Biosci. Biotech. Res. Comm. Special Issue No 1:181-194 (2017)

BBRC
Bioscience Biotechnology Research Communications

Analysis of post-processing method for dynamic models output using network data for the drought in North West of Iran

Behrooz Sari Sarraf[1], Ali Akbar Rasouli[1], Majid Habibi Nokhandan[2], Sina Samadi Naghab[3]* and Sharareh Malboosi[4]

[1]*Professor, Faculty of Geography and Planning, Tabriz, Iran*
[2]*Associate Professor, Meteorology Research Institute, Tehran, Iran*
[1,3]*PhD student of Climatology, University of Tabriz, Tabriz, Iran,*
[4]*Expert of Climatological Research Institute, Mashhad, Iran*

ABSTRACT

Since long time ago, prediction of precipitation status and investigation of drought hazards in catchment areas of North West of Iran, due to the critical importance of discharge rate of related catchments for Lake Uromia, has been one of the most important challenging issues in efficient management of water resources; management of vast capital of water resources and energy production of the country is highly affected by the aforesaid factors. Therefore, application of dynamic methods may play significant role in adjustment of such conditions concerning the frequencies of climate parameters and occurrence of imbalance behaviors in precipitation pattern of the country. Regarding improper distribution of observed data, this research firstly completes post-processing operation using precipitation data of Aphrodite network, and Model Output Statistics(MOS) post-processing methods on the output of dynamic prediction model MRI-CGCM3 in a 28-year period(1980-2007), the precipitation grid of post-processed model and upon weighting output climate variables of dynamic model for each cell of data network and also, determining statistical model coefficients of multivariable correlation; output systematic error of the model highly reduced to be used in small scale applications. Then, post-processed prediction data of dynamic model were applied for computing Standardized Precipitation Index (SPI) provided in order to predict drought. Capabilities of selected post-processing method were assessed using evaluation criteria. Findings showed that application of statistical post-processing on direct output of dynamic model results in developing the monthly prediction of precipitation up to 29% in selected post-processing method. Accuracy of Standardized Precipitation Index (SPI) predicting may increase up to 22.3% than no post-processing mode, in a way that this value reaches to 79.5% after the implementation of post-processing operation.

KEY WORDS: POST-PROCESSING, DROUGHT, DYNAMIC MODELS, SEASONAL PREDICTION

ARTICLE INFORMATION:

**Corresponding Author: sisamadi@yahoo.com*
Received 27th Nov, 2016
Accepted after revision 26th Dec, 2016
BBRC Print ISSN: 0974-6455
Online ISSN: 2321-4007
Thomson Reuters ISI ESC and Crossref Indexed Journal
NAAS Journal Score 2017: 4.31 Cosmos IF : 4.006

Online Contents Available at: http//www.bbrc.in/

INTRODUCTION

Drought has been regarded as a basic parameter in sustainable development issues; it is considered as one of the most prominent climatic hazards, both in the short and long-term scale. Concerning that drought is a prominent natural hazard in Iran, and that in the last few years, various parts of the country have been affected by this hazard; therefore, it is of particular importance to perform its assessment, monitoring and prognosis. One of the methods used for quantifying drought hazards deals with using drought indices which may be applied for determining intensity and extension of drought on a periodical style. So far, these indices have been used for monitoring drought; but, we may use output of seasonal predictions to predict such profiles. Seasonal predictions provide some information about long-term averages. Land surface properties, especially calm variability of ocean surface temperature can affect the Earth's weather. These effects are not observable in diurnal scale, but they are observable on a larger time scale of months and the seasonal averages.

A wide range of studies have been conducted within and outside the country; but, most studies applied hydro-climate observed data or climatic indices such as El Niño–Southern Oscillation (ENSO) and the North Atlantic Oscillation (NAO) and establishing interrelation of rainfall and large-scale climate signals and they rarely have used dynamic methods in the prediction of precipitation. Concerning climatic variations of the recent years and the occurrence of unusual behaviors in precipitation pattern of the most parts of the country, application of dynamic methods bear advantages than the statistical methods which are solely based on the behaviors of statistical periods. Nowadays, the most common method used in international centers for predicting rainfall on hourly to seasonal time scales is the application of the numerical dynamic models. The output of the aforesaid models can be used as input for other applied models. The main objective for predicting climatic conditions in dynamic method is predicting the future of the status of climatic variables according to their current conditions and information and the application of numerical approximations for dynamic equations. In the dynamic method, we firstly provide prediction using a general circulation model; then, dynamic downscaling will be done on the desired area using a regional model. General Circulation Models (GCM) simulate the climate system with more complexities. Dynamic part includes numerical schemes which compute large scale atmospheric transmissions. These transmissions are calculated in a physical space or a spectrum space.

Nowadays, the outputs of these models are presented to users by international seasonal predicting centers. Concerning the relatively large scale output of these models, ranged from about 0.1 * 0.1 geographical degrees to 2.5 * 2.5 geographical degrees which results in lower resolution and more errors in the direct use of the output of such models. Therefore, their output has errors especially for the near ground surface variables including precipitation which requires correction and post-processing analysis. There are a wide range of methods used for post-processing analysis of the output of numerical Prediction models of which we may name Model Output Statistics (MOS). Application of techniques and special conditions is required for determining correlation coefficient and effect of each parameter of output model with the regional climate conditions. Another problem in using post-processing methods is lack of spatial and temporal distribution of observed data to be used in the post-processing analysis of the output of dynamic model, (Azadi et al., 2011).

In this regard, application of Aphrodite data can greatly reduce calculation errors and considers proper distribution of time and place in the category of post-processing framework (Yatagai , et al., 2012). A wide range of methods have been used in the post-processing analysis of the output of dynamic methods; for example. Babaeian et al. applied linear multivariable regression method for post-processing the precipitation output of MRI-CGCM3 model, (Babaeian et al., 2013).

In another study, (Kim et al 2012) performed seasonal prediction of winter in the Northern Hemisphere using seasonal predicting systems which were recently updated using ECMWF and NCEP; through the revision of predicting period (1982-2010), the paper evaluated coupled seasonal climate prediction systems of ocean-atmosphere and using ECMWF System 4 (Sys4) and the National Center for Environmental Prediction (NCEP) for model (CFSv2); they evaluated analysis with the use of both data sets (Kim et al., 2012a). Also in another research, Wilkes (2008) presented seasonal prediction of temperature parameter in network form on North America using developed statistical methods based on the surface temperature data of the water bodies of the North Pacific. Two time-series including long-term data (from 1880 to 2007) and short term data (from 1950 to 2007) were tested the surface temperature of water bodies in terms of Extended Reconstructed Sea Surface Temperature version 2 (ERSST v.2) grid data with a horizontal resolution of 2 × 2 degrees in statistical models of Canonical Correlation Analysis (CCA) and Maximum Covariance Analysis (MCA) and it showed that application of long-term data, despite low accuracy of some of them, may result in major promotion in accuracy of seasonal predictions for winter temperature (Wilks 2008).

Also, Kim et al (2012) applied multivariable linear regression method to provide seasonal predicts in South

Korea using teleconnection indices. The present study applied a maximum of five predictive variables used for the multivariable correlation models. The results of Kim et al showed that monthly correlation coefficients of temperature varied from 0.42 to 0.65 and for precipitation changes from 0.37 to 0.63. Correction coefficients for temperature vary from 18% to 42% and for precipitation changes from 14% to 39% (Kim et al., 2012b). In a research, Lim et al (2009) performed downscaling of predicted seasonal precipitation (NCEP/CFS) with a resolution of 2.5° to spatial scale of 20km on the South-East United States, including Florida, Georgia and Alabama using CSEOF model which is based on statistical downscaling (Lim et al., 2009). Jeffery and colleagues (2005) demonstrated that the use of MOS technique (application of statistical methods on the output of dynamic models) results in development of two-week predictions. They applied this method on global models of NCEP and ECMWF. Application of MOS technique on two models results in development of prediction results higher than application of MOS technique on one model (Jeffrey, ,et al., 2005). Krishnamurti and colleagues (2000) performed a research in connection with the seasonal and climatic predictions with the use of research based corrective multi-model predicts.

Finally, statistical weight of each model was determined using linear multivariable regression. They concluded that the predictions of multiple models have better performance than single models. The findings showed that the use of statistical methods in post-processing multi-model predicts can improve multiple predict system of distinct models (Krishnamurti, T. K., et al., 2000). Some of the statistical post-processing methods do not require long-term data of the model including neural network method (Fathi et al. 2010, Hasanzadeh et al. 2012) and Genetic Algorithm method (Kishtawal 2003) or Kalman filtering method (Rastgu et al. 2010,) and the moving average method (Azadi, et al. 2011, McCollor 2008, Johnson and Swinbank. 2010).

Gene and Renwick (2003) performed Seasonal Predicting of New Zealand temperature by using linear multivariable correlation method and the parameters of temperature, rainfall and water bodies' surface temperature for Pacific Ocean. (Zheng, Renwick 2003).Quito et al. (2011) conducted a research on precipitation climate data of the Middle East using Aphrodite data and comparing them with the output of MRI-CGCM3 Model. They found that application of Aphrodite data may highly increase spatial accuracy of the research; especially, application of network data instead of station-based observed data in areas with mountainous conditions may increase efficiency of the downscaling of climate models (Kitoh et al., 2011).

In another study conducted by Kasanicky and Kobayashi (2003) evaluated the efficiency of prediction probabilities and the seasonal predictability of atmosphere using Atmospheric General Circulation Model (AGCM) at Japan Meteorological Agency (JMA), which is a global spectral model with T63 resolution. The results showed that the probable prediction contrary to definite prediction related to some seasonal and regional similarities, such as higher relative ability in winters of the Northern hemisphere, East Asia and North America (Kusunoki Kobayashi, 2003).

Meanwhile in another research, Rasa et al (2012) developed Aphrodite data by the Research Institute for Humanity and Nature (RIHN) and the Meteorological Research Institute |Japan Meteorological Agency (MRI/JMA) for wet areas and wet adjacent areas of Pakistan with a Resolution of 0.05 degrees in decade form (Rasu et al., 2012). Yasutomi et al. (2011) studied the development of long-term networked temperatures data series and its application in the separation of rain / snow at daily precipitations (Yasutomi et al., 2011)

Therefore, application of post-processing technique may develop outputs of dynamic models to be used in subscales and the outputs of these models may be implemented in macro-environment management with a more comprehensive approach. Main objective of the present research consisted of developing the accuracy of seasonal predictions of precipitation of North-west of the country using dynamic model output post-processing method used toward managing the drought hazard.

MATERIAL AND METHODS

In this study, we used three data series; the first series is observed data of monthly precipitation obtained from Meteorological Stations in the North-West of Iran, including West Azerbaijan and East Azerbaijan and Ardabil provinces (Figure 1). Selection of stations with regard to the availability of long-term observed data of precipitation (1980 - 2007) was according to predict data and Aphrodite data.

Table 1 shows existing observation stations of the studied region along with precipitation data of the observation stations, respectively presented for all seasons of the year Second Series of Data are Aphrodite Data.

Aphrodite Project was developed in 2006 with the aim of creating diurnal precipitation data in high resolution networks across Asia (Yatagai, et al. 2012). In the same year, a project named APHRODITE was developed by the Research Institute for Humanity and Nature (RIHN) and the Meteorological Research Institute |Japan Meteorological Agency (MRI/JMA)in order to establish networked diurnal precipitation databases across Asia with high spatial resolution and as per the observations

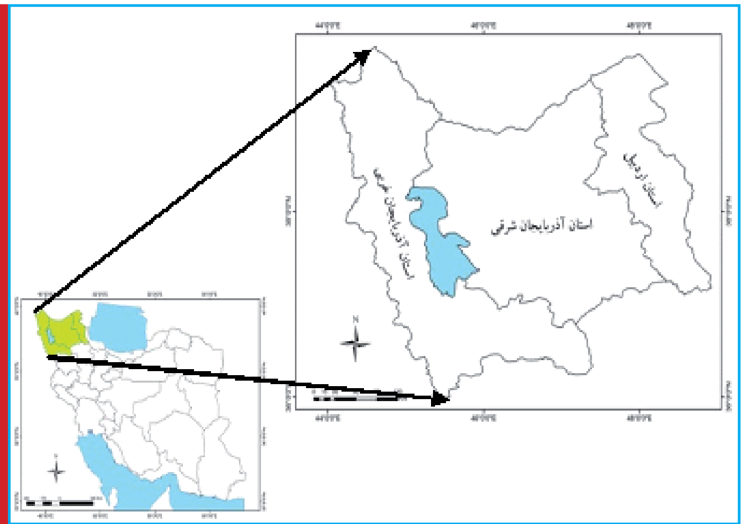

FIGURE 1. The studied region (North West of Iran)

made by rain gauge. APHRODITE consisted of an international cooperation plan for collection and analysis of rain gauging observed data collected from thousands of stations across Asia plus the reports provided by World Meteorological Organization (WMO) which resulted in providing diurnal precipitation data for 57 years. This database was provided by ADW interpolation method. Aphrodite Data consists of integrated observed data of precipitation in Asia with high-resolution which are used for evaluating water resources in form of three separate collections consist of the monsoon regions of Asia, the Middle East and Russia with the spatial resolution of 0.25 × 0.25 and 0.5 × 0.5 and with diurnal timescale.

The initial step in using such data is to perform their verification and contrast with the observed data obtained from meteorological stations which are equipped with rain gauge stations. Toward this, observed data in the

Table 1. Climate statistics of observation stations in the studied region

Province	Station	Precipitation (mm)			Total Precipitation (mm)				Precipitation Percentage (%)				Variation Range	Variance
		Average	Max	Min	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter		
West Azerbaijan	Uremia	312.3	51	2.2	114.2	14.1	91.7	92.3	%37	%5	%29	%30	48.8	307.23
	Piranshahr	662.9	106.5	1.6	170.7	7.1	196.8	288.3	%26	%1	%30	%43	104.9	1927
	Takab	337.5	60	3.1	125.3	13.3	93	105.9	%37	%4	%28	%31	56.9	395
	Khoy	263.2	52.6	6.2	114.9	29.2	64.7	54.4	%44	%11	%25	%21	46.4	163.55
	Sardasht	833.5	135.9	1.3	214.4	4.9	253	361.2	%26	%1	%30	%43	134.6	3248.13
	Mako	305.1	60.1	12.6	142.2	48.9	62.4	51.6	%47	%16	%20	%17	47.5	214.78
	Mahabad	397	63.1	1.2	115.9	6.6	124	150.5	%29	%2	%31	%38	61.9	598.42
East zerbaijan	Ahar	287.6	55.4	6.4	123.8	25.5	75.5	62.8	%43	%9	%26	%22	49	190.77
	Tabriz	247.2	46.8	3.4	102.3	13.7	65.6	65.6	%41	%6	%27	%27	33.4	180.56
	Sarab	244.4	51	7	107.7	29.1	59.6	48	%44	%12	%24	%20	44	158.97
	Mianeh	278.4	48.4	3.1	101.6	14.3	75.7	86.8	%36	%5	%27	%31	45.3	218.64
Ardebil	Ardebil	275.3	34.6	5.1	99.8	22.7	80.5	72.3	%36	%8	%29	%26	38.7	137.74
	Pars Abad	274.2	62.2	6.2	91.1	32.6	92.7	57.8	%33	%12	%34	%21	28.4	94.42
	Khalkhal	372.8		6.1	144.2	25.7	101.8	101.1	%39	%7	%27	%27	56.1	336.23

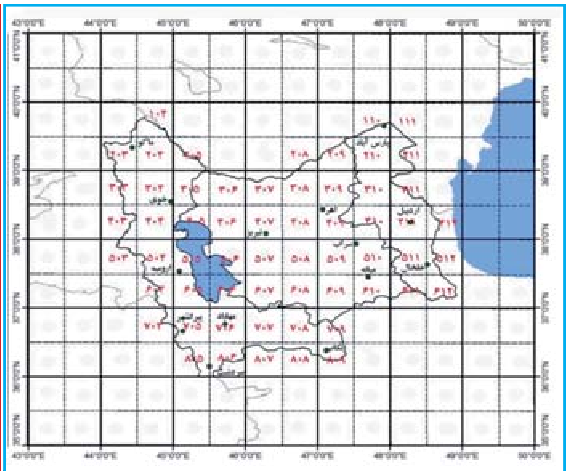

FIGURE 2. Regular grids of Aphrodite data with 0.5x0.5 degrees on the studies region

same period were compared with Aphrodite data on the synoptic station and rain gauge stations of North West region of Iran including Ardabil and East Azerbaijan and West Azerbaijan provinces. Figure 2 shows configuration of considered region in terms of using Aphrodite data. The target area has 59 grids with 0.5x0.5 degrees; where, corresponding Aphrodite data were extracted through programming and changing format.

The third series of data is retrospective predicts of rainfall and some meteorological variables affecting it, such as geo-potential height, thickness of different layers, ground level pressure and other meteorological variables of model outputs. Generally, each seasonal prediction model should be performed during each model development for a 30-year period in order to compare its results with the observed data. Comparing the predictions of the last 30-year period with observed values, accuracy of seasonal prediction model will be evaluated and in terms of verifying the aforesaid model and it will be used for the issuance of seasonal prediction.

In this research, we applied re-prediction data of MRI-CGCM model output including 14 variables and general index of the model output and 6 retrospective predictive variables related to the network of the studied stations. MRI-CGCM3 Model (Yukimoto et al., 2012) consists of two components including atmospheric general circulation model (MRI-AGCM3) and oceanic general circulation model (MRI.COM) where its atmospheric component is coupled with aerosol model of MASINGAR km^{-2}. Coupling intervals or data exchange between atmospheric and oceanic models is one hour and the same interval for Aerosol is 0.5 hour. In the atmospheric model of MRI-AGCM3, atmospheric component of the model is in spectral form in which the hydrostatic equations are used as predictors.

The horizontal resolution of Tl159 model (about 120 km) is with 48 vertical layers in ETA coordinate system. The structure of this model consists of three major components, namely: (a) the initial field input data of the model, obtained through the analysis of meteorological variables, ocean and land surface variables, (b) an integrated prediction system of the atmosphere, oceans and land and (c) the map products and error analysis and assessment system. Applied variables and indices with their explanations are given in Table 2.

Total of the first 14 parameters of the output of MRI-CGCM3 model have been used on a monthly basis at Tokyo Climate Centre (TCC) for post-processing. They have been chosen in a way to be appropriate for the climate of South-East Asia; but, a significant number of them are suitable for our climate, too. In addition to the aforesaid 14 indices, 6 other variables including H500, SLP, T2M, T850 and Model-Pr will be extracted from the model output files.

Table 2. Output Parameters of MRI-CGCM3 Model

Parameter	Variable	Parameter	Variable	Parameter	Variable
Z2030	Geopotential height of 500 millibar	NINOSST	Water surface temperature	H500	Geopotential height of 500 millibar
Z3040	Average Geopotential height of 500 millibar	NINOWESTSST	Water surface temperature	SLP	Mean sea level pressure
Z4050	Geopotential height of 500 millibar	DLRAIN	Precipitation	SST	Water surface temperature
Z5060	Geopotential height of 500 millibar	WIORAIN	Precipitation	T2M	Temperature in 2m
THMD	Thickness between 300 and 850 millibar	SAMOIRAIN	Precipitation	T850	Temperature in 850milibar
THEX	Thickness between 300 and 850 millibar	WNPRAIN	Precipitation	Model-Pr	Precipitation in Network
WIOSST	Water surface temperature	MCRAIN	Precipitation		

POST-PROCESSING OF PRECIPITATION DATA AND VERIFYING RESULTS

The method applied in statistical post-processing is linear multivariable regression method on precipitation data. Multivariable regression methods may modify both types of random and systematic errors in model outputs. The predictability of random error is much more difficult than systematic errors. In this method, prediction and observed data are divided into two courses "statistical post-processing model" and "examination". Multivariable regression method is a method of making model equation from past data series (Shimizukawa et al. 2009).

This method is one of the most powerful ways to explain the inter-relationship of observed and modeled variables. The general form of multivariable regression equation is as follows:

$$Y_t = \alpha + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \cdots + \beta_k X_{kt} + \varepsilon_t \quad (1)$$

Where, Y_t is dependent variable or predictant and X_{kt} is independent variable or predictor. Since, total of 20 seasonal prediction variables are applied for the development of multivariable correlation model and some of which have no significant relation with observed precipitation of the region; therefore, all predictors (independent variables) were inserted in model toward omission of non-effective variables; then, the variable with least correlation became omitted.

In selection of the final variables for adjustment coefficient of R^2, balanced adjustment coefficient of R^2-Adjust and F and t statistics are also effective. R^2 presents the percentage of variable changes of the predictant using predictors. R^2-Adjust or balanced R^2 will be used when the number of independent variables increased. Negative values of balanced adjustment coefficient are not accepted.

Advantage of linear multivariable correlation method is that despite the non-intervention of atmosphere physical processes, a significant relationship may be established between predictants of the region and predictors of large-scale atmospheric circulation model output and then applied its results for downscaling local parameters including precipitation (Lee, J., Y., 2003).

In this study, the 28-year period of seasonal Prediction model can be divided into two periods of 22-years and 6-years. Data of the 22years period are used for the extraction of the precipitation behavior of MRI-CGCM3 Model on the studied network points. This has been performed through determining the variable of prediction indices with highest correlation with point precipitation of the network and determining statistical model coefficients of multivariable correlation. Then, the statistical model obtained from 22 years output of MRI-CGCM3 model and precipitation network data were applied for a 6 years period to predict monthly rainfall. Jump (JMP4) software was used in this research for the determination of partial correlation between 20 variable output indices of MRI-CGCM3 Model with observed precipitation of the station. Investigations showed that if number of input variables in multivariable model exceeds from 3, post-processing errors increase the same and prediction of the precipitation points of the network increases with the same trend; therefore, multivariable model was designed based on 3 input variables.

Also, four evaluation indices of Mean Square Skill Score (MSSS), Relative Operating Characteristics (ROC), Mean Bias Error (MBE) and Relative Error (RE) were applied for investigating capabilities of selected post-processing method in predicting point precipitation of studied regional stations network.

Mean Square Skill Score (MSSS) index predicts the relative accuracy of post-processed model compared with the actual values of observed data; whereas:

$$MSSS = 1 - \frac{RMSE_f}{RMSE_c} \quad (2)$$

It is necessary to calculate the Mean Square Error (MSE) of observed data (MSE_c) and prediction (MSE_f).

$$MSE_f = \frac{1}{n}\sum_{i=1}^{n}(f_i - x_i)^2 \quad (3)$$

$$MSE_c = \frac{1}{n}\sum_{i=1}^{n}(x_i)^2 \quad (4)$$

Where fi and xi respectively are the ith predicted value and ith observed value of n data. $RMSE_f$ and $RMSE_c$ values are obtained respectively for square root of the mean square error prediction and observed values. In an accurate prediction, square root of the mean square error prediction equals 1 (MSSS=1) and in a full incorrect prediction, it equals 0 (MSSS=0). It shows that application of post-processed model output is more successful in comparison with climate means (Gheti, 2007).

In addition to the two aforementioned indices, mean bias error (MBE) and the mean relative error were also applied in examining the capabilities of post-processing method which are calculated according to the following formula.

$$MBE = \frac{1}{n}\left(\sum_1^n M_i - \sum_1^n O_i\right) \quad (5)$$

Where Mi and Oi are respectively predicted and observed values. Relative errors (RE) of predictions are calculated as follows:

$$RE = \frac{\frac{1}{n}\left(\sum_1^n M_i - \sum_1^n O_i\right)}{\sum_1^n O_i} \quad (6)$$

Table 3. Classification of SPI index as per McKee et al			
Classification of SPI drought index as per McKee et al (Ensafi moghaddam, 2007)			
Status	**SPI Index**	**Status**	**SPI Index**
Sever wet	≤2	Relatively Dry	-1 to -1.49
Very wet	1.5 to 1.99	Very dry	-1.5 to -1.99
Relatively wet	1 to 1.49	Sever dry	≥-2
Near normal	-0.99 to +0.99		

On one hand, we may calculate ROC curve and also correct Hit Rate (HR) prediction indices and False Alarm Rate (FAR) incorrect prediction indices for each class of predictions in which the ROC sub-curve area shows evaluation of the prediction; where, much more closing to 1 shows higher capability of the model (WMO, 2006).

DROUGHT PREDICTION INDEX (SPI)

Concerning the importance of being aware of drought status for the future months in planning for agriculture, water resources and environments, we may use predicted precipitations to compute Drought Prediction Index (SPI) in monthly and seasonal (3 months) scales for studied network cells. The reason for this index deals with the monthly data of Aphrodite network and consequently, in having monthly post-processing data. Since, SPI index may be calculated only if having monthly precipitation data; therefore, this index is suggested for predicting drought. SPI index was presented by McKee and colleagues to quantify the precipitation and drought observation. Wide range of applications enables SPI index to observe drought in short-term scales including soil moisture and long-term scales including surface waters and ground waters (Fattahi et al., 2007). Based on SPI method, drought period occurs when the SPI is continuously negative and reaches a value of -1 or less; and it ends when the SPI is positive, and the cumulative values of SPI show the magnitude and severity of drought period and wet periods. The classifications of SPI values are shown in Table 3 (Moghaddam 2007).

RESULTS AND DISCUSSION

This research regarded the selected course of study from 1980 to 2007; 70% of which i.e. 1980-2001 was considered as the test course and providing monthly post-processing regression equations and 30% of which i.e. 2002-2007 was considered as verification period. Aphrodite data networked in 59 network cells of 0.5x0.5 degrees were extracted for the studied region and validated with the observed data of regional stations; whereas, results showed proper accuracy of Aphrodite data which finally resulted in their application instead of sparse data of stations (Figures 3 - 7). It is to be noted that networked Aphrodite data absolutely increased accuracy of the study with regard to topographic conditions of the studied region and dispersion of stations.

In the first step and corresponding to the test period, precipitation prediction was calibrated during the period of 1980-2001; variables with highest correlation with

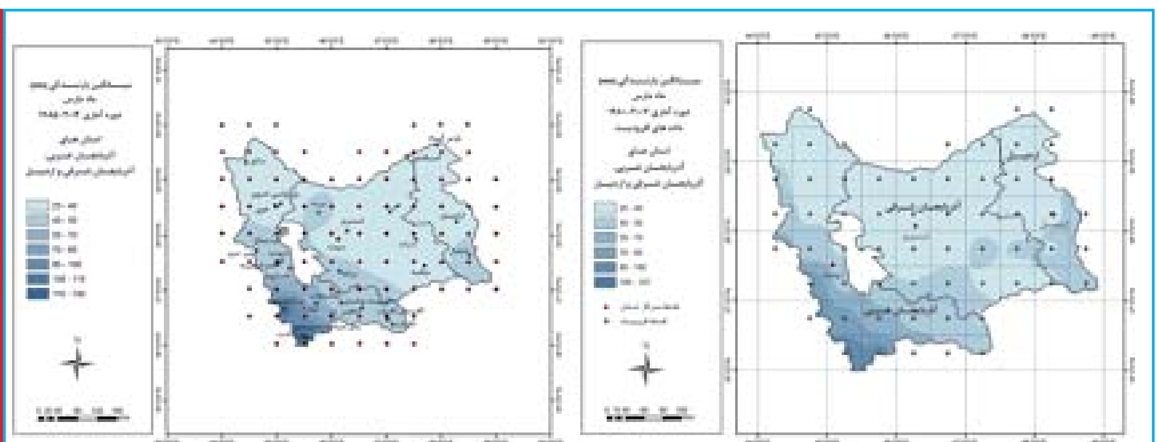

FIGURE 3. Zoning rainfall data of March; Right: Observed Data and Left: Aphrodite data

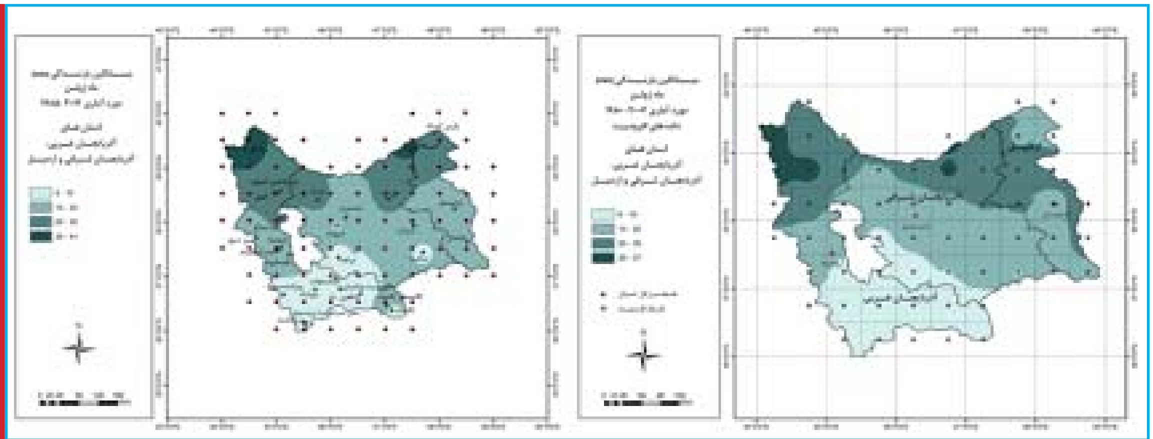

FIGURE 4. Zoning rainfall data of June; Right: Observed Data and Left: Aphrodite data

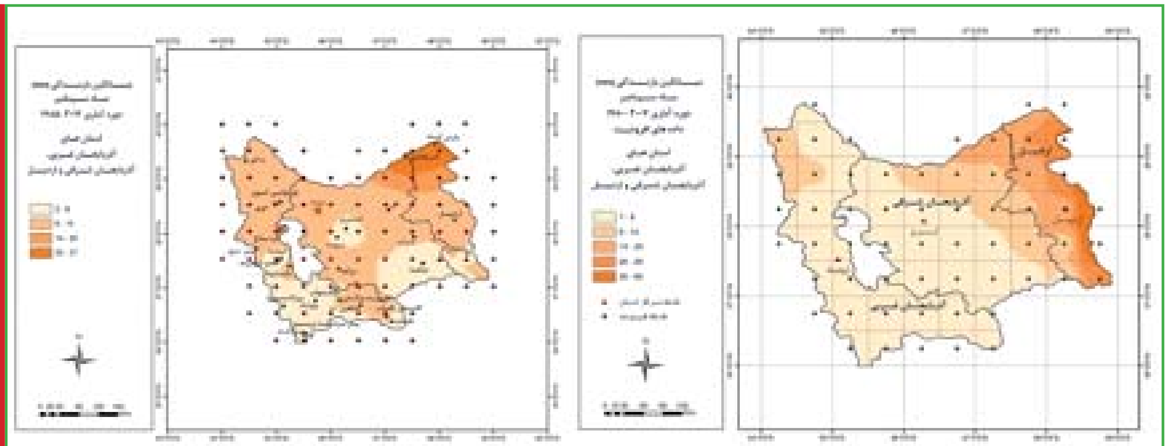

FIGURE 5. Zoning rainfall data of September; Right: Observed Data and Left: Aphrodite data

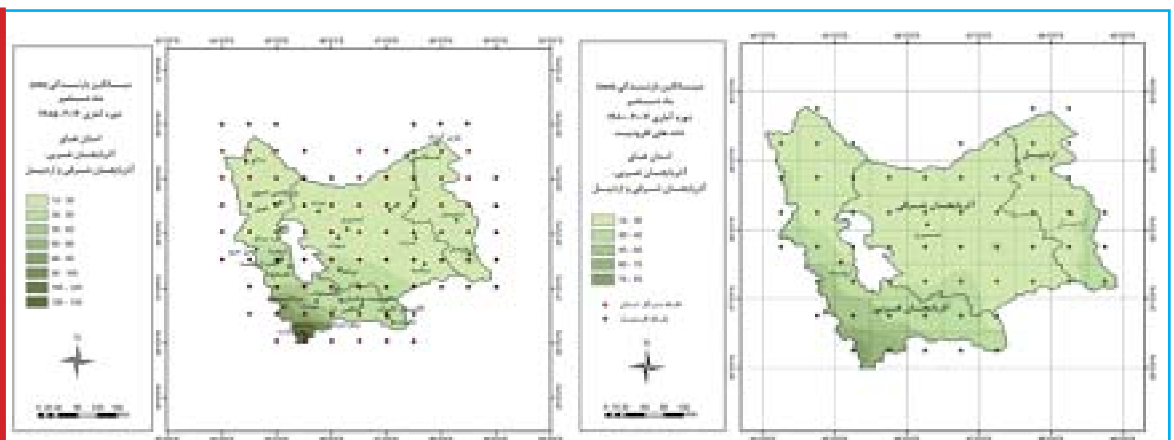

FIGURE 6. Zoning rainfall data of December; Right: Observed Data and Left: Aphrodite data

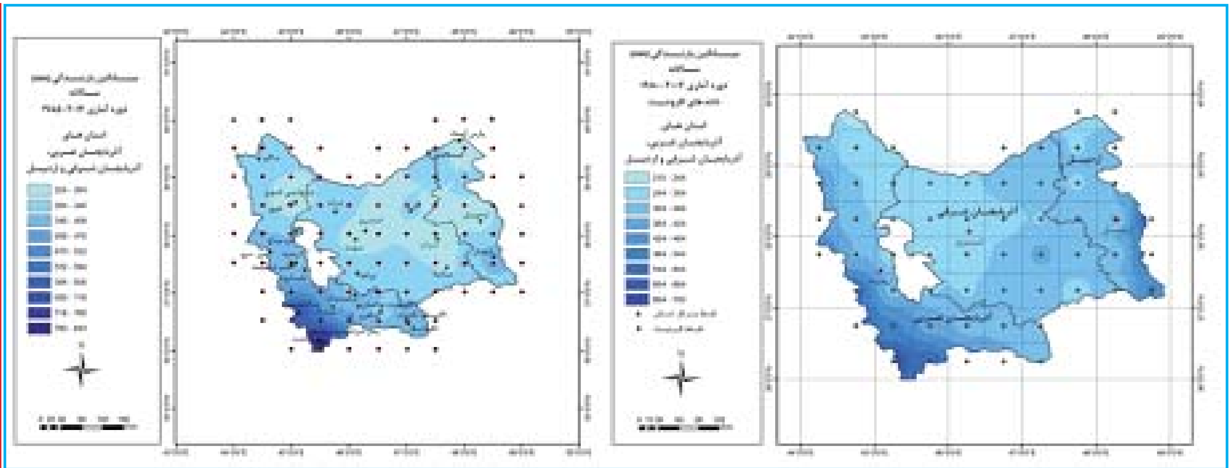

FIGURE 7. Zoning annual rainfall data; Right: Observed Data and Left: Aphrodite data

monthly precipitations were extracted for each network cell and their monthly post-processed equations were designed. In next step, gross output of MRICGCM3 Model was amended for each of the network cells using monthly post-processed equations for each network cell in the studied area; and prediction of cell precipitation was extracted for the test period of 2002-2007. Finally for the accuracy of the performance of results and equations in future predictions, results of validation period were validated using actual data. Applying the results of the precipitation predicted in SPI index, we may study zoning of drought prediction in the studied region.

Due to the high volume of maps and charts, which were carried out separately for each cell, 505 cell analysis with 45.25 degrees in longitude and 37.75 degrees in latitude were presented as samples in this research which can be generalized to other cells, as well.

Table 4 shows the input parameters for different months of the year in regarded network cells which were obtained through multivariable regression equations and they were determined for the post-processed model and they were given toward post-processed precipitation model; they are mentioned along with the accuracy of the classified prediction of monthly precipitation

Table 4. Prediction model of the parameters of MRI-CGCM3 model toward post-processing network cell rainfall No. 505 during the statistical period of 1980-2007

MRE		MBE		Accuracy of classified prediction %	MSSS	Model Index	Month
After Post Process	Before Post Process	After Post Process	Before Post Process				
0.28	1.15	-6.53	26.45	72.22	0.74	Sst, h2,IOBW Rain	Jan
-0.17	0.59	5.33	18.41	88.89	0.88	MC Rain, IOBW SST, Z4050	Feb
0.06	0.39	2.49	14.94	50.00	0.61	SST, h2, THEX	Mar
-0.33	0.25	-21.52	16.34	38.89	0.78	WIO SST, Z3040, DL Rain	*Apr*
0.34	1.40	14.17	58.63	38.89	0.57	H2, SST NNOWEST SST, NNO3	*May*
0.56	11.51	-3.57	73.45	83.33	0.16	Z2030, h2, Z4050	Jun
-0.86	11.94	-6.44	89.78	66.67	0.13	SST, Z2030, THTR	Jul
-0.86	68.39	0.99	78.65	83.33	0.19	DL Rain, IOBW Rain, MC,Rain	*Aug*
3.30	81.98	0.44	108.13	66.67	-12.22	P850, WNP Rain, TPR	Sep
0.26	1.94	6.84	50.62	75.22	0.40	MC Rain, WIO SST, DL Rain	*Oct*
0.33	1.35	-12.79	52.29	72.22	0.68	Z3040, Z4050, NNO WEST	Nov
0.74	12.63	4.77	81.69	100.00	0.30	ELO SST, WIO Rain, ELO Rain	*Dec*
0.11	76.77	6.67	55.78	67.59		Average	

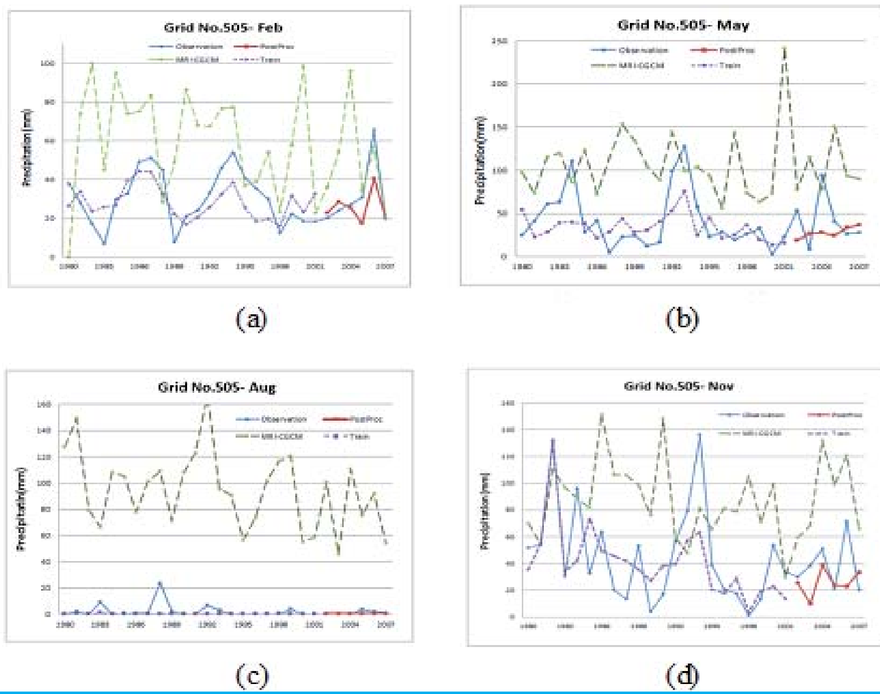

FIGURE 8. The post-processing results of MRI-CGCM3 model output during the training and prediction periods on the Aphrodite network of Grid 505(1980-2007)

and bias before and after post-processing procedure. According to the above table, the least square error (MSSS) index, the best capability of post-processing model was observed in February with a value of 0.88 and the least value was observed in July as 0.13. Therefore, monthly prediction accuracy average over the year is 67.59%. Applying statistical bias post-processing and relative error respectively reduced from 55.78 to 6.76mm and 76.87 to -0.11.

Figure 8 shows rainfall graphs predicted by the MRI-CGCM3 model for February (a), May (b), August (c) and November (d) which include data of the model before

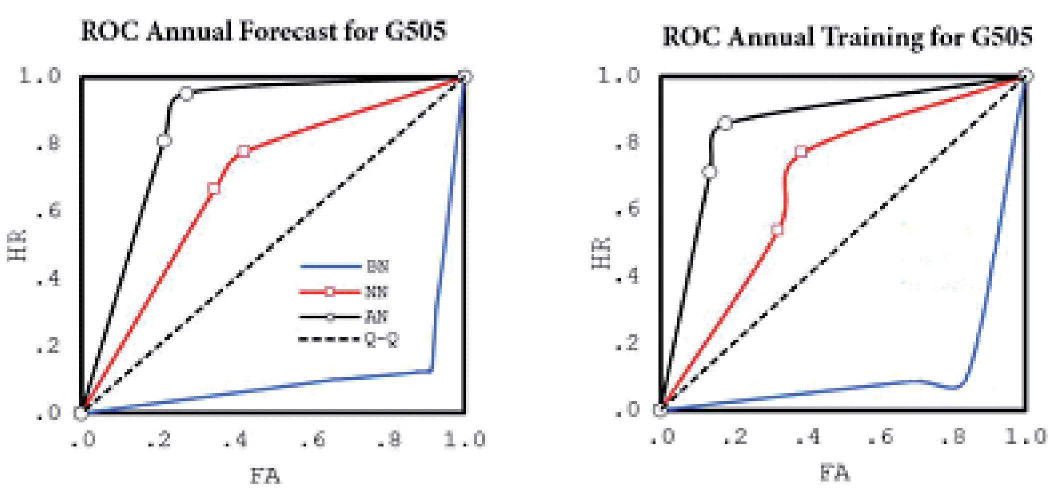

FIGURE 9. ROC curve of post-processed precipitation data using multivariable regression method for the training period (right) and prediction period (left) in an annual scale

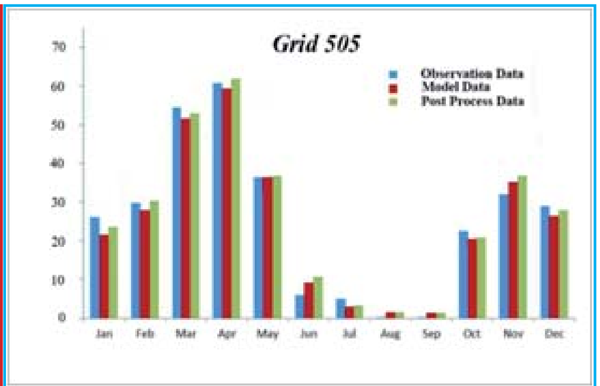

FIGURE 10. Comparison of Aphrodite network rainfall, raw model output and post-processed output obtained in multivariable regression method for the network of 505

post-processing (MRICGCM) and after post-processing (Train), Aphrodite network rainfall (Observation) and modeling test period precipitation (Post-processing) brought for 505 cells as a sample.

Figure 9 shows post-processing precipitation data of ROC curve obtained in multivariable regression method for network of 505 during the two periods of training and prediction periods in annual scale. In this graph, vertical vector indicates true prediction index and horizontal vector indicates false prediction index. Results show that highest efficiency of the model deals with the time in which precipitation is predicted in normal or a higher range. It has less accuracy in low precipitation months.

Figure 10 shows precipitation data average of Aphrodite network, raw model data and post-processed data in multivariable regression method for the network of 505 over the prediction period (years 2002-2007). The results indicated that there is a significant difference between raw predicted output and post-processed out of the model; in a way that post-processed model prediction has proper consistency with network Aphrodite data and this appropriation and consistency have better results in high precipitation months.

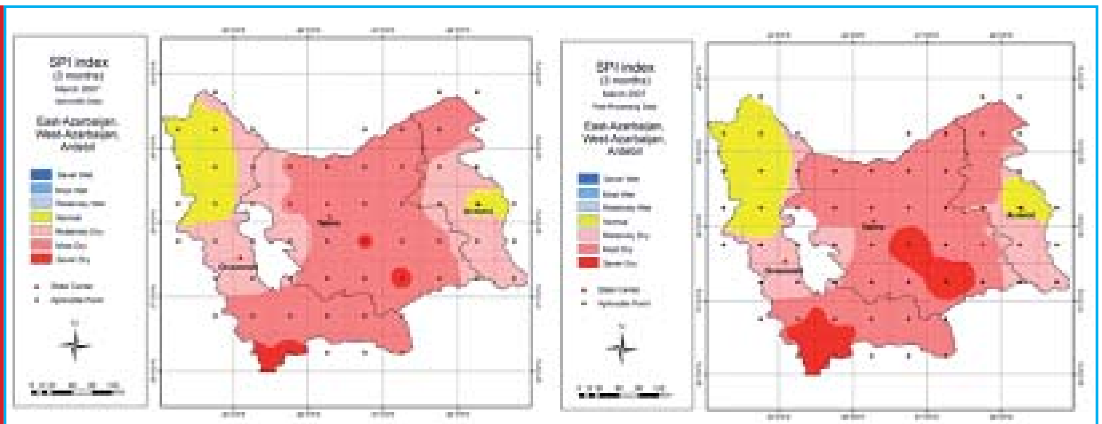

FIGURE 11. Zoning SPI index for March (winter), right: Aphrodite data and left: post-processed model data

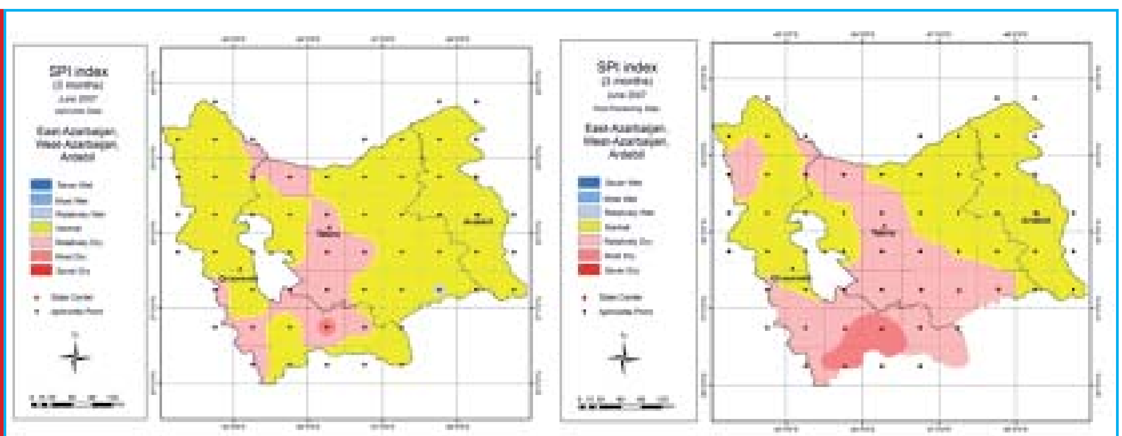

FIGURE 12. Zoning SPI index for June (spring), right: Aphrodite data and left: post-processed model data

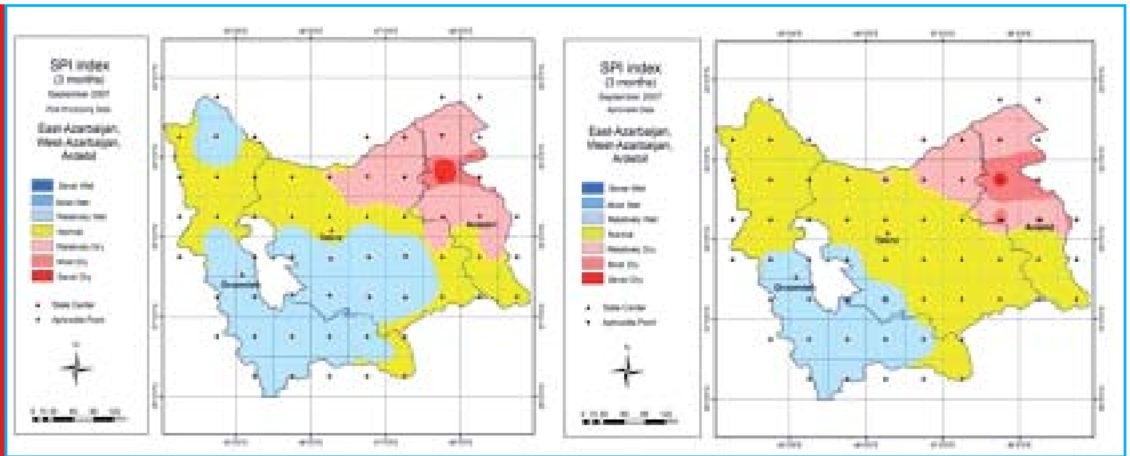

FIGURE 13. Zoning SPI index for September (summer), right: Aphrodite data and left: post-processed model data

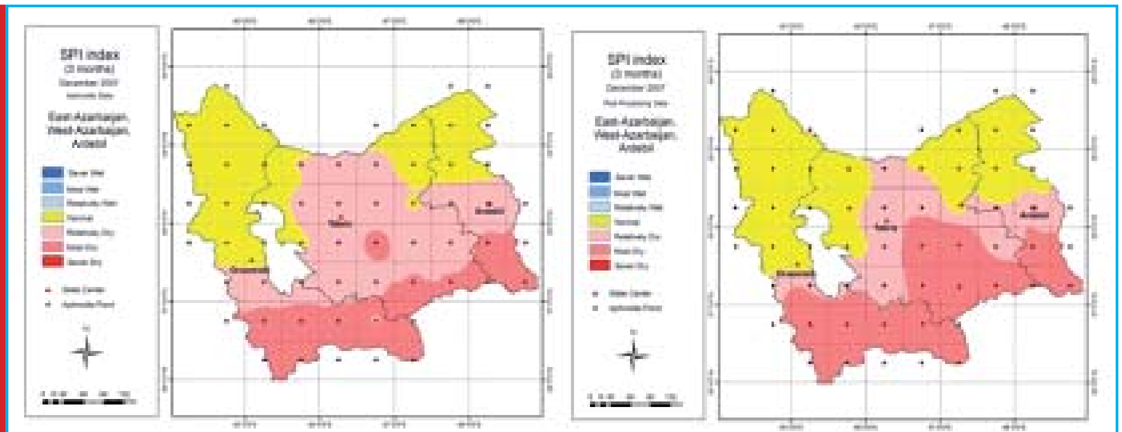

FIGURE 14. Zoning SPI index for December (autumn), right: Aphrodite data and left: post-processed model data

Figures 11 to 14 show zoning of SPI drought index modified using Aphrodite network rainfall and the rainfall predicted by MRI-CGCM3 model subject to post-processing process. In the aforesaid figures, SPI index can be seen for the three months periods leading to March (winter), June (spring), September (summer) and December (autumn).

Table 5 indicates the rate of increase in prediction accuracy of SPI index by the MRI-CGCM3 model after performing statistical post-processing process in Aphrodite network cell of 505 for the studied region. In the second and third columns of the table, the prediction accuracy rate of seasonal drought index is given as per modified classification of Maki et al.; and in two last columns, the correlation value of drought indices before and after performing post-processing process was inserted on model output.

The above table shows the accuracy of the drought index prediction in the period 2001 to 2007 for the cells

Table 5. The capability of MRI-CGCM3 model in predicting seasonal SPI indices in the network of 505 during the period of 2001 to 2007

Network	Accuracy of classified prediction %		Correlation of SPI model prediction with the Observed	
	Before Post-processing	After Post-processing	Before Post-processing	After Post-processing
505	60.9	78.4	0.068	0.46
Networks Average	61.7	79.5	0.061	0.49

of network 505 as well as the mean of 59 existing Aphrodite networks available in the studied region; in other words, there are 12 predictions for SPI index of each year. According to this table, the inter-correlation of SPI values calculated from not post-processed precipitation of MRI-CGCM3 model to network 505 was 0.068 that after post-processing, it reached to 0.46; for networks average, the amount improved from 0.061 to 0.49. Also, prediction accuracy of this index according to the classification presented in Table 5 for not post-processed SPI index for the network of 505 samples was 60.9% and for post-processed SPI was 78.4%; this amount for the studied networks improved from 61.7% to 79.5% indicating the promotion of prediction accuracy of this index valued at 22.3% after performing statistical post-processing process.

CONCLUSION

Concerning the importance having access to seasonal predictions and also the prediction of annual conditions for future months in North West of Iran and especially for three provinces of West Azerbaijan, East Azerbaijan, and Ardebil; they mostly cover catchment areas of the Lake Uremia bearing special importance in this regard. Also, management of energy and water resources in the said region is highly affected by climate conditions; this research tends to apply multivariable regression method for post-processing the output of the seasonal prediction of MRI-CGCM3 model on the aforesaid region toward promoting accuracy of monthly predictions and also, drought index. Toward realization of this, multivariable regression method was networked on 20 model indices and applying Aphrodite data which has less temporal and spatial errors than observed data of stations. Number of Aphrodite network points in the aforesaid region is 59 points with spatial distance of 0.5 geographical degrees, having highest accuracy after the validating station based data; therefore, their application for the studied region with its special topographical conditions may increase post-processing accuracy.

The applied statistical period of this research is a 28-year period (covering from 1980 to 2007) which is even in both Aphrodite and model data series. The above-mentioned period can be divided into two periods of 22-years used for determining multivariable regression equations for each point of the network and for different months of the year and also a 6-years period for presenting prediction and validating predictions with actual data. Then, results of the prediction of SPI drought index were applied. The obtained results were validated using statistical indices and findings showed that application of multivariable regression method in post-processing model output excluding spatial range, has higher accuracy in cold and high precipitation seasons and less accuracy in low precipitation seasons. Also, the monthly bias value of the precipitation decreased from the 67mm for before post-processing to 9mm for after post-processing. This indicates positive effect of applying post-processing method on model output.

Finally, correlation value of post-processed and not post-processed output indices were validated using results in SPI index which increased from 0.061 to 0.45 for mean network points and the accuracy of classified predictions improved from 61.7% to 79.5% indicating 22.5% promotion from post-processing method in model output. Findings of the present research indicated that application of post-processing method on model outputs may improve accuracy of results for smaller spatial scales; also, application of Aphrodite network data instead of station based sparse data may lead to more improved results. Application of post-processed results in SPI index may lead to codification of a comprehensive model in using drought index in drought prediction context and it provides seasonal predictions for drought hazard. This may develop future macro-management in the field of climate and drought.

REFERENCES

Azadi M., Shirgholami M., Hojam S., Sahraeean F. (2011) Post processing WRF model output for daily precipitation in Iran. Iran-Water Resources Research 7(4):71-80 (In Persian)

Babaeian I., Karimian M., Modirian R.(2013), Statistical post processing MRI-CGCM3 output for seasonal precipitation forecast over Khorasan-Razavi province. Iranian Journal of Geophysics 7(3):119-133 (In Persian).

Ensafi Moghadam T., 2007, An Investigation and assessment of climatological indices and determination of suitable index for climatological droughts in the Salt Lake Basin of Iran, 14(2): 271-288 (in Persian)

Fathi Margh A., MH.Mahdeian, (2010), Predicting winter precipitation using indicators beyond the neural barley yields: a case study for Isfahan, Iran. International Journal of Ayer 2:451-469 (In Persian)

Fattahi A., y.Sedaghatkerdar,(2007), Curve analysis of time and severity of drought frequency: Case study in south west stations of Iran, 5(10):77-90 (in Persian)

Finnis J., W. W.Hsieh, H.Lin, and W.Merryfield, (2011), Nonlinear post-processing of numerical seasonal climate forecasts: Journal of Atmosphere-Ocean, 26, 1-34.

Gheti R., 2007, Statistical post-processing of dynamical surface air temperature seasonal predictions using the leading ocean-forecd spatial patterns, MSc Thesis, McGill University, 87pp

Hasanzadeh Y., A. Abdi Kordani, A.Fakherifard, (2012), forecasting drought by using Genetic Algorithm and wavelet-neural network hybrid model. Journal of Water & Wastewater 3:48-59 (In Persian)

Jeffrey S., X. Wei, 2005, Improving week two forecast with multi-model re-forecast ensemble. Monthly Weather Rviewi, pp. 1-25.

Johnson C., Swinbank R., (2009) Medium-range multi-model ensemble combination and calibration. UK met-office Technical Note 517:31

Kamiguchi K., O. Arakawa, A. Kitoh, A. Yatagai, A. Hamada, N. Yasutomi, (2010), Development of APHRO_JP, the First Japanese High-resolution Daily Precipitation Product for More than 100 Years, Hydrol. Res. Lett., 4, 60–64.

Kim H., P.J. Webster, J.A. Curry, (2012a) Seasonal Prediction Skill of ECMWF System 4 and NCEP CFSv2 Retrospective Forecast for the Northern Hemisphere Winter, Climate Dynamics Observational, Theoretical and Computational Research on the Climate System.

Kim H., P.J. Webster, J.A. Curry, V.E. Toma, (2012b,) Asian Summer Monsoon Prediction in ECMWF System 4 and NCEP CFSv2 Retrospective Seasonal Forecasts, Climate Dynamics Observational, Theoretical and Computational Research on the Climate System.

Kishtawal C.M., S. Basu, F. Patadia, P.K. Thapliyal, (2003), Forecasting Summer Rainfall over India Using Genetic Algorithm, Geophys. Res. Lett., 30(23), 2203, doi: 10.1029/2003GL018504.

Kitoh A., Arakawa O., (2011), Precipitation Climatology over the Middle East Simulated by the High-Resolution MRI-AGCM3, Global Environmental Research, 15/2011: 139-146

Krishnamurti, T. K., C. M., Kishtawal, Z., Zhang, T., Larow, D., Bachiochi, E., Williford, (2000), Multimodel ensemble forecasts for weather and seasonal climate, Journal of Climate, NO. 13, pp. 4196-4216.

Kusunoki S., C. Kobayashi, (2003), Skill Evaluation of Probabilistic Forecasts by the Atmospheric Seasonal Predictability Experiments, Journal of the Meteorological Society of Japan, Vol. 81, No. 1, pp. 85-112, 2003 85.

Lee, J. Y., (2003), Data and Model Description, Assessment of Potential Seasonal Predictability with a Multi-Model Dynamical- Statistical Ensemble System: Ph.D. thesis, Faculty of the Graduate School of the Seoul National University.

Lim Y.K., S. Cocke, D.W. Shin, J.T. Schoof, T.E. LaRow, J.J. O'Brien, (2009), Downscaling Large-Scale NCEP CFS to Resolve Fine-Scale Seasonal Precipitation and Extremes for the Crop Growing Seasons over the Southeastern United States, Climate Dynamics Observational, Theoretical and Computational Research on the Climate System.

McCollor D., Stull R., (2008), Hydrological accuracy enhancement via post processing of numerical weather forecasts in complex terrain, Weather and Forecasting 23:131-144

Rasu A.G.G., T. Mahmood, Q. Zaman, S.B. Cheema, (2012), Validation of APHRODITE Precipitation Data for Humid and Sub Humid Regions of Pakistan, Pakistan Journal of Meteorology, Vol.9, Issue 17.

Rastgu Z, Azadi M, Hojam S , (2010), Post processing WRF model output for level 10- m wind velocity and level 2-m temperature by using Palayeh nonlinear Kalman. Journal of Climate Research 1(3 and 4):93-106 (In Persian)

Shimizukawa J, Chen C Y, Iba K, (2009), Multi-regression model for peak load forecast in demand side like university campus, In: Proc. of the International Conference on Electrical Engineering, 5-9 July, China

Wilks D.S., 2008, Improved Statistical Seasonal Forecasts Using Extended Training Data, Int. J. Climatol., 28: 1589-1598.

Yasutomi N., A. Hamada, A. Yatagai, (2011), Development of a Long-term Daily Gridded Temperature Dataset and its Application to Rain/Snow Discrimination of Daily Precipitation, Global Environmental Research.

Yatagai A., K. Kamiguchi, O. Arakawa, A. Hamada, N. Yasutomi, A. Kitoh, (2012), Constructing a Long-Term Daily Gridded Precipitation Dataset for Asia Based on a Dense Network of Rain Gauges, American Meteorological Society.

Yukimoto S, Adachi Y, Hosaka M, Sakami T, Yoshimura H, Hirabara M, Tanaka TY, Shindo E, Tsujino H, Deushi M, Mizuta R, Yabu S, Obata A, Nakano H, Koshiro T, Ose T, Kitoh A (2012) A new global climate model of the meteorological research Institute: MRI-CGCM3-Model description and basic performance. Journal of the Meteorological Society of Japan 90:23-64

WMO, (2006), Standardized verification system (SVS) for long-range forecasts (LRF), new attachment to manual of GDPFS (WMO-No. 485), Vol.1, Fina Report of the Joint Expert Teams on Long-Range Forecasting, ECMWF, April 2006

Zheng, X., and Renwick J. A., (2003), a regression-based scheme for seasonal forecasting of New Zealand temperature: Journal of Climate, 16, 1843-1853.