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Statistical modeling of the association between pervasive precipitation anomalies in Southern Alburz and global ocean-atmospheric patterns

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ABSTRACT: Precipitation patterns are influenced by many factors, such as global atmospheric circulations to name but one. Precipitation patterns in Iran have always had great fluctuations even in a smaller scale like the Alburz Mountain Range. The present research has tried to find the relationship between global atmospheric patterns and the pervasive precipitation ones in Alburz. For doing so, 17 climate indices have been chosen with the correlation between these indices and the precipitation data calculated in different lag times, using a backward correlation method (from the present time to 3 months earlier). Based on the obtained correlation results, a regression modeling has been conducted that employs a backward method. As for each lag time, one equation has been offered to estimate the amount of precipitation for every single region. Results have shown that the Bivariate ENSO Time Series (BEST) and the East Pacific Oscillation (EPO) provide the highest correlation with the pervasive precipitation time series. Also, it has been demonstrated that in multivariate correlation, the efficient index to model the relation among these indices as well as precipitation in southern Alburz alters in each lag time. Both MBE and RMSE, employed to evaluate the modeling, show relatively acceptable values, implying that the equations are acceptably capable of predicting the amount of precipitation in both northern and southern Alburz.

Keywords: Alburz, Iran, oceanic-atmospheric Indices, pervasive precipitation, regression modeling.

INTRODUCTION

Iran, located in the southwest of the Middle East, is characterized by large inter-annual variability of climatic parameters, among which precipitation seems to have the greatest fluctuation (Ghahraman, 2006; Modarres and da Silva, 2007; Modarres and Sarhadi, 2009; Tabari and Hosseinzadeh Talaee, 2011a, 2011b, 2011c). Precipitation patterns are not only affected by synoptic conditions or regional climate, but they are also greatly associated with global atmospheric circulation, though observed changes in rainfall cannot always be explained by changes in circulation (Frei et al., 1998; Goodess and Jones, 2002).

Patterns of global atmospheric circulation do play the major role in the function of planetary climate components, henceforth they greatly affect climatic parameters of world's regions. Due to their

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importance and scale, various indices have been designed to measure the intensity of each pattern, among which South Oscillation Index (SOI), North Atlantic Oscillation (NAO), and Arctic Oscillation (AO) might be known better than the rest; however, nowadays many more indices with different scales are being used to calculate the intensity of each pattern.

The link between circulation patterns, including regional and global scales, on one hand and climatic variables on the other has been much discussed in the recent years (Nazemosadat and Cordery, 2000; Alijani, 2002; Moradi, 2004; Javanmard et al., 2004; Nazemosadat and Ghasemi, 2004; Ghasemi and Khalili, 2006; Ghasemi and Khalili, 2008a; 2008b; Modarres and Sarhadi, 2009; Bannayan et al., 2010; Masih et al., 2011; Sabziparvar et al., 2011; Karbassi and Amirnezhad, 2004; Sharmad et al., 2012). Also, linear and nonlinear models have been established between precipitation variations and global atmospheric circulation to estimate or predict the amount of probable rainfall during the upcoming months.

Conducted studies on the relationship between precipitation and global atmospheric patterns in Iran are mostly focused on the statistical relationships with few teleconnection patterns (e.g. mostly SOI or NAO). Also, they have mainly concentrated on the amount of monthly or annual precipitation, especially rainfall, which is recorded by local stations and do not offer any model to predict the rainfall of upcoming months.

The main aim of this study is to identify and model the relation between large-scale, atmospheric circulation patterns and the pervasive precipitation anomalies in Alburz in order to find the most significant correlated index and predict the amount of rainfall for the coming months.

MATERIALS AND METHODS

Data

The total monthly precipitation time series, corresponding to five synoptic meteorology stations (Fig. 1, Table 1) along Alburz Mountain Range, have been obtained from the Iran Meteorological Organization for a period of time that lasted from 1965 to 2005. The time series temporal coverage is considered “good” since approximately 0.21% of the monthly observations are missing and the lag-1 autocorrelation values are considerably persistent. Also, the data has been rechecked, using double mass curve analysis, to ensure the homogeneity of the precipitation data. The results have been checked in order to contrast and use both series alternatively, when one segment from each series was missing. The missing data of some months for each station has been estimated via other available data, like the recommended method, first suggested by Allen et al. (1998) applied by many researchers (Popova et al., 2006; Cai et al., 2007; Gocic and Trajkovic, 2010). Once the required climatology data has been gathered, monthly values of 17 most frequent used Oceanic-Atmospheric indices have been extracted from the United States Environmental Organization website. They are listed in Table 2.

Table 1. Geographic characteristics of the stations used in the study

Name	Establish Date	Latitude	Longitude	Elevation	Average Precipitation	Climatic Zone
Ghazvin	1959	36.25	50.05	1279.2	316.0	Semi-arid
Semnan	1965	35.35	53.33	1130.8	140.8	Arid
Shahroud	1951	36.42	54.95	1345.3	154.4	Arid
Tehran	1951	35.68	51.32	1190.8	232.8	Arid
Zanjan	1955	36.68	48.48	1663	313.1	Semi-arid

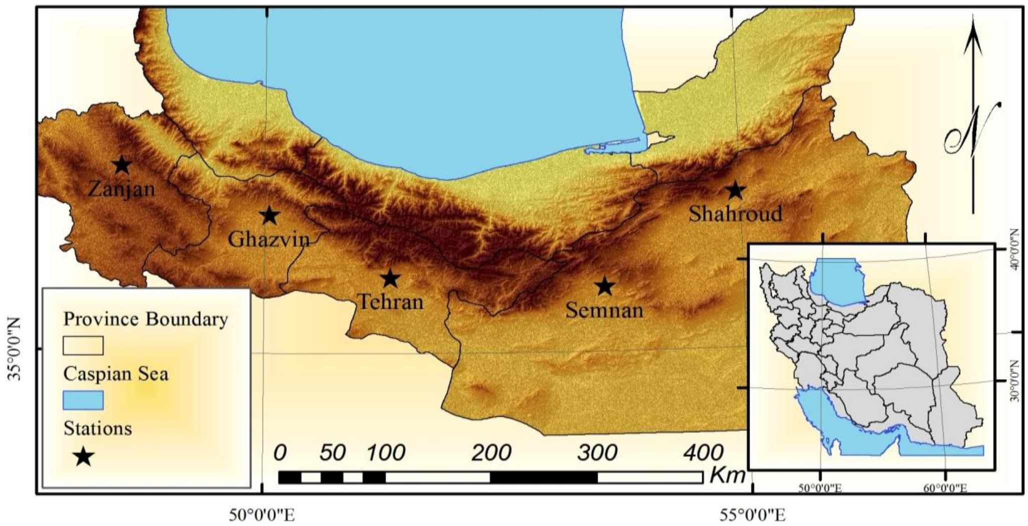

Fig. 1. Spatial distribution of the stations, used in the study

Table 2. Name and Abbreviation of the 17 Oceanic-Atmospheric Index used in the research

Index Name	Index Abbreviation	Index Name	Index Abbreviation
Oceanic Nino Index	ONI	Eastern Tropical Pacific SST	NINO3
North Tropical Atlantic Index	NTA	South Oscillation Index	SOI
Caribbean Index	CAR	North Atlantic Oscillation	NAO
Multivariate ENSO Index	MEI	Pacific North Atlantic	PNA
Bivariate ENSO Time Series	BEST	Extreme Eastern Tropical Pacific SST	NINO1+2
Arctic Oscillation	AO	East Central Tropical Pacific SST	NINO3.4
Global Mean Temperature	GMT	Central Tropical Pacific SST	NINO4
Pacific Warm Pool	PWP	Greenland Blocking Index	GBI
East Pacific Oscillation	EPO		

METHODOLOGY

All precipitation data was sorted and standardized, using the normal z method so that the months with pervasive precipitation could be recognized. Then, the months with more than ±1 standard deviation were selected while the ones, in which standard deviation of more than 75% of the stations was higher than ±1, were considered as months with pervasive precipitation. In this stage, out of the 480 studied months, for southern Alburz 69 months were selected. Then, using the Pearson correlation equation, the normalized precipitation data got correlated with oceanic-atmospheric indices data. Also, a backward correlation was conducted for one to three months (i.e. month-1, month-2, and month-3). In order to model the correlation between the precipitation and oceanic-atmospheric indices, a multi-variation regression was done, using SPSS. In this method, independent variables without a high value of dependent variable data series (or the ones whose sigma coefficient was higher than 0.1) are omitted from the process and the model is presented by employing the least variables and highest “r” coefficient values. In order to evaluate the validity and precision of the calculated regressive functions, Root Mean Square Error (RMSE) and Mean Bias Error (MBE) were applied. These methods calculate the difference between forecasted and real data, being quite appropriate for evaluation of a model's errors.

RESULTS AND DISCUSSION

Due to the amount of freedom of the data, used in the research (69 cases), the P<0.01 is significant when the correlation coefficient is higher than 0.23. Henceforth, pervasive precipitations of eight indices are considerably correlated with climate indices. The Bivariate ENSO Time Series (BEST), the Oceanic Nino Index (ONI), and the East Pacific Oscillation (EPO) show a relatively higher correlation in comparison to other indices. Among all significant indices, the SOI is in reverse correlation with precipitation. Interestingly, the significant correlation coefficients (except for $NINO_3$), have either increased in one month lag time or remained unchanged. This can signify that one may use the one-month lag time instead of the same month (zero month lag time) to predict the precipitation of the upcoming months, as it has a higher correlation coefficient for all stations (Table 3).

In both two-month and three-month lag time, indices with significant correlation coefficient (Table 4) do not change in comparison to those of the previous lag times (Table 3). The SOI still shows negative values indicating a reverse correlation between the precipitation time series and the South Oscillation Index. The coefficients do not seem to be behaving very regularly, because compared to the values shown in table 2, the m-3 lag time sometimes shows higher and sometimes lower values than the m-2 lag time. Also, the NINO 3, which was insignificant for Ghazvin and Zanjan, is now insignificant for Ghazvin, Semnan, and Tehran Stations.

Regression modeling of the relation between precipitation anomalies of Alburz and oceanic atmospheric indices

Employing the regression modeling with backward method requires all variables inserted into the model. Then, variables with the weakest correlation coefficient are omitted intermittently. Using m=0 data, two indices show the highest correlation coefficient and the least sigma coefficient (Table 5). Seemingly, East Pacific Oscillation (EPO) and Global Mean Temperature are the most correlating indices to predict the southern Alburz precipitation (Eq. 1).

Table 3. Correlation coefficient (of the same month and one-month lag) of normal z values of pervasive precipitation with oceanic atmospheric indices; the grey cells show insignificant values

Index/Station	Ghazvin		Shahroud		Semnan		Tehran		Zanjan	
	m	**m - 1**	**m**	**m - 1**	**m**	**m - 1**	**m**	**m - 1**	**m**	**m - 1**
SOI	-0.37	-0.24	-0.40	-0.25	-0.38	-0.23	-0.36	-0.24	-0.40	-0.29
PNA	-0.06	-0.09	-0.01	0.00	-0.07	0.02	-0.09	-0.07	-0.01	-0.13
NAO	0.21	0.05	0.19	-0.03	0.18	0.04	0.18	0.03	0.24	-0.03
GBI	-0.17	0.00	-0.15	-0.09	-0.15	-0.08	-0.15	-0.07	-0.15	0.04
ONI	0.37	0.39	0.35	0.39	0.36	0.36	0.35	0.36	0.41	0.44
NTA	-0.09	-0.05	-0.16	-0.13	-0.16	-0.10	-0.04	-0.07	-0.11	-0.12
CAR	0.08	0.13	0.04	0.05	0.05	0.05	0.19	0.15	0.06	0.10
MEI	0.32	0.37	0.33	0.35	0.31	0.34	0.27	0.34	0.40	0.42
BEST	0.40	0.32	0.42	0.38	0.42	0.30	0.39	0.29	0.48	0.42
NINO 3	0.22	0.19	0.23	0.24	0.24	0.23	0.24	0.23	0.22	0.24
NINO 1+2	0.12	0.09	0.17	0.13	0.17	0.12	0.02	0.12	0.08	0.07
NINO 3.4	0.31	0.38	0.30	0.27	0.31	0.31	0.27	0.31	0.39	0.42
NINO 4	0.37	0.38	0.30	0.38	0.27	0.25	0.25	0.25	0.41	0.42
PWP	0.00	-0.12	-0.13	-0.16	-0.10	-0.18	0.00	-0.14	-0.08	-0.02
EPO	0.39	0.40	0.39	0.42	0.38	0.38	0.33	0.37	0.42	0.43
AO	0.12	0.08	-0.07	0.08	-0.06	-0.03	0.00	0.00	0.12	0.05
GMT	-0.09	-0.04	-0.18	-0.01	-0.16	-0.01	-0.08	0.03	-0.16	-0.11

Table 4. Correlation coefficient (of the previous month) of normal z values of pervasive precipitation with oceanic atmospheric indices; grey cells show insignificant values

Index/Station	Ghazvin		Shahroud		Semnan		Tehran		Zanjan	
	m - 2	m - 3	m - 2	m - 3	m - 2	m - 3	m - 2	m - 3	m - 2	m - 3
SOI	-0.28	0.32	-0.24	-0.24	-0.24	-0.40	-0.29	-0.24	-0.36	-0.39
PNA	-0.22	-0.12	-0.12	-0.14	-0.13	-0.15	-0.18	-0.10	-0.14	-0.09
NAO	-0.02	0.02	-0.14	0.04	-0.14	0.03	-0.20	0.00	-0.20	0.03
GBI	0.12	0.04	0.03	-0.01	0.03	-0.01	0.04	0.10	0.16	0.08
ONI	0.24	0.35	0.25	0.37	0.24	0.31	0.24	0.31	0.42	0.41
NTA	0.00	-0.17	-0.13	-0.13	-0.11	-0.11	0.02	0.10	-0.02	-0.03
CAR	0.09	0.00	-0.02	-0.13	-0.02	-0.15	0.08	0.00	0.03	-0.07
MEI	0.29	0.24	0.29	0.25	0.25	0.24	0.27	0.24	0.42	0.30
BEST	0.32	0.40	0.31	0.38	0.27	0.36	0.32	0.37	0.42	0.43
NINO 3	0.19	0.24	0.23	0.25	0.20	0.23	0.18	0.24	0.24	0.37
NINO 1+2	0.05	0.08	0.08	0.13	0.06	0.10	0.05	0.08	0.05	0.12
NINO 3.4	0.27	0.37	0.28	0.37	0.25	0.26	0.24	0.26	0.42	0.41
NINO 4	0.30	0.32	0.28	0.26	0.25	0.25	0.25	0.26	0.42	0.38
PWP	-0.13	-0.16	-0.20	-0.21	-0.20	-0.22	-0.11	-0.13	-0.18	-0.22
EPO	0.34	0.31	0.33	0.35	0.29	0.30	0.30	0.30	0.44	0.41
AO	-0.21	-0.02	-0.20	-0.03	-0.21	-0.04	-0.21	0.04	-0.21	-0.07
GMT	-0.09	0.11	-0.11	0.00	-0.10	0.00	-0.02	0.09	-0.08	0.05

Table 5. Results of multi-regression model for m=0 lag time

Model 15	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.245	.203		1.208	.231
EPO	.821	.186	.492	4.408	.000
GMT	-.014	.006	-.254	-2.276	.026

$$P = 0.245 + (EPO * 0.821) + (GMT * -0.014) \quad (1)$$

In the backward correlation (m-1) both indices in the previous lag time have changed (table 6). In one-month lag time, NINO 3 and NINO 4 have replaced EPO and GMT. Also, the equation to predict the southern Alburz precipitation is demonstrated as Equation (2)

$$P = M - 1 = -23.931 + (NINO3 * 0.232) + (NINO4 * 0.632) \quad (2)$$

For the two-month lag, both indices have changed again and the PNA and MEI have had the highest correlation coefficient (Table 7); therefore, the equation can be demonstrated as Equation (3).

$$P = M - 2 = -0.121 + (PNA * -0.285) + (MEI * 0.547) \quad (3)$$

The three-month time lag, again changes the two indices (Table 8), replacing the former two with SOI and BEST, which would define the southern Alburz precipitation as Equation (8).

$$P = M - 3 = -0.23 + (SOI * 0.382) + (BEST * 1.063) \quad (4)$$

Model evaluation

In order to evaluate the functionality quality of the models for the estimation of the standardized precipitation amounts, 20% of the studied months (i.e. 13 months) were selected in random. Then, using Equations (1) to (4), the average standardized precipitation was calculated and compared with real precipitation data (Fig. 2). Also, Mean Bias Error (MBE) and Root Mean Square Error (RMSE) were calculated to evaluate the model's precision (Table 9). According to the results from this comparison, the amount of the MBE for the southern Alburz (in m-1lag time) reaches to 0.58 at its apex and is about 0.0101 in m-2 lag time. Also, the RMSE of only two lag times is below 1, indicating that it will be better to use the other two since they have less error. The MBE increases from m=0 to m-1, then to decrease drastically and increase slowly once more. The RMSE, however, increases from m=0 to m-1 and then decreases. According to RMSE values, the evaluation of the model seems to be acceptable. Although some RMSE values are relatively high, they can be accepted, considering the variable nature of precipitation. Regarding both MBE and RMSE values, the lag times 0 and 3 (m=0 and m=1 respectively) are better to be used (Eqs. 1 and 4).

Table 6. Results of multi-regression model for m-1 lag time

Model 15	**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**
	B	**Std. Error**	**Beta**		
(Constant)	-23.931	6.937		-3.450	.001
NINO 3	.232	.129	.210	1.801	.076
NINO 4	.632	.247	.298	2.560	.013

Table 7. Results of multi-regression model for m-2 lag time

Model 11	**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**
	B	**Std. Error**	**Beta**		
(Constant)	-0.121	0.160		-0.756	0.453
PNA	-0.285	0.156	-0.212	-1.830	0.072
MEI	0.547	0.167	0.379	3.270	0.002

Table 8. Results of multi-regression model for m-3 lag time

Model 11	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
(Constant)	-0.230	0.161		-1.427	0.158
SOI	0.382	0.199	0.453	1.916	0.060
BEST	1.063	0.308	0.816	3.451	0.001

Table 9. Values of Mean Bias Error and Root Mean Square Error for northern and southern Alburz for different lag times

	m = 0	**m - 1**	**m - 2**	**m - 3**
MBE	0.2232	0.5835	0.0101	0.0229
RMSE	0.6127	1.7715	1.0852	0.9446

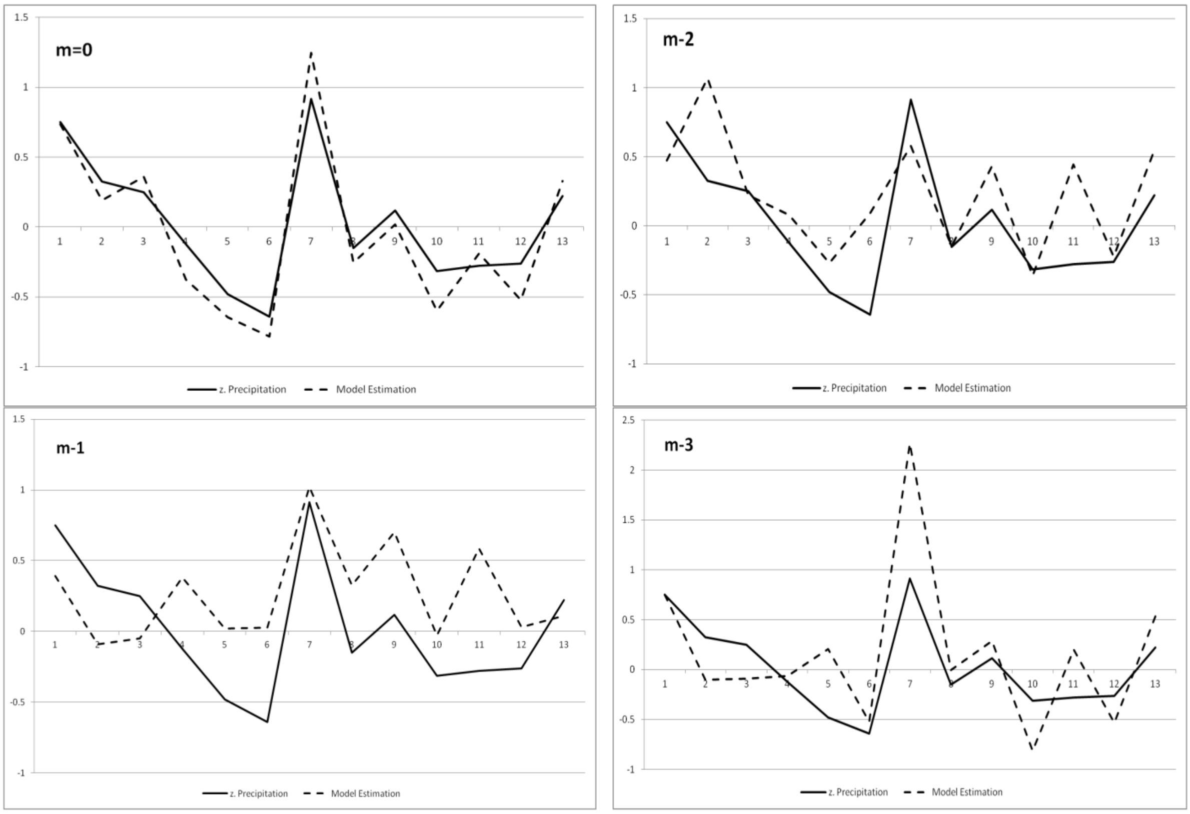

Fig. 2. Comparative values of normalized precipitation data (line) and model results (dashed) for Southern Alburz

CONCLUSION

In this research, the authors have tried to find a reliable significant equation, with which one can predict the amount of pervasive precipitation on the southern side of the Alburz Mountain Range, by means of oceanic- atmospheric indices. According to the results of the correlation calculation, less than 25% of precipitations are caused by global atmospheric patterns as the highest correlation coefficient is about 0.48 (which results the r square coefficient to fall below 0.24).

The results, however, show that some oceanic and atmospheric indices seem to have high potentials for predicting or modeling the amount of precipitation over the northern and southern Alburz as the Bivariate ENSO Time Series (BEST) demonstrate significantly lofty correlation with $P<0.01$ (approximately 0.4 with a freedom degree of about 70) as well as pervasive precipitation in southern Alburz. In multivariate modeling, the indices, correlating with pervasive precipitation, change over each month of lag time. Also, the values of MBE and RMSE show acceptable values for modeling which can indicate that the equations of this research are greatly capable of predicting the pervasive precipitation of the southern Alburz for up to three-month lag time.

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