.7	13.0	19.1	15.0
Quarter3	Station		26.7	26.8	25.2	12.5	18.8	13.4
	Neural network	A2	27.5	27.6	26.0	13.3	19.6	14.2
		B2	27.2	27.3	25.7	13.0	19.3	13.9
	HADCM3	A2	28.9	29.7	28.7	16.0	30.4	15.6
			28.1	28.9	27.9	15.0	19.5	15.6

Table 2 shows only the general characteristics of temperature variations at the studied stations. Therefore, *Tables 3* and *4* indicate monthly temperature variations based on HadCM3 and neural network outputs for the A2 and B2 scenarios.

Table 3. Prediction of temperature variations at the studied stations based on the neural network for the period 2015–2025.

A2	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Abadan	0.7	0.8	0.9	1.2	1.0	1.1	1.0	1.7	0.8	1.0	0.6	0.7
Ahwaz	0.8	1.1	0.8	1.1	1.0	1.0	0.9	1.2	0.8	1.0	1.1	0.9
Dezful	0.5	0.4	0.2	0.3	0.3	0.3	0.01	0.3	0.1	0.3	0.6	0.8
Hamadan	0.5	0.8	0.7	0.7	0.6	0.8	0.8	0.8	0.7	0.9	0.4	0.6
Khorramabad	0.3	0.4	0.2	0.6	0.3	0.5	0.4	0.5	0.3	0.4	0.1	0.4
Shahrekord	0.5	0.6	0.3	0.3	0.1	0.0	0.2	0.1	0.1	0.2	0.2	0.5
B2	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Abadan	0.9	1.1	1.1	1.4	1.3	1.4	1.2	1.9	1.1	1.3	0.9	1.1
Ahwaz	1.1	1.3	1.1	1.3	1.3	1.2	1.1	1.5	1.14	1.3	1.3	1.1
Dezful	0.9	0.6	0.5	0.6	0.5	0.5	0.3	0.6	0.35	0.61	0.91	1.2
Hamadan	0.8	1.1	1.0	0.9	0.8	0.83	1.2	1.1	1.03	1.1	0.7	0.9
Khorramabad	0.6	0.6	0.5	0.8	0.6	0.7	0.7	0.8	0.62	0.7	0.7	0.6
Shahrekord	0.8	0.8	0.6	0.6	0.3	0.2	0.5	0.4	0.37	0.5	0.53	0.6

Table 4. Prediction of temperature variations at the studied stations based on HadCM3 outputs for the period 2015–2025.

A2	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Abadan	1.7	1.5	1.6	2.3	1.2	2.0	2.6	3.9	0.2	2.4	1.4	1.9
Ahwaz	3.2	3.3	3.0	1.2	1.2	2.7	2.9	3.3	1.1	3.5	3.5	3.5
Dezful	3.1	2.9	3.5	1.6	1.9	2.7	2.6	3.0	1.3	3.8	2.7	2.8
Hamadan	2.2	3.1	2.4	2.9	3.2	3.2	0.7	-0.5	0.0	-0.4	0.4	3.8
Khorramabad	3.0	4.5	3.4	2.6	3.6	1.5	-0.5	2.2	-2.2	-1.9	0.1	2.7
Shahrekord	2.2	5.0	2.8	2.9	2.7	-0.4	0.7	-0.3	-0.2	-1.2	-0.6	2.1
B2	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Abadan	1.7	1.3	1.4	1.7	0.7	1.8	2.8	7.3	0.0	2.2	1.2	1.7
Ahwaz	2.8	3.1	2.8	0.6	1.1	2.5	2.7	3.1	0.9	3.3	3.3	3.3
Dezful	2.9	2.7	2.3	1.4	1.7	2.5	2.4	2.5	1.1	2.7	2.5	2.6
Hamadan	1.6	2.8	2.9	2.7	1.8	3.0	0.5	-0.7	-0.6	-0.7	-0.6	3.6
Khorramabad	2.8	2.3	2.2	3.4	3.4	1.3	-0.7	-2.2	-1.4	-1.2	-0.1	2.5
Shahrekord	3.0	2.8	2.6	2.7	2.5	-0.6	-1.5	-0.5	-0.4	-0.4	-0.8	1.9

Evaluation of temperature variations based on neural network outputs up to 2025 showed temperature increases in every month. As mentioned earlier, the neural network made better predictions than the HadCM3 model at most of the stations. Moreover, neural network outputs were acceptable at mountain stations, especially at Shahrekord, where the temperature increased by 0.1–0.3 C in all months based on the A2 scenario. In February, the increase was 0.6˚ C, which was the highest among the months. However, the temperature increased by nearly 0.89˚ C for the B2 scenario. In April, Khorramabad station showed the same increase, and the temperature was the highest among the months. In plain stations, mostly located in Khuzestan Province, the highest increases were observed among all the studied stations. The hot months of the year showed much more significant increases than the other months of the year.

Nevertheless, the B2 scenario outputs showed much more considerable increases in the hot months at plain stations. For instance, the temperature increased on average by up to 1.23 °C from April to October for the B2 scenario. The mountain stations showed smaller increases than the plain stations. The reason for this could be the role played by the highlands in temperature moderation at the mountain stations. Among the mountain stations the Hamadan showed a higher than 1 °C increase in temperature from June to October for the B2 scenario. However, the increase was lower than 1 °C at the other stations. According to Table 3, temperatures at the studied stations increased for both the A2 and the B2 scenarios based on the neural network outputs. The estimates of temperature variations are a little different based on the outputs of the HadCM3, so that these outputs showed an increasing trend in temperature in some months at the mountain stations (Khorramabad, Hamadan, and Shahrekord) but a decreasing trend in some months. Nevertheless, neural network outputs showed better results at these (mountain) stations. Temperature showed an increasing trend based on HadCM3 outputs for both the A2 and the B2 scenarios at plain stations (Abadan, Ahwaz, and Dezful). For instance, the temperature will approximately increase by 3 °C at the Abadan station during the next 90 years in April, whereas the neural network showed an approximately 1.2 °C increase until 2025 (*Table 5*). Based on the A2 scenario outputs, the increase will be 0.3 °C in September at Dezful station, although the B2 scenario predicted a 0.8 °C increase for the same month. Conditions are more diverse at the mountain stations. Increased and decreased temperatures at mountain stations, as mentioned before, can indicate large increases and decreases in diurnal temperatures in these areas in the future. Nevertheless, the uncontrolled increase in temperature can affect cultural factors, which will have economic implications in the countries. For instance, some studies in the the Sahara Desert indicate that, on average, 50% of crops will be changed by 2100 due to the sharp decrease of the uncontrolled increase in temperature (*Blanc et al.*, 2010). However, HadCM3 outputs showed substantial decreases in temperature from January to September at mountain stations for both the A2 and the B2 scenarios.

Table 5. Prediction of temperature variations at the studied stations based on the neural network and HadCM3 outputs for the period 2010–2099.

	Neural Network		**HadCM3 outputs**	
	A2	**B2**	**A2**	**B2**
Abadan	0.95	1.25	1.70	1.95
Ahwaz	0.95	1.20	1.40	2.70
Dezful	0.30	0.59	2.30	2.60
Hamadan	0.71	0.98	1.40	1.67
Khorramabad	0.42	0.66	1.00	1.57
Shahrekord	0.25	0.55	0.90	1.20

Table 6. Temperature variations at the studied stations based on HadCM3 outputs for the A2 scenario for the period 2010–2099.

	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
							2010–2039					
Abadan	0.7	0.5	0.6	1.3	0.7	1.0	1.6	2.9	-0.8	1.4	0.4	0.9
Ahwaz	0.2	2.3	2.0	0.2	0.3	1.7	1.9	2.3	1.0	2.5	2.5	2.5
Dezful	2.1	1.9	2.5	0.6	0.9	1.7	1.6	2.0	0.3	2.8	1.7	1.8
Hamadan	1.2	2.1	1.4	1.9	2.0	2.2	-0.3	-1.5	-1.0	-1.5	-1.4	2.8
Khorramabad	2.0	3.5	2.4	1.6	2.6	0.5	-1.5	1.0	-3.2	-3.0	-0.9	1.7
Shahrekord	1.2	4.0	1.8	1.9	1.7	-1.4	-0.3	-1.3	-1.2	-3.2	-1.6	1.1
							2040–2069					
Abadan	1.6	1.2	1.3	2.0	1.4	1.7	2.3	3.6	-0.1	2.1	1.1	1.6
Ahwaz	2.7	3.0	2.7	0.9	1.0	2.4	3.6	3.0	0.8	3.2	3.2	3.2
Dezful	2.8	2.6	3.2	1.3	1.6	2.4	2.3	2.7	1.0	3.5	2.4	2.5
Hamadan	1.9	2.8	2.1	2.6	2.7	2.9	0.4	-0.8	-0.3	-0.8	-0.7	3.5
Khorramabad	2.7	4.2	3.1	2.3	3.3	1.2	-0.8	1.7	-2.5	-2.3	-0.0	2.4
Shahrekord	1.9	4.7	2.5	2.6	2.4	-0.7	0.4	-0.6	-0.5	-2.5	0.9	1.8
							2070–2099					
Abadan	1.7	1.5	1.6	2.3	1.7	0.2	2.6	3.9	0.2	2.4	1.4	1.9
Ahwaz	3.0	3.3	3.0	1.2	1.3	2.7	2.9	3.3	1.1	3.5	3.5	3.5
Dezful	3.1	2.9	3.5	1.6	1.9	2.7	2.6	3.0	1.3	3.8	2.7	2.8
Hamadan	2.2	3.1	2.4	2.9	3.0	3.2	0.7	-0.5	0.0	-0.5	-0.4	2.8
Khorramabad	3.0	4.5	3.4	2.6	3.6	1.5	-0.5	2.0	-2.2	-0.2	0.1	2.7
Shahrekord	2.2	5.0	2.8	2.9	2.7	-0.4	0.7	-0.3	-0.2	-2.2	-0.6	2.1

Table 7. Temperature variations at the studied stations based on HadCM3 outputs for the B2 scenario for the period 2010–2099.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
					2010–2039							
Abadan	1.1	0.7	0.8	1.1	0.1	1.2	2.2	3.1	-0.6	1.6	0.6	1.1
Ahwaz	2.2	2.5	2.2	0.0	0.5	1.9	2.1	2.5	0.3	2.7	2.7	2.7
Dezful	2.3	2.1	2.7	0.8	1.1	1.9	1.8	1.9	0.5	2.1	1.9	2.0
Hamadan	1.3	2.2	2.3	2.1	1.2	2.4	-0.1	-1.3	-1.2	-1.3	-1.2	3.0
Khorramabad	2.2	1.7	1.6	2.8	2.8	0.7	-1.3	-2.8	-2.0	-1.8	-0.7	1.9
Shahrekord	2.4	2.2	2.0	2.1	1.9	-1.2	-2.1	-1.1	-1.0	-1.0	-1.4	1.3
					2040–2069							
Abadan	1.9	1.5	1.6	1.9	0.9	2.0	3.0	3.9	02	2.4	1.4	1.9
Ahwaz	0.3	3.3	3.0	0.8	1.3	2.7	7.9	3.3	1.1	3.5	3.5	3.5
Dezful	3.1	2.9	3.5	1.6	1.9	2.7	2.6	2.7	1.3	2.9	2.7	2.8
Hamadan	2.1	3.0	3.1	2.9	2.0	3.2	0.7	-0.5	-0.4	-0.5	-0.4	3.8
Khorramabad	3.0	2.5	2.4	3.6	3.6	1.5	-0.5	-2.0	-1.2	-1.0	0.1	2.7
Shahrekord	3.2	3.0	2.8	2.9	2.7	-0.4	-1.3	-0.3	-0.2	-0.2	-0.6	2.1
					2069–2099							
Abadan	2.1	1.7	1.8	2.1	1/1	2.2	3.2	4.1	0.4	2.6	1.6	2.1
Ahwaz	3.2	3.5	3.2	1.0	1.5	2.9	3.1	3.5	1.3	3.7	3.7	3.7
Dezful	3.3	3.1	3.7	1.8	2.1	2.9	2.8	2.9	1.5	3.1	-2.9	3.0
Hamadan	2.3	3.2	3.3	3.1	2.2	3.4	0.9	-0.3	-0.2	-0.3	-0.2	0.4
Khorramabad	3.2	2.7	2.6	3.8	3.8	1.7	-0.3	-1.8	-1.0	-0.8	0.3	2.9
Shahrekord	3.4	3.2	3.0	3.1	2.9	-0.2	-1.1	-0.1	0.0	0.0	-0.4	2.3

For a more accurate analysis of temperature variations at the studied stations, changes in temperature for the different months were presented for three baseline periods. *Tables 6* and *7* show the results for the A2 and B2 scenarios. As shown in the tables, these variations follow an annual pattern with the difference that temperature variations are more considerable for both the A2 and the B2 scenarios. Other characteristics are totally observed in the tables, although the B2 scenario shows a higher increase (*Table 7*). According to *Tables 6* and *7*, the temperature decreased at the mountain stations in the first period (2010–2039) much more than in the other periods (2040–2069 and 2070–2099). For instance, in the downscaling SDSM based on the outputs for the A2 and B2 scenarios at the mountain stations (Khorramabad, Shahrekord, and Hamadan) in October, there were decreases of 2.5 and 1.24 °C on average, respectively. However, the intensity of decrease declined towards the recent periods so that the predicted decreases were 1.5 and 0.36 °C, respectively, during 2070–2099. Regarding the studies on climate fluctuations, the temporal index is very important, because climate, as a system, results from a series of meteorological conditions that have been tangible through the data of several previous decades, and their occurrence and recurrence are probable in the future decades. Therefore, the current climate, to which we have well been adjusted, is described by the data of several previous decades. Nonetheless, the neural network, which predicted up to a fourth of the studied period (i.e., up to 2025), predicted more tangible changes in some plain stations, especially Abadan and Ahwaz. This region in Iran is affected more by fluctuations of the Persian Gulf due to its proximity, so that studies indicate an increase up to 2 °C in the temperature of surface water in the Persian Gulf (*Rigel*, 2002). However, mountain stations showed slight increases. AGCMs, regarded as some of the most reliable tools for the analysis of climate change impacts on different systems, and are capable of simulating climate parameters for a long period of time by using the scenarios confirmed by IPCC (*Kilsby* et al., 2007), predicted an increase of 1–2 °C in temperatures at these stations.

Nevertheless, both scenarios produced similar predictions in downscaling considering the nature of the definitions of these scenarios. This may be due to the fact that greenhouse gases, which are considered by scientists to be the main factor causing climate change (*Jahanbakhsh et al.*, 2010), are not measured at the studied stations, especially at the mountain stations. Consequently, the NCEP data were measured mainly based on estimates and interpolation. Therefore, most researchers have predicted greater increases in temperature. The results showed that the Hamadan Station would encounter an almost 1.2 °C of increase by 2099. At the same time, the outputs of two AGCMs (HadCM2, ECHAM4) and of the MAGICC-ECHAM4 model predicted that the temperatures of all Iranian provinces would experience a 2–3.6 °C increase on average by 2100 (*Abbasi* and *Asmari,* 2012). If the behaviors and data series predicted based on both methods are taken into account, we will notice that they exhibit similar behaviors and fluctuations in general, but the fluctuation range of the HadCM3 is wider than that of the neural network. As stated earlier, the temperatures at the studied stations increased by 0.5–1.5 °C on average. However, the IPCC estimated the average temperature will increase from 0.5 to 1 °C based on the HadGEM and by 3 °C based on the HadCM3 for the studied region, assuming that CO_2 concentration will increase by 1% in the atmosphere. These results are almost consistent with those of the present research (*Fig. 2*). Some researchers have predicted that Iran's temperature will increase by 1–3 °C (*Abbasi et al.*, 2010). For instance, the temperature increased by up to 2.5 °C on average at some parts of the mountain stations. In addition, the temperature rise was nearly 1.5 °C at the mountain stations based on HadCM3 outputs for the A2a and the B2a scenarios. Nonetheless, most researchers have predicted a temperature raise (*Ashraf et al.* 2011*a*; *Parvin*, 2010). As mentioned earlier, the estimates of temperature increase for the A2a and B2a scenarios, despite the different natures of these two scenarios, were almost similar, because greenhouse gases were not measured. At some stations, such as Ahwaz and Abadan, the temperature will exhibit a 1.0–2.5 °C increase on average by 2099. However, the neural network showed that changes would be negligible up to 2025.

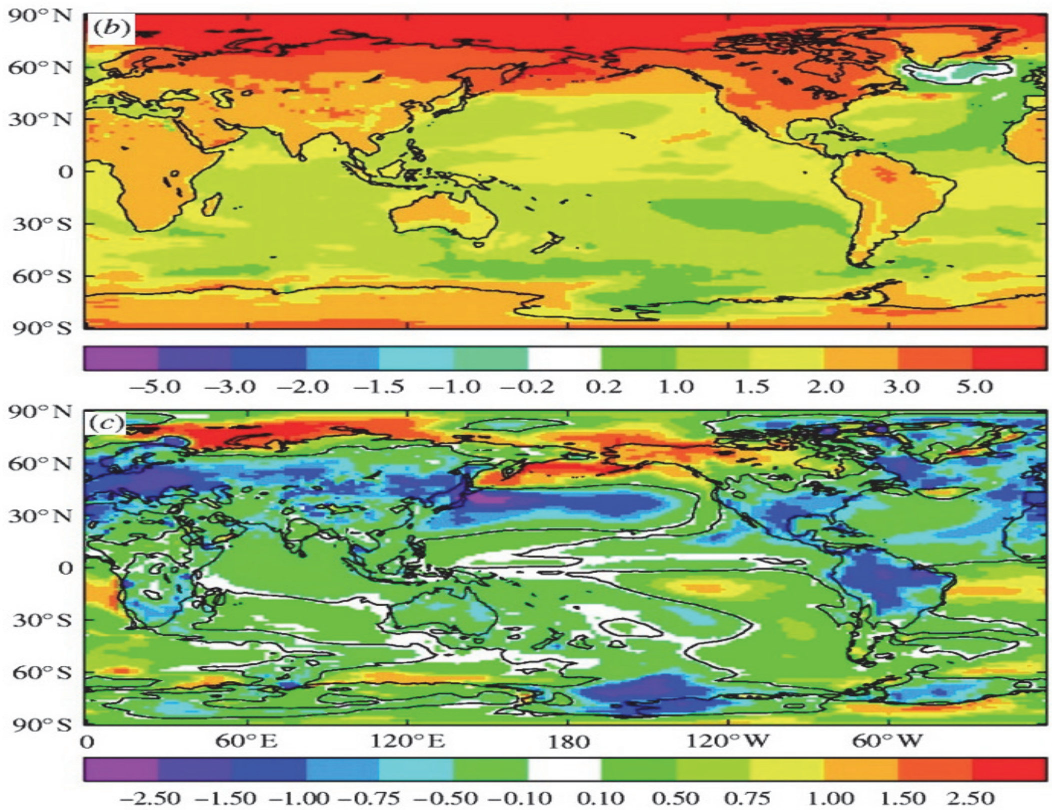

Fig. 2. Mean temperature variations of the world based on (a) Had GEM and (b) HadCM3 (source: IPCC)

4. Summary and conclusions

Climate is considered one of the fundamental pillars of human life, and its protection assumes a daily increase in importance considering the global progress and development. Climate change is one of the most complicated problems that we are facing now and will confront in future. Humans are the main cause of climate change by neglecting the rules governing nature and lacking enough knowledge of environmental problems related to climate. The uncontrolled interventions have caused climate parameters to continuously change on temporal and spatial scales. These changes represent one of the natural characteristics of the atmospheric cycle resulting from abnormalities or fluctuations in the trends of meteorological parameters such as precipitation and temperature. Subjects related to climate change have been raised, and human activities in relation to emission of greenhouse gases such as CO_2 and methane as well as other topics pertaining to climate change have been discussed at universities and research centers indicating that great losses will result from climate change. Nowadays, climate change prediction is very important in macro planning activities. In this regard, GCMs are among the most powerful existing tools that are evolving for simulation of climate change. These models are highly reliable on global and planetary scales. For this purpose, temperature changes were estimated using the HadCM3 model and a neural network in southwest Iran at plain stations (Abadan, Ahwaz, and Dezful) and mountain stations (Hamadan, Khorramabad, and Shahrekord). The research data included the diurnal average temperature of synoptic stations in southwest Iran, NCEP reanalysis data, and the outputs of a third-generation global climate model HadCM3 under the A2 and B2 scenarios for the baseline period (1961–1990). The following results were obtained:

1) HadCM3 outputs at plain stations (Abadan, Ahwaz, and Dezful) yielded more appropriate results than at mountain stations (Hamadan, Khorramabad, and Shahrekord). However, the neural network showed better estimates at mountain stations and at plain stations. The amounts of error of the neural network and HadCM3 outputs were not so significantly different at plain stations that one of them could be preferred to the other in evaluating temperature variations. Nevertheless, conditions were more diverse at mountain stations.
2) Evaluation of temperature variations based on the neural network and HadCM3 outputs suggested that, in general, plain and mountain stations would encounter an increasing trend in temperature. However, temperature rise would be more remarkable at plain stations. Regarding the monthly scales based on HadCM3 outputs, plain stations will show increasing trends in temperature mainly from January to April.
3) Comparison of the evaluations on climate change based on the A2 and B2 scenarios revealed that both of them predicted a rise in temperature, but the latter showed a greater increase in the trend of temperature rise at the studied stations. However, both scenarios showed nearly similar results for the neural network. All in all, it can be concluded that HadCM3 outputs would be reliable only in yielding an overall estimate for the entire region, and care should be exercised in using it to study fluctuations, increases, and decreases in temperature. On average, based on the outputs of HadCM3, temperatures will rise by 1.4 and 1.9 °C in the southwestern part of Iran by 2099 for the A2 and B2 scenarios, respectively. As mentioned earlier, temperatures at most stations showed increasing trends, resulting in many problems. Surface evaporation caused by global warming will dry out rivers and lower the quality of water. This problem will be much more evident in drier areas such as desert and semi-desert regions. In addition, increased salts in drinking water can decline its quality through water evaporation. At the same time, the available water for agricultural purposes will decrease, and drought will endanger food security. Drought can also make villagers migrate to cities, resort to marginalization, and decide to work false jobs. It can also worsen social abnormalities.

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