The impact of climate change on water level of Urmia Lake

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Received: 2017-01-16 *Accepted: 2017-04-21*

Abstract

The Urmia Lake is one of the largest and most important natural ecosystems in Iran. Rising temperature, high variations in precipitation, and the frequent droughts have been caused high fluctuations in the lake's water level. In this research, the monthly change of the Urmia Lake water level due to climate change was simulated by the Adaptive Neuro-fuzzy Inference System (ANFIS) from 2000-2100 by the HadCM3 model under Special Report on Emissions Scenarios (A2 and B2). Monthly inputs to the model are the precipitation over the lake, the temperature mean values, and the total inflow discharge. The effect of climate change on future water level based on the projection of the results from HadCM3 model under A2 scenario showed increase in average annual temperature and decrease in average annual lake's level by 2.80 °C and 4.60 m, respectively. The B2 scenario predicted enhancement in the average annual temperature and reduce in the average annual lake's level by 2.35 °C and 3.93 m, correspondingly. Comparing the A2 and B2 scenarios concluded that the A2 scenario predicted a more critical state for the Urmia Lake.

Keywords: Climate change; GCM projections; ANFIS; Urmia Lake.

1. Introduction

Climate change is a natural event and happens in the long time duration. The most important factors that intensify climate change are: variations in; the reflected solar radiation, earth orbit, greenhouse gases, and continental drift. As an example of climate change, the warmest years in the England during 1959-1975 can be noted. In fact, considerable changes in rainfall, seasonal variations, and continued drought are predictable actions of global warming. One of the most effects of climate change in recent years is air temperature rising (Araghi Nejad, 2005). According to Intergovernmental Plan on Climate Change (IPCC) report, the earth temperature increased about 0.3 to 0.6 ºC during last century due

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to greenhouse gases emission. Furthermore, based on the Special Report on Emission Scenarios (SRES) it has been estimated that the temperature will increase about 1 to 3.5 ºC until year of 2100, and the Asian regions will be more vulnerable (IPCC, 1999; IPCC, 2001; IPCC, 2007). Moreover, water level in lakes has significant relation with the climatic factors, thus, water level fluctuations in the lakes should be analyzed (Harrison, 1989).

To investigate the Urmia Lake surface fluctuations and risk analysis in coastal area with simultaneous entering of evaporation and precipitation over the lake along with input river discharge, the water level fluctuation of Urmia Lake was simulated based on the HadCM3 model under climate change scenarios using artificial neural network (Delavar, 2005). The results showed that water level in both scenarios of A2 and B2 will reduce during future years.

In another study, the effects of climate change on temperature, precipitation and runoff in catchment area of Zayanderud, Isfahan, were investigated based on the general circulation model of HadCM3 for two different periods 2010-2039 and 2070-2099 with two scenarios of A2 and B2 in an artificial neural network (Massah Bavani and Morid, 2005). The results indicated the increasing of temperature and sequence of drought years, and decreasing of precipitation and inflow in both periods, were under A2 and B2 scenarios.

Mistry and Conway (2003) studied the effects of climate change on the rising of water level of Victoria Lake in the east of Africa. The study outcome represented that there was a direct correlation between water level fluctuations and precipitation over the lake. In addition, a long latency was observed between maximum precipitation and water level pick point. In another research, Eitzinger *et al.* (2006) evaluated the climate change affections on the level of a shallow water lake, Neusiedler in the east of Australia, for two decades; 2020 and 2040. They showed the rising temperature, and the reducing of precipitation and water level of lake during 2040 relative to the 2020.

To study the effect of climate change on the water level fluctuations of Bikal Lake in southern Siberia, Atsushi *et al.* (2004) studied how the water level changes in 100,000 years using sediment sampling from the lake bottom in various climatic periods. The results showed the water level rising during warm periods and falling of water level during cool periods considerably. This was due to the greater volume of water inlet to the lake in warm period. In addition, Ayenew (2004) studied the water level trend for Abyata Lake in Africa during 1976 to 2000. The study results indicated a declining trend in water level up to 4-m depth in the lake. Moreover, Gunn *et al.* (2005) examined the effects of climate change on the increase of sea level elevation in Malaren Lake for the years of 2070-2100. The study used the ECHAM4 model of GCM model series by A2 scenario. The results showed that the level of Malaren Lake was as much as 50 cm for the future period. Furthermore, Araghi Nejad and KarAmooz (2005) mentioned to long-term runoff prediction using artificial neural networks and fuzzy inference system. The most important objective of the study was the development of prediction model for water level variations in Urmia Lake using Nero-fuzzy networks and applying it in climate change scenarios to the end of current century.

2. Material and methods

In this research, the monthly average data of 30 years (1971-2001) includes of precipitation on the Urmia Lake, total inflow, and temperature in the Urmia Lake station which were collected from Water Research Institute of the Ministry of Energy and Iran Meteorological Organization (IRIMO). Using the data, the inflows to the lake and the lake's level were simulated by ANFIS model. In the next step, the data of 100-year (2000-2100) climatic variables of temperature and precipitation by different scenarios A2 and B2 of the HadCM3 model taken from the IPCC website were downscaled. Finally, using climatic variables of temperature and precipitation from HadCM3 model were simulated by ANFIS model (IPCC, 2007).

Although previous studies represented acceptable methods to simulate Urmia lake level, the neural networks were used in all these studies. In this study, a new method, ANFIS, was used to simulate the lake elevation. In fact, the Nero-Fuzzy networks are superior to the neural networks because of their easy learning and fast optimization and effective correction (Shaban Nia and Saeidnia, 2007; Haghroosta and Ismail, 2015).

2.1. Study area

The Urmia Lake in the Northwest of Iran is considered as the twentieth lake in the world in terms of area. The Lake basin area is 52355 km^2, which about 5822 km^2 of the lake is directly related to its elevation that will change with its rising or falling. The bottom elevation from the freedom of the seas is 1268 meters.

The average annual temperature in the area is about 11 °C and the mean annual rainfall is between 180 to 500 mm. Major rivers of the basin are Nazloochay, Barandoezchay, Aji-chay, Zarrinehroud, Siminehroud, Mahabadchay, Zolachay and another set of rivers in the west part of the Lake. Figure 1 shows the location of study area in Iran and the main rivers flow into the lake (ShabaniNia and Saeednia, 2007).

The water level of lake is one of the important features, which has a direct relationship with the lake's water balance. In recent years, changes in the precipitation rate and climate change such as increasing temperatures and decreasing rainfall in Urmia Lake led to a sharp reduction in the lake's level. Understanding the water level fluctuations in lakes can be effective in the interpretation and consideration of changes in water supply as well as the issues related to planning for water resources management, environmental issues and coastal construction.

2.2. General circulation models

According to the IPCC recommendation, most reliable models for simulating the processes in the climate systems are based on the increasing of greenhouse gases (IPCC, 2007). Atmosphere-

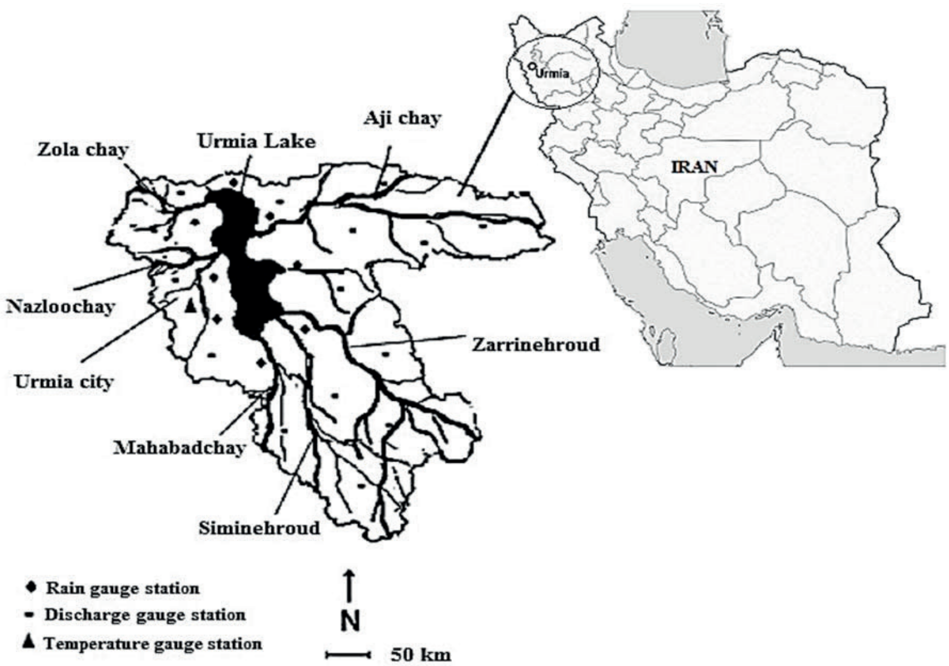

Figure 1. The location of study area in Iran and the main rivers flow into the lake

Ocean General Circulation Models (AOGCM), are based on the basic laws in physics that are presented by mathematical equations. These equations are resolved in a three-dimensional network on the Earth's surface. Precision of horizontal displacement of the model in land surface is typically 250 km and its vertical spatial resolution is 1 km, while in oceans, the accuracy of vertical displacement is 200-400 meters and in horizontal direction is 125-250 km.

The models in recent decades have been considerably developed by increasing computer power. So far, various research centers have provided several models of general atmospheric circulation such as HadCM3, HadCM2, GISS, UKMO, GFDLT, GFDL, ECHAM4, and CSIRO. In all these models eight variables; rainfall, mean sea level pressure, solar radiation, mean air temperature, dew point temperature, minimum temperature, maximum temperature and wind speed at 10-m height above ground level by the year of 2100 have been simulated under various scenarios (Flato and Boer, 2001; Wilby *et al.*, 2004). In this study, the outputs of HadCM3 model in scale of 2.5 (latitude) × 3.75 (longitude) were used under the scenarios of A2 and B2. The A2 scenario emphasizes on the moderate growth rate in the economy and technology, and the rapid growth rate of the world population distinct from the current situation. The B2 scenario focuses on the economic and social activities, sustainable environment, and moderate economic growth (Gleick, 1987).

2.3. Downscaling data

The major problem of GCM model outputs in the studies on the effect of climate change in the regional level is large-spatial scale of computational cell relative to the study area. Therefore, it is necessary to perform some corrections on them. The corrections includes of two steps; statistical downscaling and spatial downscaling.

2.3.1 Statistical downscaling HadCM3 model outputs

Monthly time series of climatic variables, temperature and precipitation, of the model were extracted from the IPCC website for the 30-year period using the GCM-RDP software (GCM-Retrieve Data Program) [Massah Bavani and Morid, 2005]. Then, the correction and adjustment of monthly temperature and precipitation were performed using the method of Alcamo *et al.* (1997), which is based on the annual average difference between the observed and simulated data.

$$T'_{GCM} = T_{GCM} - (\bar{T}_{GCM} - \bar{T}_{CRU}) \qquad (1)$$

$$P'_{GCM} = P_{GCM} \times (\bar{P}_{CRU} / \bar{P}_{GCM}) \qquad (2)$$

which T'_{GCM} and P'_{GCM} are respectively corrected temperature and precipitation for the considered month, and T_{GCM} and P_{GCM} are simulated uncorrected temperature and precipitation, $\bar{T}_{GCM}$ and $\bar{P}_{GCM}$ are respectively the average annual temperature and precipitation for the period of 30 years based on the GCM model, $\bar{T}_{CRU}$ and $\bar{P}_{CRU}$ are correspondingly the observed average annual temperature and precipitation for the 30-year period. The final step is to convert the cells' coordinates from the longitude and latitude to Cartesian. For this purpose, a very common method, Area Cylindrical Projection system in MATLAB was used. In this method, the Earth's surface is inscribed on a cylindrical surface. Therefore, cells' areas on the Earth were weighted such a way that in the imaging of cylindrical system had the same area.

2.3.2 Spatial downscaling of the HadCM3 model outputs using inverses distance weighting (IDW) method

In the spatial downscaling data, the interpolation of neighboring cells was used in the study area to eliminate discontinuity in changes between simulated climatic variables in the sites close to each other in two different cells. For interpolation calculations, it should be noted that the important thing in the interpolation method is the required number of cells in around of main cell (Wilby *et* *al*., 2004; Hewitson and Crane, 2006). In this study, 24 cells and IDW method were used. The method assumes that the points close to the interpolation point (center point) are more effective than more distant points on the quantity of interpolation.

$$Z^*(x_j) = \sum_{i=1}^{n} Z(x_i) \frac{\frac{1}{(d_{ij})^P}}{\sum_{j=1}^{n} [\frac{1}{(d_{ij})^P}]} \quad (3)$$

In Equation (3), is the estimated quantity in x_j, is the measured quantity in x_i, d_{ij} is the distance between the points of , and , and P is the weighting value. The weighting value of P indicates the reducing rate of the points' weight relative to increasing the points' distance from the estimated point which was assumed equal to 1 (Ahrens, 2006).

Table 1 compares the annual average of observed climatic variables with HadCM3 model under two scenarios A2 and B2. The average of monthly mean temperature in the HadCM3 under A2 and B2 scenarios showed respectively 2.8 and 2.35°C increase relative to the observation period. Furthermore, the mean monthly rainfall under the scenarios A2 and B2 indicated respectively, 11% and 5% reduction relative to the study period. In addition, the monthly mean discharge simulated under the scenarios A2 and B2 respectively showed 13.5% and 2.5% decrease relative to the discharge during the observation period. In fact, the reduction in discharge under both scenarios was resulted from the rising temperature and evaporation, and lessening the precipitation.

2.4. ANFIS model

In fact, the ANFIS is a combination of Artificial Neural Networks and Fuzzy systems. Using an input-output data set, the fuzzy logic toolbox function in ANFIS makes a Fuzzy Inference System (FIS) that the membership function (MF) parameters are adjusted with the Back Propagation method in alone or in combination with Least Square method. In fact, the FIS generates the outputs from the training process on the inputs. This process corrects the MF parameters based on the selected errors. In order to assess the quality of the FIS model in output prediction, it is necessary to do the validation process. In this case, the untrained FIS model shows an input vector from input-output data to trained FIS model to validate the model examined (Jang, 1993). The first step in simulating in ANFIS model is choosing the membership function. Gaussian membership function, Gauss2mf, and Bell membership function, gbellmf, are the most common membership functions because of their smoothness and low complexity. In this study, all MFs were examined and the MF related to the best Gaussian

Table 1. Comparison of monthly mean values of observed climatic variables with HadCM3 model outputs under A2 and B2 scenarios

Climatic variable	Statistical parameters	Observation period 1971-2000	HadCM3 model (2000-2100)	
			A2	B2
Precipitation (mm)	Mean	23.24	20.67	22.09
	Maximum	45.72	35.93	39.51
	Minimum	1.12	1.90	1.03
	Standard deviation	20.94	16.86	16.63
Mean temperature (ºC)	Mean	11.17	13.97	13.52
	Maximum	26.30	32.95	29.49
	Minimum	-1.93	-0.39	-0.43
	Standard deviation	8.87	9.46	9.33
Discharge (cms)	Mean	162.44	140.21	158.77
	Maximum	472.79	428.82	479.12
	Minimum	40.41	34.75	45.29
	Standard deviation	75.63	67.09	72.06

function output was selected for the output and input of the ANFIS model. The Back-propagation method was used for learning and optimizing the model. To simulate the water level in the lake, the FIS included of 27 Fuzzy rules and 3 independent variables of temperature, precipitation, and water discharge.

2.4.1 ANFIS model inputs

The most effective factors on water level fluctuations are the most important parameters for the model inputs selection and the model designing. These factors are called basis inputs which are water inlet to the river, temperature, and precipitation. In this research, to select the network inputs and to simulate water level fluctuations, from 12 models introduced by Mahsafar (2008), six effective models are represented as follows:

1- $H_t=f(P_t, T_t, Q_t)$
2- $H_t=f(P_{t-1}, T_{t-1}, Q_{t-1})$
3- $H_t=f(P_{t-3}, T_{t-3}, Q_{t-3})$
4- $H_t=f(P_t, T_t, Q_t)$
5- $H_t=f(P_{t-1}, T_{t-1}, Q_{t-1})$
6- $H_t=f(P_{t-3}, T_{t-3}, Q_{t-3})$

In the equations, H_t (msl) is the lake level in time t, Q_t (cms) is the mean value of monthly input discharge to the lake in the month of t, P_t (mm) is the level of monthly precipitation in the month of t, T_t (^{0}C) is monthly mean temperature in the month of t, and H_t is the water level variation in the current month relative to the previous month. In this study, 80% of the data were used as training data and 20% of the data were used for validation process (Haghroosta and Ismail, 2015).

2.4.2 Network evaluating indexes

To evaluate the performance of Neuro-Fuzzy networks, two indexes were applied; correlation coefficient (R^2) and root mean square error (RMSE). It is a measure of the strength and direction of the linear relationship between the simulated and observed values. Higher values of R^2 show better performance of the model. Furthermore, the smaller the RMSE value, the better the model's performance (Haghroosta *et al.*, 2014).

$$R^2 = \frac{\sum_{i=0}^{n} X_i Y_i}{\sqrt{\sum_{i=0}^{n} X_i^2 Y_i^2}} \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=0}^{n} (X_i - Y_i)^2}{i}} \tag{5}$$

which Xi are the observation values, Yi are the estimated values, and n is the number of data.

2.4.3 ANFIS Model inputs for lake level simulating

To evaluate the models and to select the best model for simulating the lake's level, different models were

Table 2. Input Models' performance for simulating the lake's level

	Training			Validation		
Model	R	R^2	RMSE (m)	R	R^2	RMSE (m)
1	0.64	0.41	0.36	0.39	0.15	1.50
2	0.68	0.46	0.38	0.36	0.13	1.70
3	0.70	0.49	0.40	0.47	0.22	1.30
4	0.92	0.83	0.42	0.90	0.81	0.34
*5	0.94	0.88	0.31	0.92	0.85	0.41
6	0.82	0.67	0.72	0.89	0.79	0.48

*: the model number 5 was selected as the best model for this study

compared in training and validation processes (Table 2). The results showed that the model (5) had the best performance relative to the other models. Therefore, the model (5) was selected for simulating the water level in the future analysis based on the climatic variables. Figure 2 illustrates the comparison between observed and simulated water level in the training and validation processes by the model (5). Figure 3 shows the MFs of different inputs; precipitation (input1), temperature (input2), and water discharge (input3), before and after training step by the model (5) for simulating the lake's level.

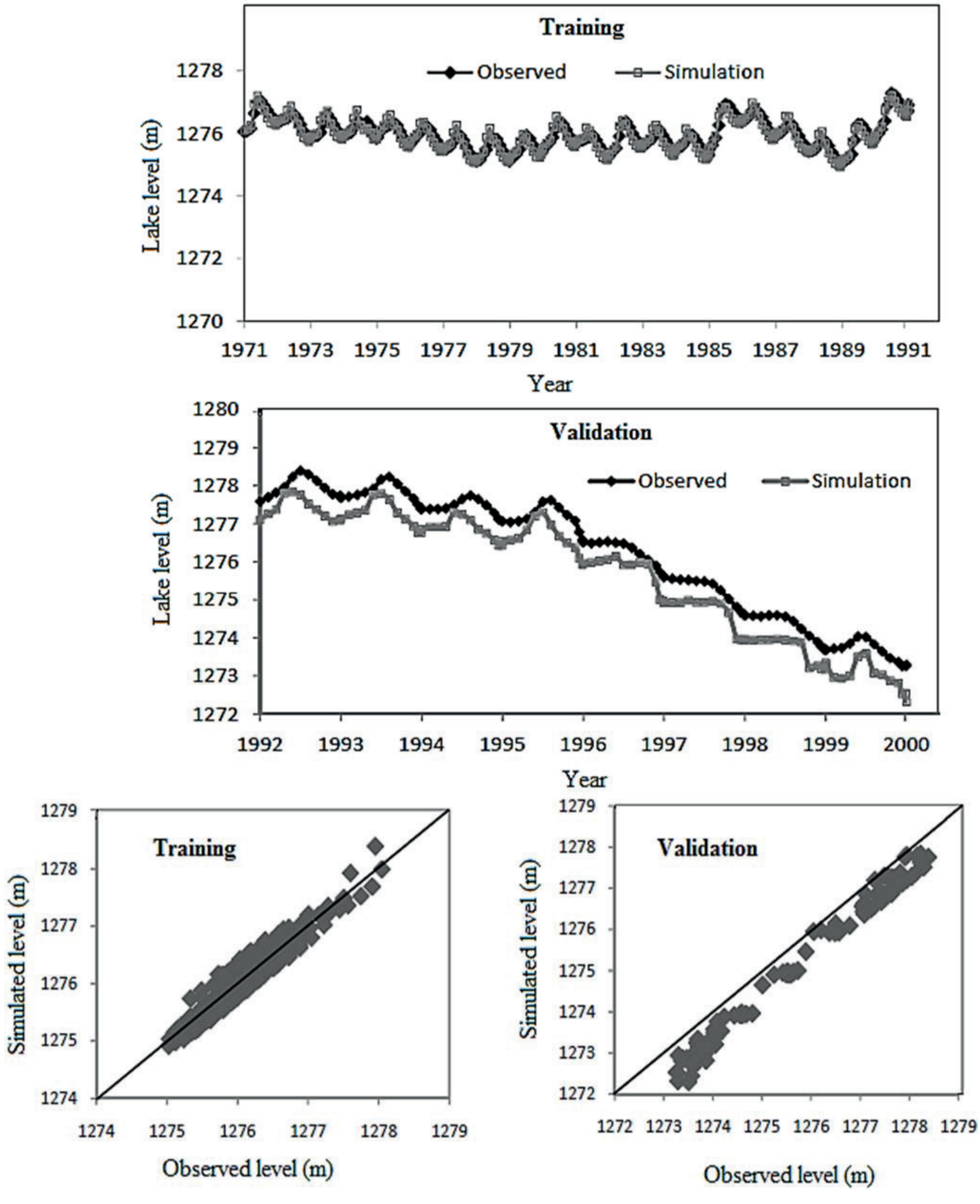

Figure 2. Comparison between simulated level and observed level based on the model (5) in training (1971-1991) and validation (1992-2000) processes

3. Results and Discussion

3.1. Precipitation and temperature analysis

The results of downscaling the climatic variables for the study area represented a increasing trend in surface temperature and decreasing trend in precipitation over the lake under two scenarios, A2 and B2, during 2000-2100. The annual average of temperature in HadCM3 under the scenarios A2 and B2 were estimated 13.97 ºC and 13.52 ºC, and the annual average of precipitation were simulated 20.67 mm and 22.09 mm, until the year of 2100, correspondingly. Actually, the annual average of precipitation under the scenarios of A2 and B2, respectively showed 11 and 5 percent reduction relative to the observation period (Table 1).

The highest increase of the monthly mean temperature under the scenario of A2 happened on November with the amount of 8.86 ºC and under the scenario of B2 occurred on October with the amount of 8.67 ºC relative to the observed values. Moreover, the highest increase of the monthly mean precipitation under A2 and B2 were respectively 69.55% on August and 19% on December, and the most reduction of monthly mean precipitation under the scenarios A2 and B2 occurred in that order of 47.69% on July and 27% on May (Figures 4a and 4b) (Table 3).

3.2. Discharge analysis

To simulate the lake level, it is necessary to simulate the lake discharge by the ANFIS model during 2000-2100 based on the variables of temperature and precipitation. As it is available in Table 1, the average of input discharge to the lake in the next 100 years, under climatic scenario showed a declining trend. The annual averages of discharge were estimated by HadCM3 model under the scenarios of A2 and B2 in that order of 140.21m^3/s, and 158.77m^3/s until the year of 2100. The simulated annual averages under A2 and B2 showed respectively 13.5 and 2.5 percent reduction relative to the observed discharge. The simulated inflow showed increase up to 38.72% under A2 scenario on August and up to 85.08% under B2 scenario on October relative to the observed values. The highest inflow reductions obtained under the scenarios of A2 and B2 on March with the amounts

Table 3. Comparison of the observed climatic variables variations with the simulated values under A2 and B2 scenarios

Month		Jan	Feb	March	April	May	June	July	Aug	Sep	Oct	Nov	Dec
Climatic variable	Scenario												
ΔT(ºC)	A2	4.93	0.52	-1.99	-3.53	-0.75	-1.21	0.54	4.74	7.52	8.72	8.86	7.80
	B2	5.32	-0.25	-2.88	-4.12	-1.65	-1.68	-0.27	3.98	6.87	8.67	8.17	7.10
P (%)	A2	-0.70	-23.85	-0.35	-26.29	-22.85	-38.53	-47.69	69.55	-19.90	-4.81	11.52	7.47
	B2	13	-8.00	-7.00	-16.00	-27.00	-7.00	-5.00	-8.00	-17.00	8.00	4.00	19.00
Q (%)	A2	-51.21	-46.07	-65.42	-9.35	-9.30	26.40	22.46	38.72	36.88	36.18	-38.96	-58.52
	B2	-50.08	-40.48	-62.19	2.55	1.34	34.40	35.05	76.29	71.21	85.08	-25.91	-45.93
ΔH (m)	A2	-4.24	-4.13	-4.10	-4.06	-4.09	-4.16	-4.28	-4.45	-4.60	-4.57	-4.51	-4.38
	B2	-3.40	-3.38	-3.42	-3.48	-3.57	-3.61	-3.58	-3.66	-3.73	-3.72	-3.49	-3.44

ΔT (ºC): Difference of observed and simulated temperature
Q (%): The percentage of difference between observed and simulated discharge
P (%): The percentage of difference between observed and simulated precipitation
ΔH (m): Difference between observed and simulated water level

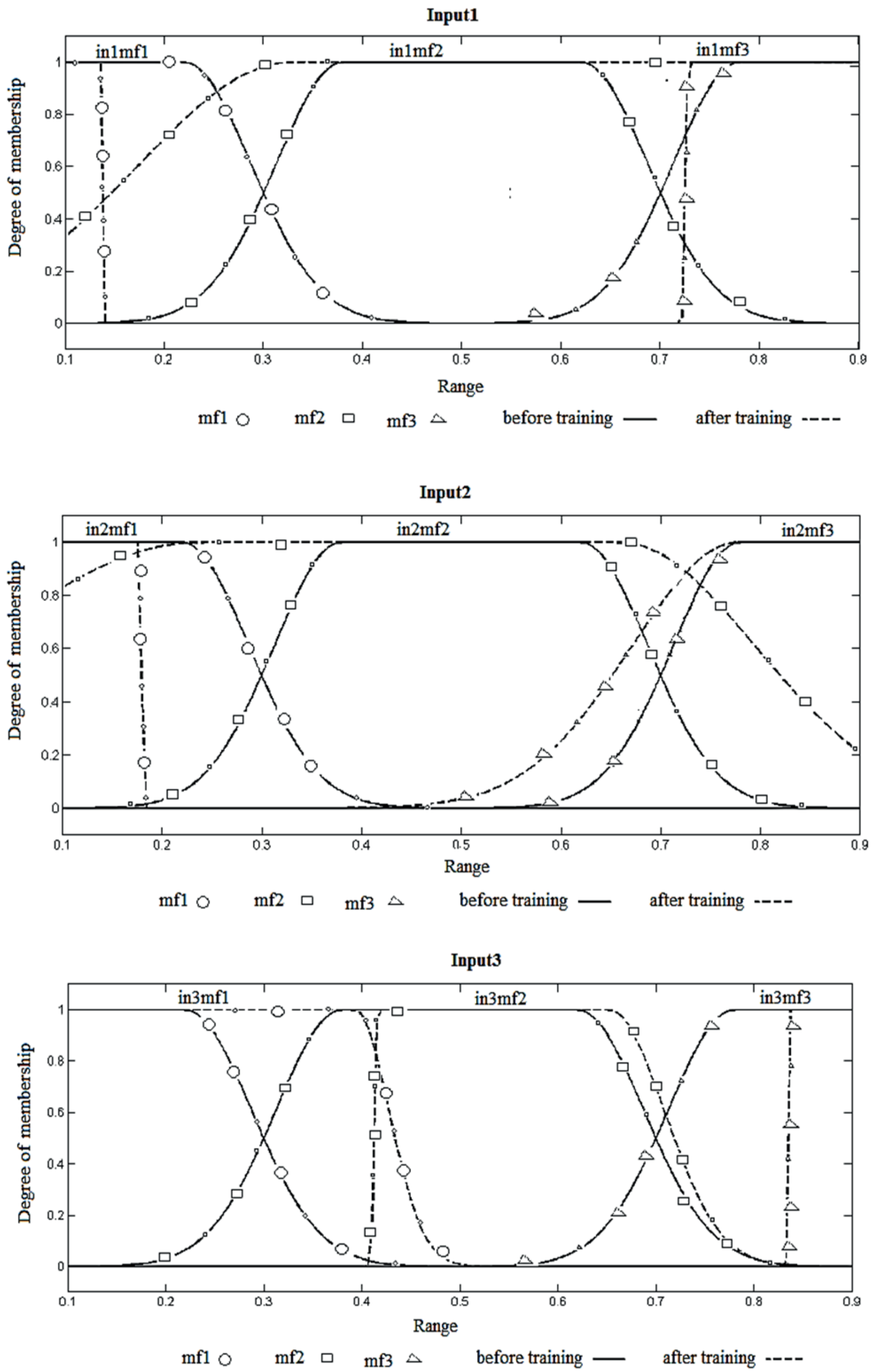

Figure 3. Membership functions (MFs) of precipitation (input1), temperature (input2), and discharge (input3) in before and after training the model (5) to simulate the lake's level

of up to 65.42% and 19.62%, respectively, relative to the observed values (Figure 4c and Table 3).

3.3. Lake's level analysis

The results of lake's level simulation during 2000-2100 based on the climatic variables showed a declining trend in the water level in the future. The highest reduction values in the lake's level, simulated by HadCM3 model under scenarios of A2 and B2 by the year of 2100, were respectively 4.60m and 3.73m on September. This may be due to the sharp rise of temperature in the months of August to February and a remarkable decline in inflows to the lake in the months of November to April. The Lake's level under the scenario of A2, will equivalent with the

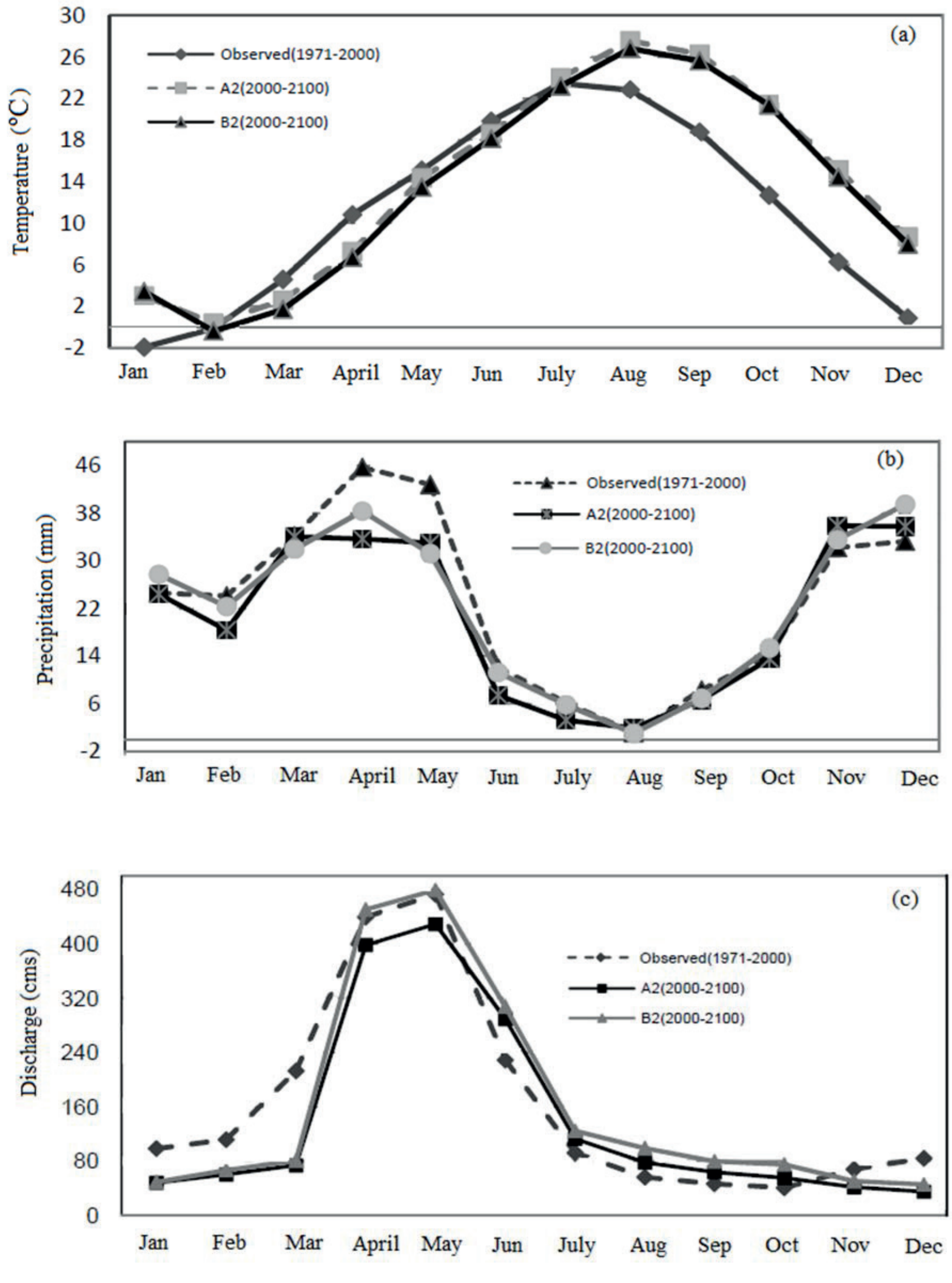

Figure 4. Monthly mean of observed values of temperature (a), precipitation (b), and water discharge (c) in comparison with the simulated values by the scenarios A2 and B2

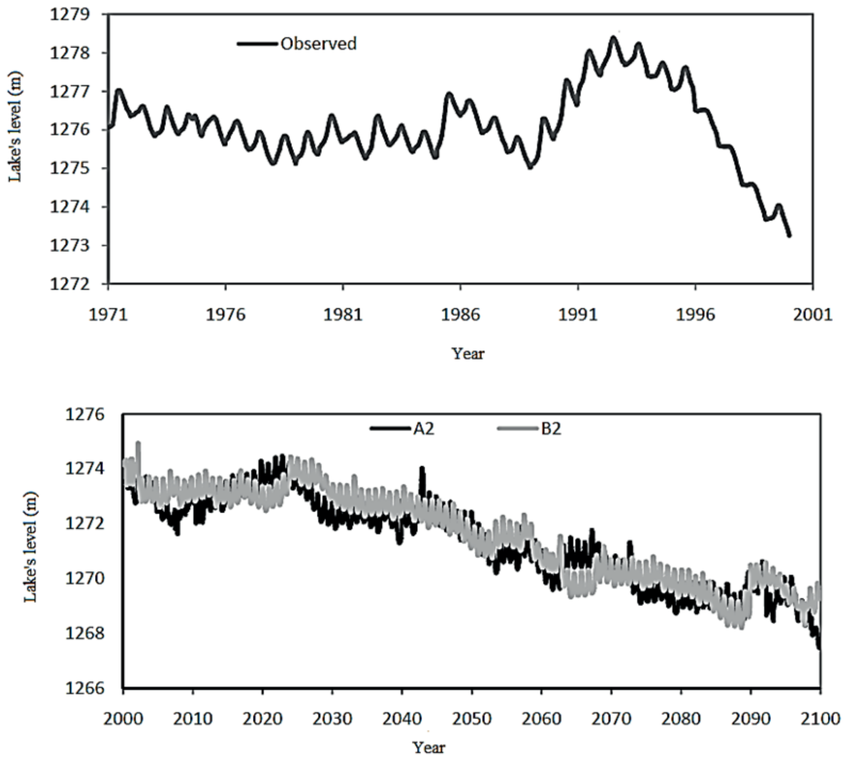

Figure 5. Observed values of lake's level (up) in comparison with the simulated levels by HadCM3 model under the A2 and B2 scenarios

average level of lake's bottom (1286m above sea level) by 2100. Figure 5 and Table 3 indicate the lake's level in observed mode and simulated mode under the scenarios of A2 and B2 in HadCM3 model.

Conclusion

In this paper, the effects of climate change on the level of Urmia Lake were analyzed, using an ANFIS model based on the HadCM3 model under two scenarios of A2 and B2, from SRES during 2000-2100. The results showed the sensitivity of the study area to the climate change factors. Data analysis on temperature indicated its increasing trend under both scenarios, A2 and B2. So that, the annual average of temperature increased about 2.80 °C under scenario of A2 and 2.35 °C under scenario of B2. Moreover, the mean annual precipitation under the scenarios of A2 and B2 reduced relative to observed values with amount of 11 and 5 percent, respectively. In fact, increasing temperature, reducing precipitation and consequently the reduction of input discharge to the lake, caused a decrease in lake level. Furthermore, the lake level size decreased about 4.60m under scenario A2 and 3.93m under B2. Finally, the year of 2100 estimated as the driest year for the Urmia Lake and the lake will be completely dried by 2100 under scenario of A2.

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