Impact Of Climate Change On The Inflow Of The Aras, Ghorichai And Sattarkhan Dams

Hafezparast[1], Sharifazari[2]

[1]Corresponding author: Assistant Professor, Department of Water Engineering, College of Agriculture, Razi University, Kermanshah, Iran. E-mail: m.hafezparast@razi.ac.ir cell phone number: +989131270848.

[2]Salman Sharifazari: Faculty member of Zabol university, Department of water engineering, Faculty of soil and water, University of Zabol, Email: s.sharifazari@gmail.com

***Abstract*—The 1074 km long Aras River is located in the Aras River basin is in the North West of Iran. The impact of climate change in the Aras basin is investigated with respect to changes in the precipitation and temperature data. The data from climate stations (1981-2005) was used in a developed K-Nearest Neighbor (K-NN) Non-parametric Regression Algorithm, to downscale the General Circulation Models (GCM),the CGCM3T63(Canadian Centre for Climate Modeling and Analysis) and HADCM3 (Hadley Centre Coupled Model of United Kingdom) models with the SR-A1B emission scenario. The future inflow to the dams will be related to changes in runoff, so the amounts of inflow to the dams are predicted by the Artificial Neural Network (A-NN) for 2011-2060 in the whole watershed. The results selected are shown for three main climate stations: Bohlolabad, Ahar, Jafarlo, and their related dams: Aras, Satarkhan and Ghorichai in West Azerbaijan, East Azerbaijan and Ardebil respectively. The annual rainfall in the whole large scale Aras basin has raisen ~2.2% in CGCM3T63 and reduced ~18% in HADCM3 but the maximum temperature has increased ~0.21ºC and ~0.5ºC and the minimum of temperature has increased ~0.5ºC and ~0.58ºC in CGCM3T63 and HADCM3 for all the stations. The predicted inflow to the Aras water systems a result of climate change has decreased by ~1.4% and ~5.4% in the A-NN model relative to CGCM3T63 and HADCM3.**

Keywords—Climate change, K Nearest Neighbor, Artificial neural network, dam inflow

Nomenclature

A-NN	Artificial Neural Network
CCCMA	Canadian Centre for Climate Modeling and Analysis
CGCM3T63	Coupled Global Circulation Model 3T63
FFNN	Feed Forward Neural Network
HADCM3	Hadley Centre Coupled Model of United Kingdom
GCM	Global Circulation Models
K-NN	K-Nearest Neighbor

1. Introduction

Climate observations over the last century have shown that global mean annual surface temperatures have increased by approximately 0.4 to 0.8°C (IPCC, 2001, 2007, 2013). A further acceleration of these warming trends during this century is projected by all global circulation models (GCMs) (Kattsov et al., 2005) and has direct impacts on precipitation and evaporation (IPCC, 2007) by intensifying the global hydrological cycle (Brutsaert and Parlange, 1998). The increasing concentration of greenhouse gases is an important reason for global warming from the last century with high confidence (Yang et al 2011). On the other hand, climate change and human activities can affect the hydrological cycle of river basins throughout the world (e.g. Changnon and Demissie, 1996; Bronstert et al., 2002; Legesse et al., 2003; Pfiste et al., 2004; Xu, 2005; Piao et al., 2007).In this regard, there are many studies that have investigated the impact of climate change on runoff such as, Aus der Beek et al. (2011),which have analyzed the effects on the Amu Darya and Syr Darya Rivers for the period from 1958 to 2002. In Iran, downscaling for 37 climate stations, for 2010 to 2040 and 2070 to 2100 from the Canadian Global Coupled Model (CGCM) for scenarios A1B, B1, and A2, have shown that in general, wet regions of the country will receive more rainfall, but dry regions will receive less (Abbaspour et al.,2009). For downscaling of climate data, several models have been developed for generating weather variables (Jones et al. 1972, Bond 1979, Nicks and Harp. 1980, Bruhn et al. 1980, Larsen and Pense. 1981). These models are based on sound statistical principles; however, they lack general applicability and ease of use (Richardson and Wright. 1984). So the method of downscaling developed in this paper is very useful for large scale basins with more stations and parameters. Climate projections and their associated applications have become an important topic these days. Several researchers develop models to Simulate current climate and its future evolution under different greenhouse gas and aerosol scenarios (Buser et al 2009). Evaluation of the changes in river discharge in the *Aras* basin over the next 50 years by climate change is important because of the industrialization of cities, the inter-basin transportation to the *Urmia* Lake in the south and the growing population. Furthermore, the *Urmia* Lake which is the third largest saltwater lake on Earth and the largest lake in the Middle East, has already been suffering from drought. One of the options considered preventing drying *Urmia* Lake is transfer water from the *Aras* River. As a result, there will be some severe challenges in governance of the water use allocation. Similar kinds of studies have also been undertaken by Chattopadhyay and Jha (2014) for Haw river watershed in North Carolina (USA), Szépszó et al. (2014) for Rhine and Upper Danube rivers in Europe, Morán-Tejeda et al. (2014) for 27 mountain rivers in Spain, Tekle and Tadele (2014) for Bilate Watershed in Ethiopia, and by Wu et al. (2014) for Heihe river basin in China, respectively. In 92 % of the case studies, impacts on river ecosystems were reported in response to modifications of certain flow parameters (Poff and Zimmermann ,2010)

Precipitation and temperature are the main variables of input run off to the *Aras* water system. In this paper, the climate of the large scale *Aras* basin in Iran is studied with respect to changes in the precipitation and temperature data. The study is based on the data from climate stations in the Aras basin, and a developed K-Nearest Neighbor Non-parametric Regression Algorithm is used to downscale the climate data based on the CGCM3T63(Canadian Centre for Climate Modeling and Analysis (CCCMA), Canada) and HADCM3(Hadley Centre Coupled Model of United Kingdom) models with the SR-A1B emission scenario. Another aim of this study is to simulate the river runoffs for the next 50 years from 2011-2060 for inflow of the Aras, Ghorichai and Sattarkhan dams by the Artificial Neural Network (ANN).

2. Methodology

The methodology of this study is included two important steps:

1) Downscaling using developed K-Nearest Neighbor algorithm,

2) Runoff forecasting by monthly Artificial Neural Network.

For the first step the data of the two GCM models, CGCM3T63 and HADCM3, are downloaded from www.cccsn.ec.gc.ca and the developed K-NN algorithm used to downscale monthly climate data to the stations in the Aras basin. The stations were selected upstream of the main rivers that are an inflow to the Aras basin system, before all the dams. The second step is calculating the river run off to show the impact of climate change for the input flow to the dams. The simulation of the water resources system and the evaluation of the allocation to the all users due to climate change have been performed by the author and will be published in the following paper.

2.1 Study area

Aras River Basin is located in the North-West of Iran. The region covers 39534 km^2. The latitudes of the area are between 38 to 40 degrees north. This basin is located through three provinces: Ardebil, East Azerbaijan and West Azerbaijan (Figure1 and Figure2). The Aras Basin is enclosed at the West and North side by the state borders of Iran with Turkey, Armenia and Azerbaijan. On the south and east, the *Aras* Basin is enclosed by the *Urmia* Lake Basin and the *Balharoud* River Basin. The entire population of the *Aras* Basin in the year 2000 was approximately 2.4 million people. In this regard, with 63 persons per sq. km, the *Aras* River Basin is one of the most populated regions within Iran. Agricultural and industrial developments in this basin were in recent years substantial. *Ardabil*, *Julfa*, *Khoi*, *Marand* and *Pars-Abad* are the main cities located within the basin. There are 11 dams operated and constructed for control the surface water for agricultural, domestic and industrial demands.

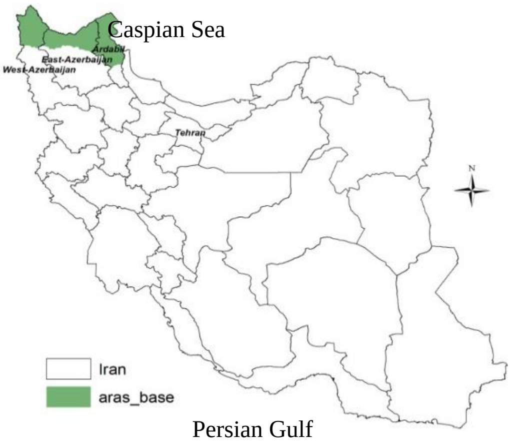


Figure 1. The location of Aras basin in the map of Iran

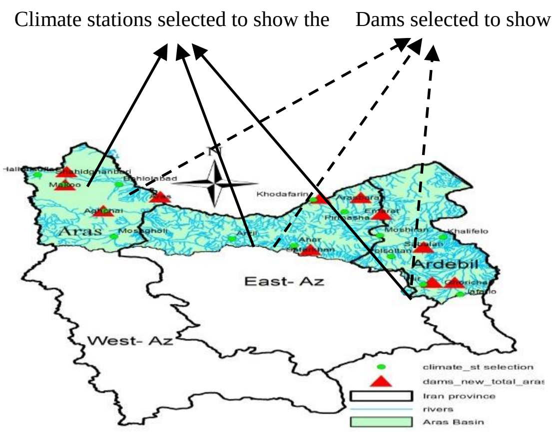


Figure 2. The Dams and Climate stations in the Aras basin

2.2 Data Collection

The geographical information and the mean observed climate data for the stations of the watershed for the baseline years between 1981and 2005 are presented in Table 1and Figure2.

2.3 Downscaling using Developed K-Nearest Neighbor

Downscaling models make use of a strong observed empirical relationship between one or several large-scale predictors and a variable of interest at a regional scale. The relationships between these scales can be determined by parametric and non-parametric methods (Goyal and Ojha, 2012). Non-parametric methods can circumvent many problems associated with the parametric methods. The most promising non-parametric technique for generating weather data is the K-nearest neighbor (K-NN) resampling approach. Recently, application of these techniques for generating synthetic weather datahas gained interest.

Table1. The information of the climate stations for each dam

Dams	Climate station name	Elevation (m)	Latitude (deg)	Longitude (deg)	mean precipitation (mm)	mean temperature (°C)
Aras	Bohlolabad	900	39.14	44.59	249.9	12.31
Badavali	Halhalsofla	2050	39.17	44.14	159.4	5.90
Baroon	Baroon	1740	39.11	44.29	373.5	7.90
Fishel	farm	1712	39.10	44.25	290.5	7.91
Khodafarin	Khodafarin	320	38.46	46.57	315.1	15.10
Arasbaran	Pirmasha	1220	39.02	46.58	305.2	15.10
Aghchai	Ghorolsofla	1270	38.52	44.54	288.9	10.96
Hajilarchai	Arzil	1350	38.34	46.12	364.7	8.10
Emarat	Moshiran	680	38.43	47.31	220.3	13.59
Satarkhan	Ahar	1350	38.28	47.03	177.5	10.98
Sabalan	Khalifelo	1300	38.42	48.07	272.3	13.59
Ahleiman	Polsoltan	1450	38.24	47.40	282.3	11.17
Yamchi	Nir	1560	38.02	47.59	334.0	8.89
Ghorichai	Jafarlo	1680	37.55	48.21	281.4	8.89

A lot of researchers such as Young (1994), Lall and Sharma (1996), Lall et al. (1996), Rajagopalan and Lall (1999), Buishand and Brandsma (2001), and Yates et al. (2003)

describe applications of the K-NN resampling scheme for simulation of weather data (Sharif and Burn, 2007). The main drawback is that point values not seen in the historic record cannot be simulated. By fitting a local polynomial to the K-NN identified above (Lall and Sharma, 1996) and using the resulting regression fit to estimate the mean and the variance, new values can be simulated (Prairie et al., 2006).An improved weather-generating model that allows nearest neighbor resampling with perturbation of the historic data is applied to generate weather data based upon plausible climate scenarios by Sharif and Burn,2006.Toavoid of problems with local polynomial degree estimation in Prairie model and contemporaneous generation of multiple variable, we use the K-NN forecasting model instead of the local polynomial. Also, residual strategic resampling (based strategic resampling by Yates et al. 2003) for a simulated hydrologic time series in line with climate changes was presented. This method is used in this study to generate precipitation and temperature data in the Aras basin based on climate scenarios. The flowchart of this method is presented in Figure3.

Consider that the monthly historic vector consists of p variables. Suppose the number of stations considered in the model is q and data are available for N years and N_g is the number of years required for data generation. So, the main steps of this method are:

1) Fitting K-NN non-parametric regression for time series forecasting

$$Y_{n,t} = \sum_{k=1}^{K} K(k) X_k \qquad (1)$$

Where $K(k)$ is the probability which X_k is resampled and $Y_{n,t}$ is the forecasted vector of $X_{n,t}$ that $X_{n,t} = (x^1_{1,n,t}, \dots, x^j_{i,n,t}, \dots, x^q_{p,n,t})$ and $x^j_{i,n,t}$ represents the value of the i th variable for j th station in month t and year n (where $t = 1, \dots, 12$, and $n = 1, \dots, N$).

2) Calculate the residual series

$$\mathrm{E}_{n,t} = X_{n,t} - Y_{n,t} \qquad (2)$$

3) Using strategic resampling from residual series by an index function (Yates et al., 2003) of the following form.

$$I^j_{i,t} = INT[N \times (1 - r^{S^j_{i,t}})] + 1 \qquad (3)$$

Where $I^j_{i,t}$ refers to the index of the year in the ranked list for month t and variable i at jth station, $r \subset (0,1)$ is a random number, $s^j_{i,t}$ is a shape parameter and N is the number of years in the historical data set.

4) Using k nearest neighbor bootstrap to generate synthetic weather time series.

$$Z_{n_g,t} = X_k + E_{k'} \qquad (4)$$

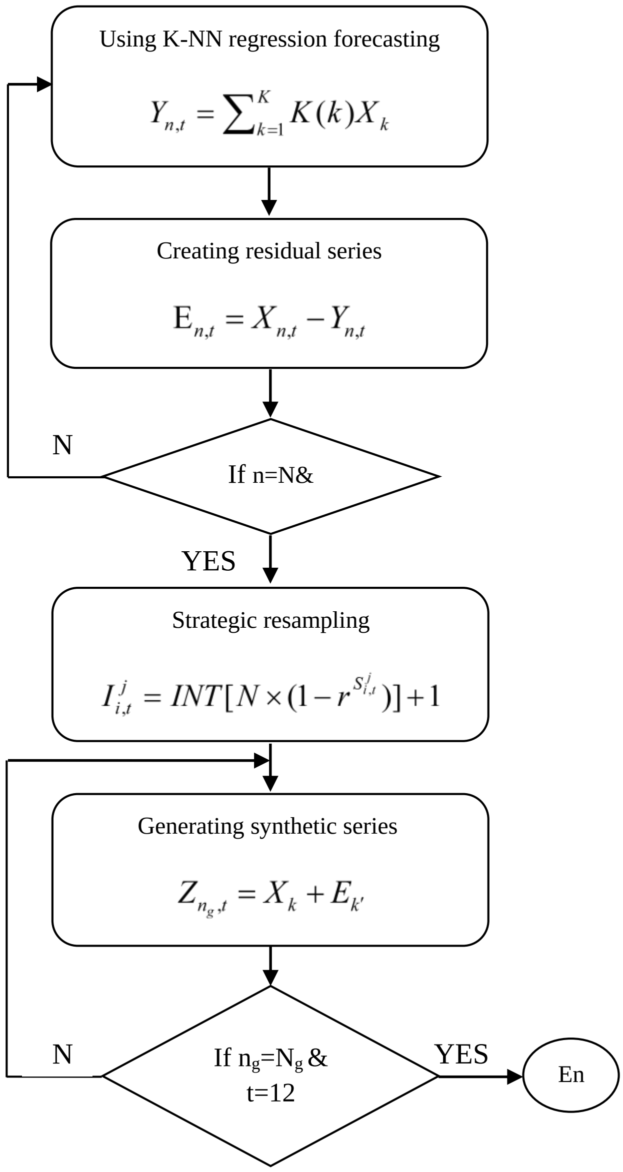


Figure3. The flowchart of downscaling by developed K-NN algorithm

The performance of the *K* -NN model depends upon the proper setting of various parameters whose values must be determined before the evaluation of the model can be carried out. Two important model parameters in a *K*-NN based resampling approach are the width of the temporal window, *w*, and the number, *K*, of nearest neighbors and the shape parameter $s_{i,t}^{j}$. Lall and Sharma (1996) suggested both an objective criteria based on generalized cross validation and a heuristic scheme to select a K, the number of nearest neighbors. They stated that the heuristic scheme does not appreciably change K, compared with the GCV. Rajagopalan and Lall (1999) and Yates et al (2003) recommended the use of a heuristic method for choosing K according to equation 5. Therefore we use a heuristic scheme to determine the number of K:

$$k = \sqrt{N} \qquad (5)$$

For our case study the values of the shape parameter to reproduce the historical series without significant changes in statistics were found equal to 1 for temperature and 0.7 for precipitation in the model calibration stage (Figure4).

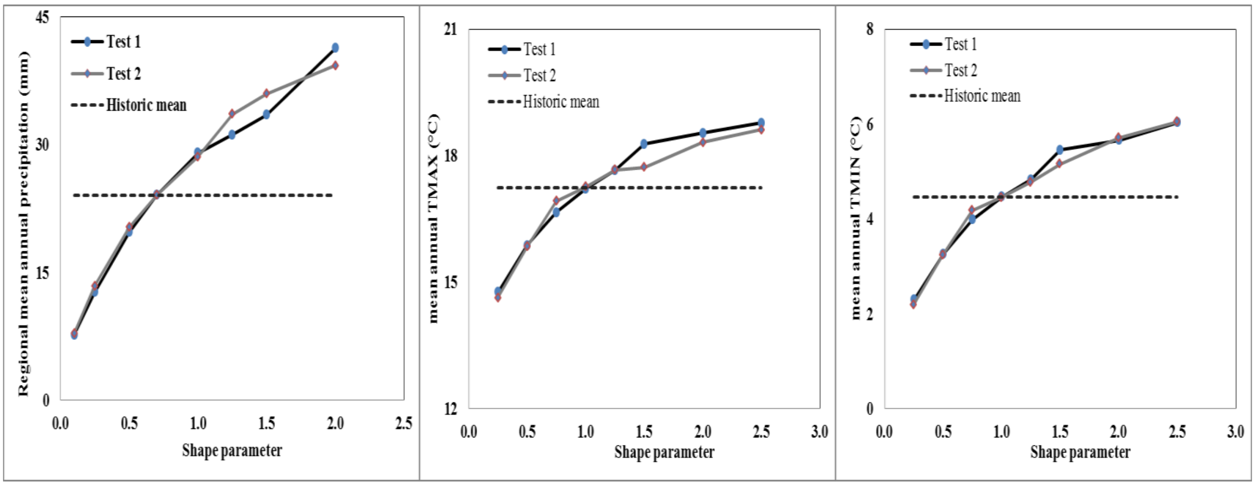
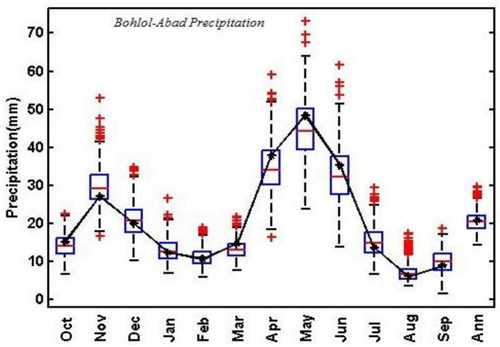
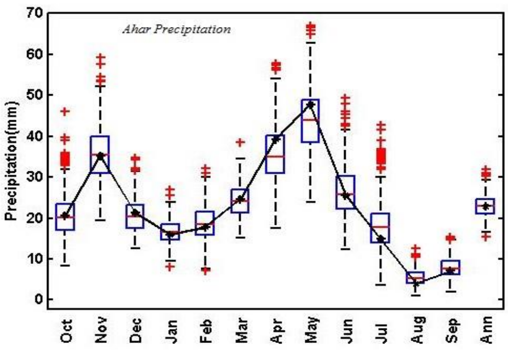


Figure4.Result of the K-NN model calibration stage

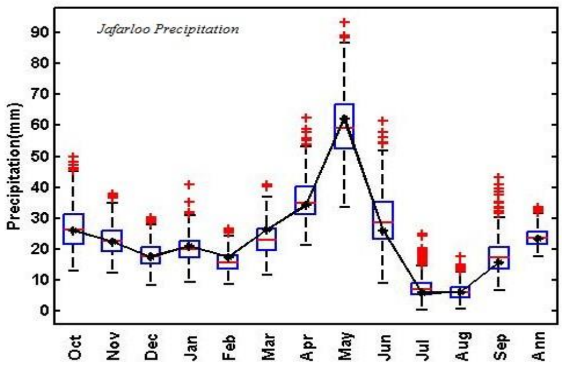
We generated 250 simulations in two tests from the proposed model, each of the same length as the historic. The values of the shape parameter to generate weather data are based upon plausible climate scenarios obtained from the calibration stage. To verify the K-NN results, the statistical attributes of the historic data and simulated data are compared by using box plots. Box plots (precipitation, T_{max}, T_{min}) are a preferred method of data analysis as they show the range of variation in the statistics of simulations and provide a straightforward method of comparing the statistics of simulations with the historical data as shown in Figures 5, 6 and 7.



(Bohlolabad)

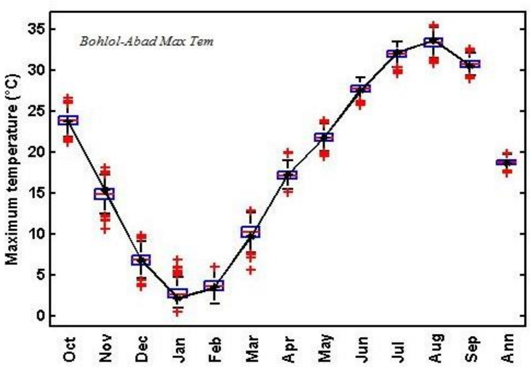


(Ahar)

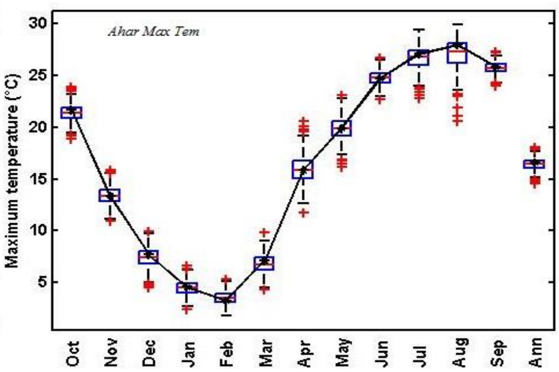


(Jafarlo)

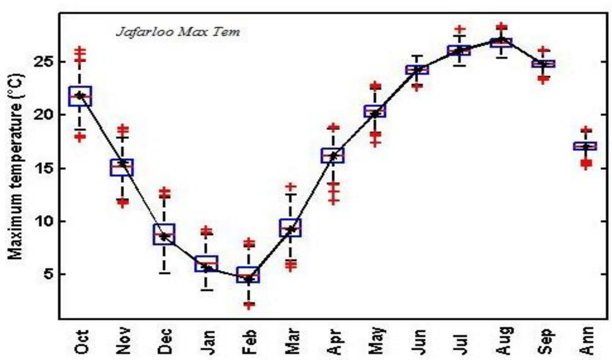
Figure5.Box Plot of precipitation in the Bohlolabad, Ahar and Jafarlo stations respectively



(Bohlolabad)

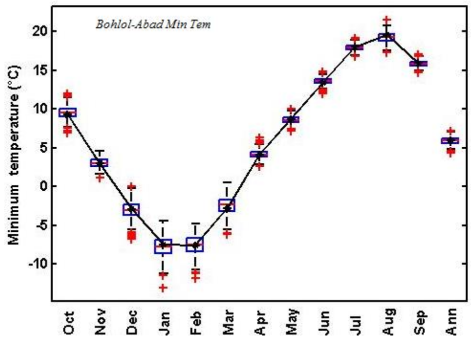


(Ahar)

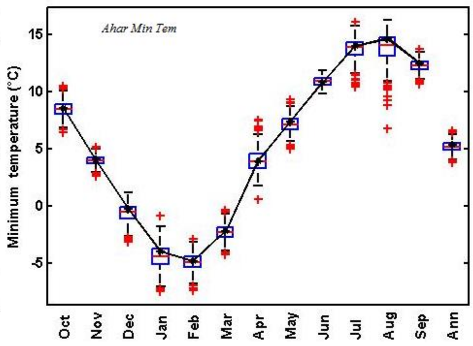


(Jafarlo)

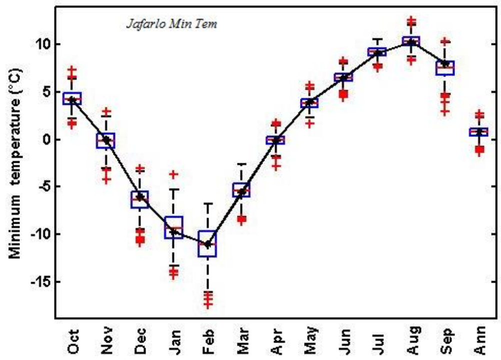
Figure6.Box Plot of Maximum temperature in the Bohlolabad, Ahar and Jafarlo stations respectively



(Bohlolabad)



(Ahar)



(Jafarlo)

Figure 7.Box Plot of Minimum temperature in the Bohlolabad, Ahar and Jafarlo stations respectively

2.4 Runoff forecasting by Artificial Neural Network

Stream flows are at risk of changes due to climate change because ecological processes are strongly influenced by seasonal patterns of precipitation, runoff, and temperature (Carpenter et al. 1992; Allan 1995). Modeling stream hydrological response to climate variation can be performed with a variety of techniques. If detailed watershed and climate data are available for parameterization, one can use mass balance models, such as hydrological budget models (e.g. Gleick 1987). However, for many stream systems, detailed watershed data are lacking, making the mechanistic modeling of hydrological response to climate difficult. Furthermore, traditional empirical models (e.g. regression models) may not perform well due to structural constraints (e.g. linearity) and paucity of data. Neural network analysis is a recently developed modeling technique that may be useful in simulating hydrological response to climate change in basins with limited data. Forecasting monthly stream flow, the Feed Forward Neural Network (FFNN), is used in this study. The formulation of this method is illustrated in equation 6.

$$Q_t = G\left[\sum_{i=1}^{S} w_i^2 F\left(\sum_{d=0}^{D}\sum_{j=1}^{R} w_{i,j,d}^1 P_{j,t-d} + b_i^1\right) + b^2\right] \quad (6)$$

Where Q_t is the output of the network, *R* is the number of input variables, *S* is the number of neurons in the hidden layers, *D* number of delays, $P_{j,t-d}$ is the *j*th variable at *t-d*, th input from *j*are the weights between of the w_i^2 and $w_{i,j,d}^1$ delay *d* and *i*th neuron at the hidden layer and between *i* th neuron at the hidden layer and output layer neuron respectively, b_i^1 and b^2 are the biases of *i*th neuron at the hidden layer and output layer neuron respectively; *G* and *F* are the activation functions for the hidden layer and output layer respectively.

2.4.1 Model development

In this study, the structure of evaluated models and the number of neurons in the hidden layer and also the weights that are used for training, validation and testing have been optimized by programming in a MATLAB environment. As shown in Table 2,predictors for the runoff prediction are:

precipitation (P), maximum temperature (T_{max}) and minimum temperature (T_{min}).Moreover, the total monthly observation was divided into training, validation and test sets and different percentages were used for them, including (60%,20%,20%),(70%,15%,15%), (80%,10%,10%) respectively. Also the number of neurons in the hidden layer is calculated in this program within one to ten neurons. The process of training is based on the error-correction learning rule of Levenberg Marquardt.

Table2. The parameters of the Artificial Neural Network

Number of input	1		Input: precipitation
	2		Input: precipitation, Max Temperature, Minimum Temperature
lag	0	0	Without any Lag
	1	0	With one Lag
Dividing	1		Train=60%,validation=20%,test=20%
	2		Train=70%,validation=15%,test=15%
	3		Train=80%,validation=10%,test=10%

3. Results and discussion

The data from 14 weather stations from whole Aras river basin was gathered from 1981-2005 and the parameters of monthly precipitation, minimum temperature and maximum temperature were used as an input data. The K-Nearest Neighbor (K-NN) algorithm was used as weather generator to generate synthetic data in climate downscaling for CGCM3T63 and HADCM3 models. The output of the K-NN has shown the precipitation (mm) and temperature (°C) changes for 2011-2060with respect to the observed data, and emission scenarioA1B that indicates a future of balanced socioeconomic and environmentally based development.

3.1 Changes in the precipitation and temperature

To evaluate the effects of A1B emission scenario for HADCM3 and CGCM3T63 models, the mean monthly precipitation and temperature is compared by using the K-NN model. The predictions are calculated for the period from 2011 to 2060 for all the stations and the results are shown in Table 3 to Table 5 and Figure7 to Figure12 for the *Bohlolabad*, *Ahar* and *Jafarlo* stations in West Azerbaijan, East Azerbaijan and Ardebil respectively. The highest reduction of precipitation is in the warm season of the *Bohlolabad* station, -21.7% by HADCM3 and the highest increase of temperature is in the cool season of *Bohlolabad* station +1.7(ºC) by HADCM3 . The CGCM3T63 predicted the increase of precipitation in the warm season of the Aras station and the HADCM3 shows the reduction of rainfall in three stations.

Table3. Changes in precipitation and temperature in the *Bohlolabad* station.

2011-2060	CGCM3T63 (A1B)	HADCM3 (A1B)
%Change in Annual Precipitation	1.80%	-18.80%
%Change in cool season Precipitation	6.30%	-1.12%
%Change in warm season Precipitation	-21.70%	-14.40%

2011-2060	CGCM3T63 (A1B)	HADCM3 (A1B)
Change in AnnualTemperature(ºC)	+0.44	+1.08
Change in cool season Temperature(ºC)	+0.44	+1.71
Change in warm season Temperature(ºC)	+0.43	+0.43

Note: Cool season defined as October through March, While Warm season is defined as April through September

Table 4. Changes in precipitation and temperature in the *Ahar* station.

2011-2060	CGCM3T63 (A1B)	HADCM3 (A1B)	2011-2060	CGCM3T63 (A1B)	HADCM3 (A1B)
%Change in Annual Precipitation	8.90%	-19.50%	Change in AnnualTemperature(ºC)	+0.44	+0.92
%Change in cool season Precipitation	6.30%	-19.6	Change in cool season Temperature(ºC)	+0.3	+1.03
%Change in warm season Precipitation	11.54%	-19.40%	Change in warm season Temperature(ºC)	+0.58	+0.81

Note: Cool season defined as October through March, while warm season is defined as April through September

Table 5. Changes in precipitation and temperature in the *Jafarlo* station.

2011-2060	CGCM3T63 (A1B)	HADCM3 (A1B)	2011-2060	CGCM3T63 (A1B)	HADCM3 (A1B)
%Change in Annual Precipitation	9.30%	-10.50%	Change in Annual Temperature(ºC)	+0.82	+0.87
%Change in cool season Precipitation	13.00%	-0.08%	Change in cool season Temperature(ºC)	+1	+1.4
%Change in warm season Precipitation	5.90%	-12.63%	Change in warm season Temperature(ºC)	+0.6	+0.3

Note: Cool season defined as October through March, while warm season is defined as April through September

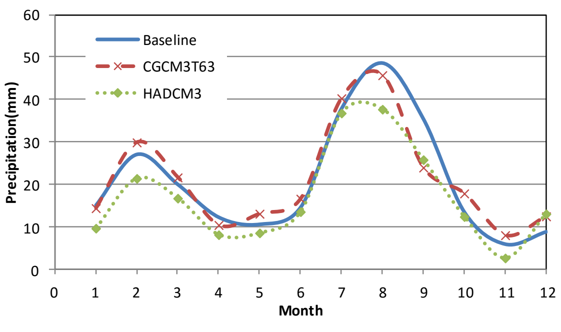


Figure7.Mean monthly precipitation of CGCM3T63 and HADCM3 for 2011-2060with respect to the baseline for the *Bohlolabad* station (in the WestAz.)

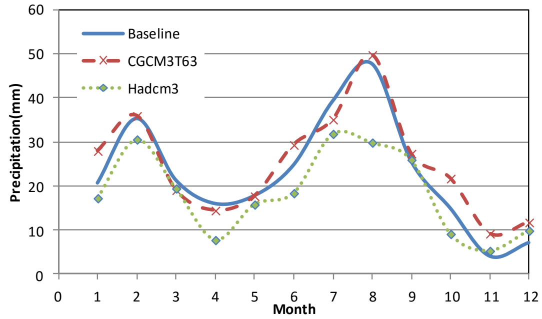


Figure8.Mean monthly precipitation of CGCM3T63 and HADCM3 for 2011-2060 with respect to the baseline for the *Ahar* station (in the EastAz.)

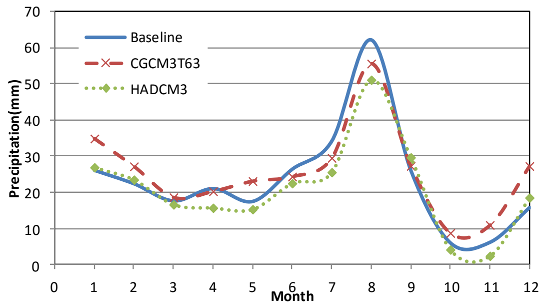


Figure 9.Mean monthly precipitation of CGCM3T63 and HADCM3 for 2011-2060 with respect to the baseline for the *Jafarlo* station(in the Ardebil)

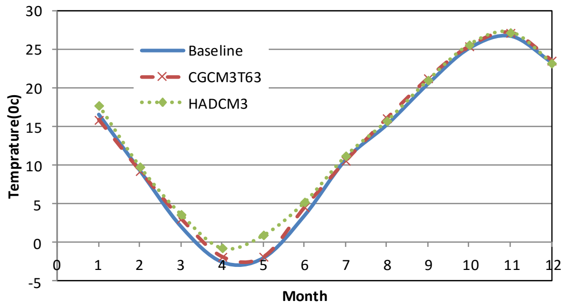


Figure10.Mean monthly temperature of CGCM3T63 and HADCM3 for 2011-2060 with respect to the baseline for the *Bohlolabad* station (in the WestAz.)

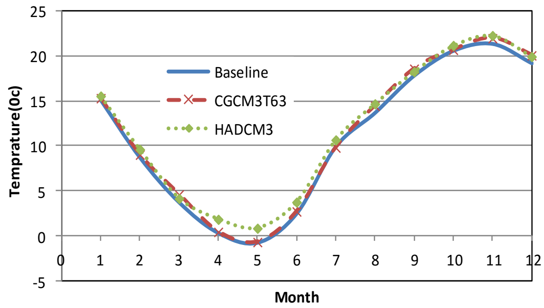


Figure 11.Mean monthly temperature of CGCM3T63 and HADCM3 for2011-2060 withrespect to the baseline for the Ahar station (in the EastAz.)

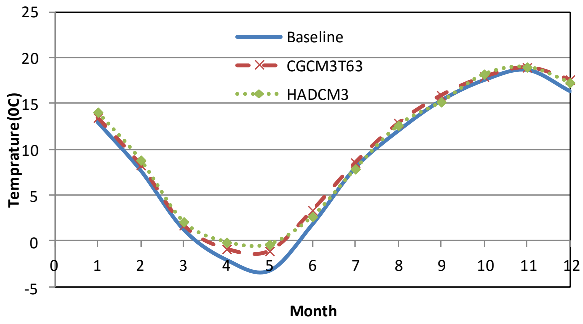
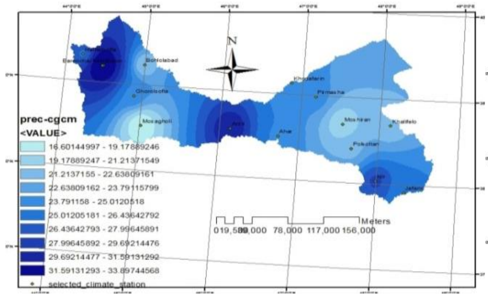
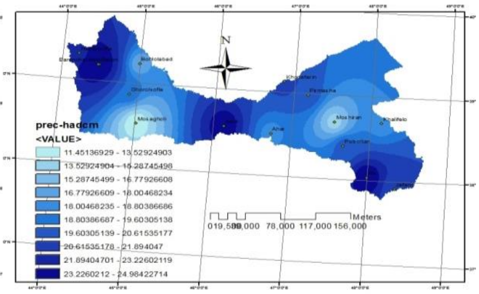


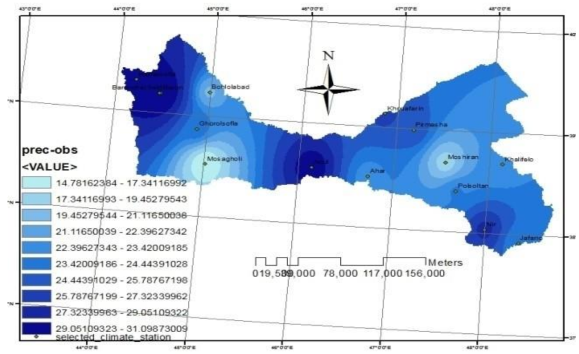
Figure 12.Mean monthly temperature of CGCM3T63 and HADCM3 for 2011-2060 with respect to the baseline for the *Jafarlo* station (in the Ardebil)

The changes for the precipitation and temperature of all 14 stations are shown in Figures13 and 14 using the GCM model of HADCM3 and CGCM3T63 and emission scenario A1B.



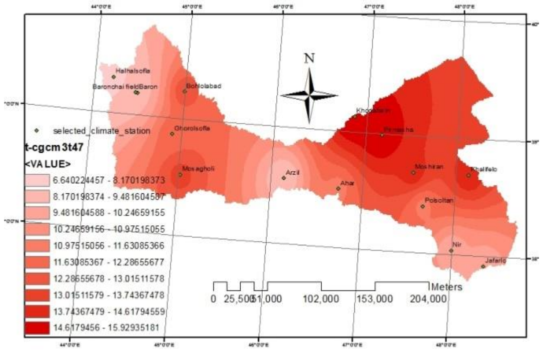


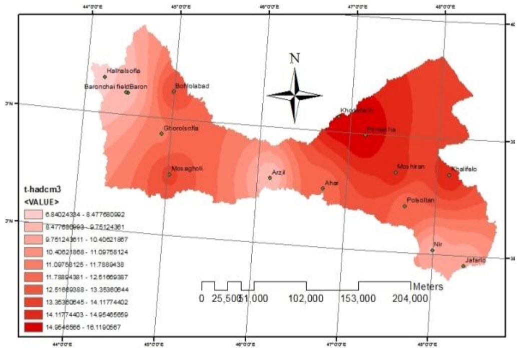
(CGCM3T63) (HADCM3)



(Observed)

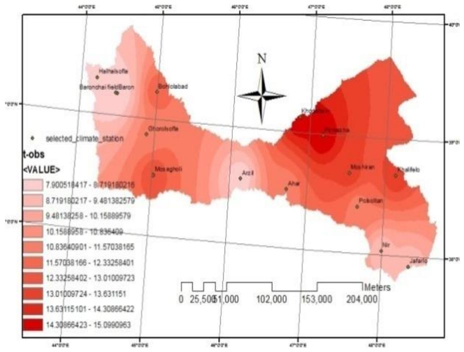
Figure13.Projected changes in the precipitation (mm) with the Observed (1981-2005),HADCM3 and CGCM3T63 and emission scenario A1B in the period from 2011 to 2060.





(CGCM3T63)

(HADCM3)



(Observed)

Figure 14.Projected changes in the temperature (°C) with the Observed (1981-2005), HADCM3 and CGCM3T63 and emission scenario A1B in the period from 2011 to 2060.

3.2 Changes in the Runoff

There are 17 stream flows as an input to the *Aras* watershed system, that are simulated by Artificial Neural Networks (section2.4) to show the impacts of climate change to the river inflow to the dams in 2011-2060. Three main dams; the *Aras* Dam on the upstream of the Aras River in the West Azerbaijan, the *Satarkhan* Dam on the *Ahar* River in the East Azerbaijan and the *Ghorichai* Dam on the *Ghorichai* River in the Ardebil province, are selected to show the results.

3.2.1 The impact of climate change on the inflow of the *Aras* Dam

The most important river in the *Aras* watershed is the *Aras* River. The river has length of 1072 km in its upstream (Figure15). The hydrometric data of the Aras station were used with the A-NN model and the characteristic of the best network in each month is presented in Table6. The estimated hydrographs are shown in Figure16. It's clear that the peaks of the predicted hydrographs are a shifted slightly to the left resulting in an increase of temperature which causes the snow to melt earlier in April. The runoff will be decreased in the next 50 years and the inflow to the Aras dam will also be reduced. The amount of reduction in runoff is about 0.8% by CGCM3T63 and 3% by HADCM3.

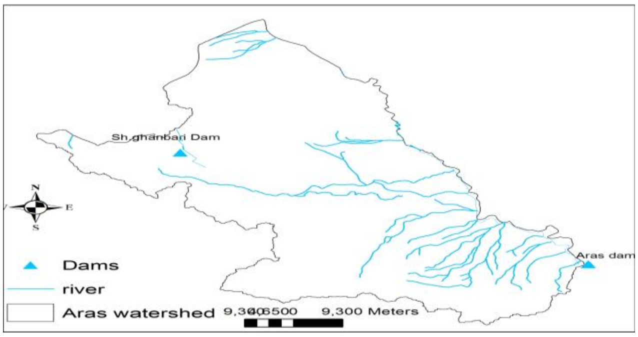


Figure 15.Position of *Aras* watershed in the West Azerbaijan

Table6. The characteristic of the best network in each month for the *Aras* station

Month	Number of input	Number of neuron	lag		RMSE			R^2			Dividing
					Train	Valid	test	Train	Valid	test	
1	2	10	0	1	0.03	0.06	0.07	0.87	.87	.85	3
2	2	8	0	1	0.42	0.13	0.23	0.6	.78	.72	3
3	2	8	0	1	0.22	0.32	0.32	0.72	.68	.71	3
4	2	8	0	1	0.11	0.14	0.20	0.73	.71	.80	3
5	2	6	0	0	0.03	0.05	0.01	0.85	.88	.77	3
6	2	10	0	0	0.02	0.07	0.05	0.93	.84	.82	3
7	2	10	0	0	0.18	0.26	0.16	0.85	.86	.81	3
8	2	1	0	0	0.16	0.13	0.12	0.78	.74	.71	3
9	2	2	0	1	0.78	0.12	0.26	0.71	.75	.73	3
10	2	9	0	1	0.26	0.10	0.21	0.86	.83	.72	3
11	2	4	0	1	0.02	0.05	0.05	0.95	.88	.77	3
12	2	7	0	0	0.01	.04	.02	0.91	.86	.76	3

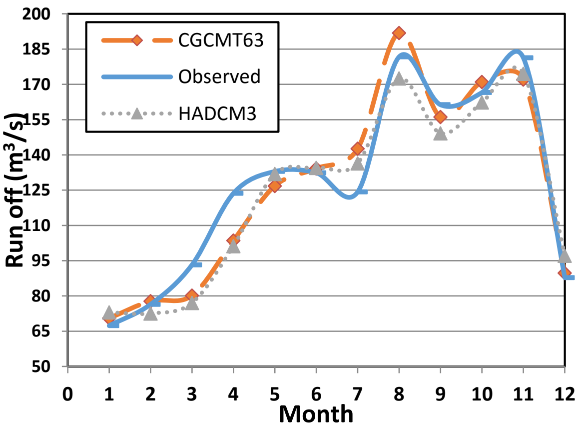


Figure16. Impacts of the climate change on the hydrograph of the *Aras* River at Aras station.

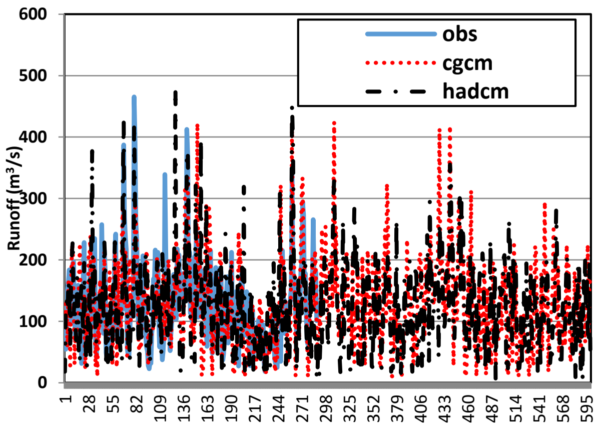


Figure17.Monthly river runoff in base period and future in *Aras* station

3.2.2 The impact of climate change in the inflow of the *Satarkhan* Dam

The Satarkhan Dam is located on the 240km long *Ahar* river (Figure18). It is in the south of East Azerbaijan and the hydrometric data of the *Ahar* station was used to predict the inflow of the *Satarkhan* dam based on climate change. The predicted hydrographs are plotted in Figure19.The peaks of the hydrographs are reduced in both HADCM3 and CGCM3T63 models. The reduction of inflow to the *Satarkhan* Dam is 0.7% in the CGCM3T63 and 1.1% in the HADCM3.The monthly river runoff for the observed data and simulated data for the future is shown in Figure20.

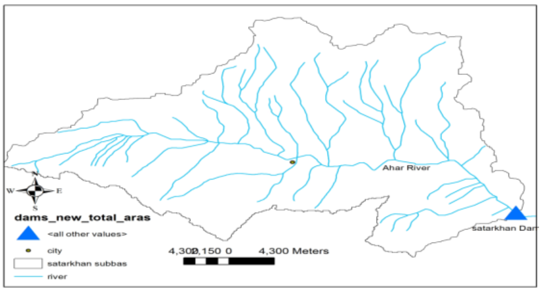


Figure18.Position of *Aharchai* watershed in East Azerbaijan

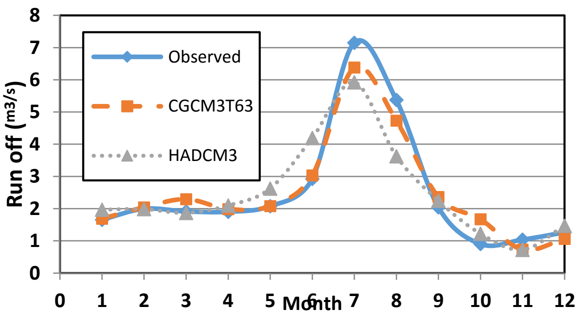


Figure19.Impacts of the climate change on the hydrograph of the *Ahar* River at *Satarkhan* station.

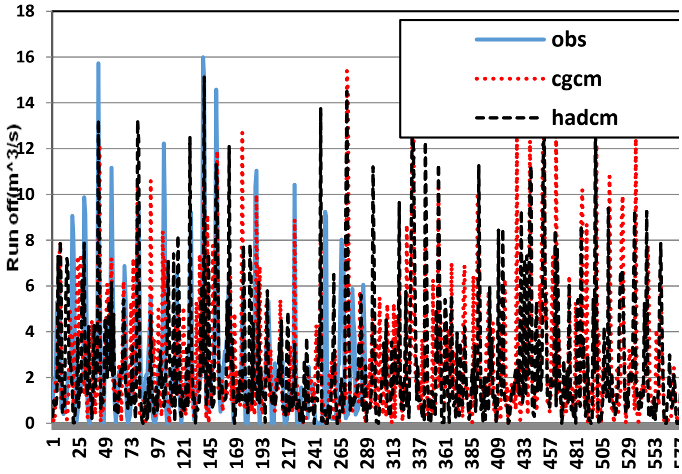


Figure20.The monthly river runoff in base period and future in *Ahar* station

3.2.2 The impact of climate change in the inflow of the *Ghorichai* Dam

The *Ghorichai* Dam is constructed on the river located in the Ardebil province (Figure21). The domestic water for the city of Ardebil is supplied by this dam. The inflow to the dam is predicted by the A-NN model and the hydrograph is shown in Figure22.The monthly river runoff for the observed data and simulated data for the future is shown in Figure23.The inflow to the dam is 29.5MCM and it increased to 30.0MCM in the CGCM3T63 and decreased to 29.2MCM in HADCM3.Therefore, the percentage of increment is 1.7% and the reduction is 1.02%, showing that the peaks of the hydrograph will be reduced in the future.

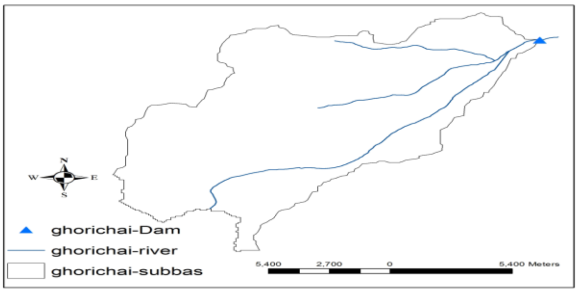


Figure21.Position of Ghorichai watershed in Ardebil

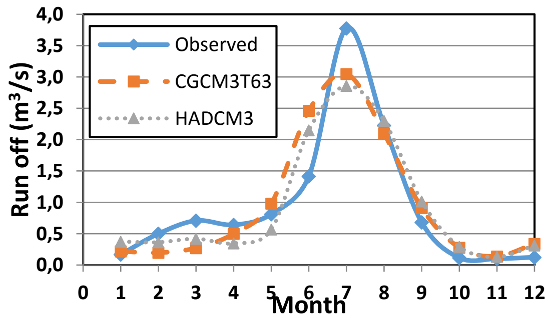


Figure22. Impacts of the climate change on the hydrograph of the *Ghorichai* River at *Ghorichai* station.

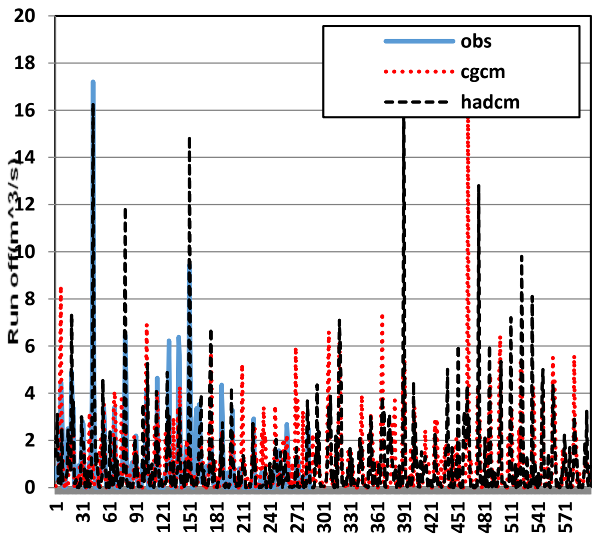


Figure23.The monthly river runoff in base period and future in *Ghorichai* station

The result of this study shows that the discharge of rivers in the Aras basin will decrease in the next 50 years, and the most important aspect is the reduction of the peak of monthly discharge hydrographs that other researchers like Zarezade Mehrizi et al.(2012), Heydari (2011), Massah et al. (2006), Huang et Al.(2013), Zarghami et al.(2011) are also in agreement with. The discharge of some rivers in the Aras basin will slightly increase for a few months of the year, which is consistent with the research of Abbaspour et al.,(2009) and Ashofte et al.(2013) in the north west of Iran.

4. Conclusion

The main aim of this paper is to downscale the GCM models for all of the 14 stations of the *Aras* large scale basin through use of the developed K Nearest Neighbor method for the three parameters: precipitation, max temperature and minimum temperature simultaneously. Calibration and verification of this model shows that the results are in good agreement. However, in the future the *Aras* watershed will face more droughts as a result of less rain and high temperatures due to climate change predictions. The mean total observed annual precipitation in all stations is ~23.8mm and this value, after downscaling by K-NN, is ~24.3mm by CGCM3T63 and ~19.5 by HADCM3.This concludes that the HADCM3 predicts more crisis situations in future than CGCM3T63. The mean observed annual discharge of 17 hydro stations that are an inflow of the Aras basin water system is 14.57m^3/s, which will be decreased to ~14.37 m^3/s by CGCM3T63 and ~13.78 m^3/s by HADCM3 in the future. The simulation of this water system due to the changes of the river discharge by the effects of climate change and develop a decision support system to calculate sustainability indices based on d-p-s-i-r framework by visual basic have been performed by the author and will be published in next paper.

References

Abbaspour, K.C., Faramarzi, M., Ghasemi, S.S., Yang, H.,(2009). Assessing the impact of climate change on water resources in Iran. Water Resources Research 45, W10434.

Allan, J. D. 1995. Stream ecology: Structure and function of running waters. Chapman & Hall.

ParisaSadat Ashofteh, OmidBozorg Haddad, and Miguel A. Mariño (2013). ”Climate Change Impact on Reservoir Performance Indexes in Agricultural Water Supply.” J. Irrig. Drain Eng., 139(2), 85–97.

Aus der Beek, T., Voß, F., and Fl¨orke, M.(2011).Modeling the impact of Global Change on the hydrological system of the Aral Sea basin, Phys. Chem. Earth, 36, 684–695.

Buser C M, Kunsch H R, Luthi D, Wild M and Schar C 2009 Bayesian multi-model projection of climate: bias assumptions and interannual variability Clim. Dynam. 33 849–68

Bronstert, A., Niehoff, D., and Burger, G.(2002). Effects of climate and land-use change on storm runoff generation: present knowledge and modeling capabilities,Hydrol. Process., 16, 509– 529.

Brutsaert, W. and Parlange, M. B. (1998). Hydrologic cycle explains the evaporation paradox,Nature, 396, 29–30.

Bruhn, J. A., W. E. Fry, and G. W. Fick. (1980). Simulation of daily weather data using theoretical probability distributions, Journal of Applied Meteorology and Climatology, 19(9): 1029-1036.

Bond, D. C. (1979).Generating daily weather values by computer simulation techniques for crop yield forecasting models. USDA-ARS (formerly USDA-ESCS), Statis. Res. Div., 38 pp. Washington, D.C.

Buishand, T. A., and Brandsma, T. (2001).“Multisite simulation of daily precipitation and temperature in the Rhine Basin by nearest-neighbor resampling.” Journal of Water Resources research, 37(11), 2761–2776.

Carpenter, R., S.G. Fisher,N. B. Grimm, and J.F. Kitchell. (1992). Global change and freshwater ecosystems .Annual Review of Ecology and Systematic. 23: 119-l 39.

Changnon, S. A. and Demissie, M.(1996). Detection of changes in stream flow and floods resulting from climate fluctuations and land use-drainage changes, Climatic Change, 32, 411–421.

Chattopadhyay S, Jha MK (2014) Hydrological response due to projected climate variability in Haw River Watershed, North Carolina. Hydrol Sci J. doi:10.1080/02626667.2014.934823

Gleick, P. H. (1987). The development and testing of a water balance model for climate impact assessment: Modeling the Sacramento basin. Water Resources Research.23: 1049-l 06 1.

Goyal, M.K., Ojha,CSP .,(2012).Downscaling of Surface Temperature for Lake Catchment in Arid Region in India using Linear Multiple Regression and Neural Networks.International Journal of Climatology 32 (4), 552-566

Huang, S., Krysanova, V., &Hattermann, F. F. (2013). Projection of low flow conditions in Germany under climate change by combining three RCMs and a regional hydrological model. ActaGeophysica, 61(1), 151-193.

IPCC (2001), Climate Change (2001): Third Assessment Report of the Intergovernmental Panel on Climate Change (Cambridge: Cambridge University Press)

IPCC: Meehl, G. A., Stocker, T. F., Collins, W. D., and Fridelingstein, A. T. 2007. Global climate projections, Climate Change (2007): The Physical Science Basis, Cambridge University Press, Cambridge, UK, and New York, 747–845,.

IPCC (2013), Climate change (2013): the physical science basis Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change ed T. F., Stocker, D Qin, G K Plattner, M Tignor, S K Allen, J Boschung, A Nauels, Y Xia, V Bex and P M Midgley (Cambridge: Cambridge University Press)

Jones, J. W., R. F. Colwick, and E.D. Threadgill.(1972). A simulated environmental model of temperature, evaporation, rainfall, and soil moisture. Trans. ASCE 15 (2):366-372.

Kattsov, V.M., KÄLLÉN, E., Cattle, H., Christensen, J., Drange, H., Hanssen-Bauer, I., JÓHANNESEN, T., Karol, I., RÄISÄNEN, J., Svensson, G., and Vavulin, S. (2005). Future climate change: Modeling and scenarios for the Arctic. In: Arctic climate impact assessment. Cambridge: Cambridge University Press. 100– 146.

Lall, U., and A. Sharma (1996).“A nearest neighbor bootstrap for resampling hydrologic time series.” J. Water Resources Research., 32(3), 679-693.

Lall, U., Rajagopalan, B., and Torboton, D. G. (1996). “A nonparametric wet/dry spell model for resampling daily precipitation.” J. Water Resour. Res., 32(9), 2803–2823.

Legesse, D., Vallet-Coulomb, C., and Gasse, F.(2003): Hydrological response of a catchment to climate and land use changes in Tropical Africa: case study South Central Ethiopia, J. Hydrol., 275, 67–85.

Larsen, G. A. and R. B. Pense.(1981). Stochastic simulation of daily climatic data.USDA-SRS, Statis.Res. Div. Rpt. No. AGES810831. Washington, D. C.

Massah Bavani A.R., (2006), Risk assessment of climate change and its impacts on water resources, Case study: *Zayandeh Roud* basin, PhD thesis, Tarbiat Modarres University, Iran. P. 189 (in Persian).

Nicks, A. D. and J. F. Harp.(1980). Stochastic generation of temperature and solar radiation data. J. Hydrology 48:1-17.

Morán-Tejeda E, Lorenzo-Lacruz J, López-Moreno IJ, Rahman R, Beniston M (2014) Stream flow timing of Mountain Rivers in Spain: recent changes and future projections. J Hydrol 517:1114– 1127

Prairie.J.R, Balaji.Rajagopalan and Terry .J.Fulp. (2006) .Modified K-NN Model for Stochastic Stream flow Simulation.Journal of Hydrologic Engineering. 11(4): 371-378.

Pfister, L., Kwadijk, J., Musy, A., Bronstert, A., Hoffmann, L.(2004).Climate change, land use change and runoff prediction in the Rhine-Meuse basins, River. Res. Appl., 20, 229–241.

Piao, S. L., Friedlingstein, P., Ciais, P., de Noblet-Ducoudre, N., Labat, D., and Zaehle, S.(2007). Changes in climate and land use have a larger direct impact than rising CO2 on global river runoff trends, Proc. Natl. Acad. Sci. USA, 39, 15242–15247.

Poff, N. L. and Zimmerman, J. K. H.(2010).: Ecological responses to altered flow regimes: a literature review to inform the science and management of environmental flows, Freshwater Biol., 55, 194– 205, doi:10.1111/j.1365-2427.2009.02272.x

Rajagopalan, B., and Lall, U. (1999).“A k-nearest neighbour simulator for daily precipitation and other variables.” J. Water Resour. Res., 35(10), 3089–3101.

Richardson, C. W., and D. A. Wright.(1984). WGEN: A model for generating daily weather
variables. U.S. department of agriculture, Agricultural Research Service ARS-8:83.

Sharif, M. and Burn, D. (2006) . Simulating climate change scenarios using an improved K-nearest neighbor model Journal of Hydrology,325,179-196.

Sharif , M. and D. H. Burn .(2007). ”Improved K-Nearest Neighbor Weather Generating Model.” J. Hydrol. Eng., 12(1), 42–51

Szépszó G, Lingemann I, Klein B, Kovács M (2014) Impact of climate change on hydrological conditions of Rhine and Upper Danube rivers based on the results of regional climate and hydrological models. Nat Hazards 72(1):241–262

Tekle A, Tadele K (2014) Assessment of climate change impact on water availability of Bilate watershed, Ethiopian Rift Valley Basin. J Environ Earth Sci 4(15):148–156

Wu F, Zhan J, Wang Z, Zhang Q (2014) Stream flow variation due to glacier melting and climate change in upstream Heihe River Basin, Northwest China. Phys Chem Earth. doi:10.1016/j.pce.2014.08.002

Xu, J. X.(2005). The water fluxes of the Yellow River to the sea in the past 50 years, in response to climate change and human activities, Environ. Manag., 35, 620–631.

Yang, T., Hao, X., Shao, Q., Xu, C. Y., Zhao, C., Chen, X., and Wang, W. (2011). Multi-model ensemble projections in temperature and precipitation extremes of the tibetan plateau in the 21st century Global Planet Change 80-81 1–13

Yates, D., Gangopadhyay, S., Rajagopalan, B., and Strzepek, K. (2003).“A technique for generating regional climate scenarios using a nearest-neighbor algorithm.” J. Water Resour. Res., 39(7), 7-1–7-14.

ZareZadeh M., Morid S., Salavitabar A and Madani K. (2012) Evaluating the Impacts of Climate Change and New Developments on Water Scarcity in Iran's Qezelozan-Sefidrood River Basin. Journal of Irrigation and Drainage 6(3): 93-104.

Zarghami, M., Abdi.,Babaeian, I., Hassanzadeh, Y., Kanani, R., (2011). Impacts of Climate Change on runoffs in East Azerbaijan, Iran.Global and Plantary Change. 78, 137–146