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Stochastic and time series drought forecast using rainfall oscillations in arid and Semi-arid environments

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Abstract

The importance of water supplies in the world, underscores the need for estimating and forecasting the trend of meteorological phenomena, understanding atmospheric phenomena and its trend in economic management. This includes optimization of profitability and productivity impact, especially in arid and semi-arid schedules. Conversely, climate and rainfall are highly non-linear and complicated phenomena, which require non-linear mathematical modeling and simulation for trusted accurate prediction. In this study, monthly rainfall data were obtained from 10 synoptic stations from 1985 to 2014. Thereafter, R software was employed in predicting the height of rainfall in 10 synoptic stations (2003 to 2014) using monthly height of rainfall data (1985 to 2014). In this research, five models (AR, MA, ARMA, ARIMA, and SARIMA) with 12 different structures were tested. After deciding on the optimal model to be used for each station, rainfall was forecast for 120 months (2014 to 2024) and then for the years 2014 and 2024 iso-rainfall maps were outlined. From the findings of this research, it was observed that in 80% of data, ARMA (2,1) had better results than the other models and according to the simulated and predicted rainfall by time series models, the drought situation was evaluated using standardized precipitation index (SPI). The result thus revealed that in comparison to 2014, severe drought will have decreased by the end of 2024.

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Introduction

One of the effective studies in micro and macro scales of social economic planning is that of selecting an appropriate model for forecasting monthly and annual rainfall. This will result in having reliable information about the situation of rainfall in future years. Also, directors and planners, and also different social sectors can be additionally prepared to deal with adverse events, such as taking action to deal with optimal utilization of water, soil and human resources (Nazemosadat *et al*., 2006).

In this context, the precipitation forecast of the agriculture based economy in developing countries, especially in arid and semi-arid areas is important. Since the study area (Khorasan Razavi province) falls within this category and should be aware of the precipitation situation in the future, it requires such information to optimize management.

Additionally, rainfall ranks among the most complex and challenging elements of the hydrological cycle as regards understanding and modeling due to the complexity of atmospheric processes that generate rainfall and the tremendous variation over a wide range of scales both in space and time (French *et al*., 1992).

Thus, in operational hydrology, accurate rainfall forecasting has remained one of the greatest challenges despite many advances in weather forecasting in recent decades (Gwangseob and Ana, 2001).

In this day and age, researchers, due to innovation and scientific development of intelligent techniques that are powerful devices, flexible and dynamic models are becoming independent in their search for ways of modeling and forecasting important meteorological parameters (Firouzi *et al*., 2012). Time series is a sequence of values or events measured at equal intervals that can be used to predict any future event. Time series analysis identifies any hidden pattern in previous data and predicts a future pattern. Agriculture, climatology, sales, transport and tourism sectors are some examples of different forecasting areas.

Traditional methods, such as time series regression, exponential smoothing, and auto-regressive integrated moving average (ARIMA), are available for stochastic time series analysis. Development of time series models consists of three phases: identification, estimation and diagnostic checking (Shirmohammadi *et al*., 2013). It is widely recognized that time series modeling, can be a better option for an area where there is virtually nothing but the hydrological time series data in hand (Kumar *et al*., 2012). A number of stochastic time series models such as the Markov, Box-Jenkins (BJ) Seasonal Auto- Regressive Integrated Moving Average (ARIMA), depersonalized Auto-Regressive Moving Average (ARMA), Periodic Auto-regressive (PAR), Transfer Function Nois (TFN) and Periodic Transfer Function Noise (PTFN), are currently being used for these purposes (Box *et al*., 1994; Hipel and Mcleod, 1994; Brockwell and Davis, 2010). Models of time series analysis (Box-Jenkins models and ANN models) are widely applied in various fields of hydrology and rainfall forecasting in irrigation schedule, some of which are described below.

Through the use of ANN and ARMA models to forecast rainfall, Toth *et al*. (2000) demonstrated the success of both short-term rainfall forecasting models for forecast floods in real time. Also, in using the ARMA model for forecasting short-term rainfall, Burlando *et al*. (1993) utilized hourly rainfall data from two gauging stations in Colorado, USA, and from several stations in Central Italy, to show that the event-based estimation approach yields better forecasts.

Regarding daily rainfall prediction using artificial neural network model, Saplioglu *et al*. (2010) used ARIMA (1,1) modeling variable seasonal flows in Rivers Yampayr monthly and White 3 in north-western California. Haltiner *et al*. (1988) modeled parameters compared from the maximum likelihood method and the moment neural networks were used to forecast rain. Also, the results of Tokar *et al*. (1999)

showed that the runoff model precipitation of artificial neural networks in comparison with other statistical methods is more accurate and less time is spent on the model.

In the present study, a comparative study of rainfall behavior was conducted as obtained by AR, MA, ARMA, ARIMA, and SARIMA with 12 different structures and comparison of iso-rainfall in 2014 and 2024 (while 2014 is real data, 2024 is predicted data) and also provides SPI for the years mentioned. These models are applied in this research to help develop rainfall estimation models for Khorasan Razavi Province station, to compare the results of models and to evaluate the potential for estimating monthly rainfall.

Materials and methods

Study area

According to the global desertification vulnerability map presented at the 1: 5'000'000 scale (USDA-NRCS, 1995), the high vulnerability regions of the world are mainly located in the arid zone belts of Middle East countries. Iran, with more than 85% arid and semi-arid areas, includes a wide range of different types of ecosystems, characterized by high vulnerability to desertification and soil degradation processes. The study was conducted in Khorasan Razavi Province, which is in the second metropolitan city of Iran, Mashhad. This province is one of the regions at high erosion risk in Iran. The studied area covers about 116511 km² and is approximately located between East longitude 56°19' to 61°16' and between North latitude 33°52' to 37°42' (Fig. 1). More than 60% of the province comprises desert and semi-desert areas. Thirteen cities are completely located in desert area, or a part of them is desert, and are characterized by difficult living conditions. It has low rainfall (about 210 mm/year) and extremely low vegetation cover. Typical vegetation formations are various species of *Artemisia*, *Astragalus*, *Stipa*, *Luctuca*, *Festuca* and *Amygdalus*. Clay plains (Dagh in Persian), playas, salty land and moving sand dunes are widespread morphologies.

The most widespread soil types are *aridisols, entisols, lithosols* and *rigosols*. These conditions are highly vulnerable to wind and water erosion, and prone to desertification.

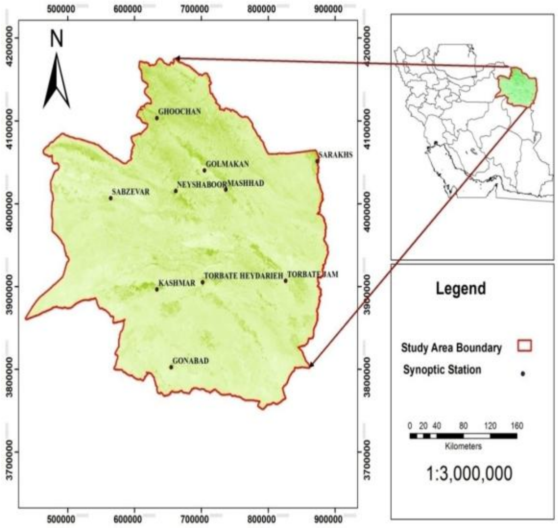

Fig. 1. The location of Khorasan Razavi province in the north east of Iran.

Time series models

Time series data show many forms and represent different stochastic processes. Linear relationships are common models for time series. There are three basic types of linear models: autoregressive (AR), moving-average (MA), and ARMA models. In this study AR, MA, ARMA, ARIMA, and SARIMA models are used for evaluating time series performances.

AR Model

In a series where persistency is observed, that is, the event outcome of (t+1), the period is dependent on the present period magnitude and those preceding values. Hence, for such a series, the observed sequences X1, X2,...., Xt is used to fit AR model.

Auto-Regressive model (AR) (p) can be expressed as Equation (1):

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + ...\phi_p z_{t-p} + a_t \quad \text{Eq. (1)}$$

Where ϕ_1, ϕ_2 and ϕ_p are coefficient and model parameters and a_t is random term of the data followed by normal distribution with zero mean (Hannan, 1971).

MA Model

Moving average models are simple covariance stationary and argotic time series models that can capture a wide variety of auto-correlation patterns. Moving Average model (MA (q)) can be expressed as Equation (2):

$$z_t = \theta_1 a_{t-1} + \theta_2 a_{t-2} + ...\theta_q a_{t-q} + a_t \quad \text{Eq. (2)}$$

Where θ_1, θ_2 and θ_q are coefficient and model parameters and a_t is random term of the data followed by normal distribution with zero mean (Hannan, 1971).

ARMA Model

The ARMA model is a combination of an Auto-Regressive (AR) model and a Moving-Average (MA) model. The auto-regressive moving average (ARMA) model forms a class of linear time series models that are widely applicable and parsimonious in parameterization. Autoregressive moving average (ARMA) model ARMA (p, q) can be expressed as Equation (3):

$$Y_t = \delta + \sum_{i=1}^{p} \varphi_i y_{t-1} + \sum_{j=1}^{q} \phi_j e_{t-j} + e_t \quad \text{Eq. (3)}$$

Where δ is the constant term of the ARMA model, φ_i indicates the i^{th} autoregressive coefficient, ϕ_j is the j^{th} moving average coefficient, and shows the error term at time period t, with Y_t refers to the observed or forecasted value of groundwater level at time period t (Erdem and Shi, 2011).

ARIMA and SARIMA models

Auto-regressive integrated moving average (ARIMA) models are among the most important linear models for time series forecasting. ARIMA models emanated from the combination of auto-regressive models (AR) and the moving average models (MA). ARIMA fits a Box-Jenkins ARIMA model to a time series (Shirmohammadi *et al.*, 2013). ARIMA is aimed at modeling time series behavior and generating forecasts. Its modeling uses correlation techniques and can help to model patterns that may not be visible in plotted data (Box *et al.*, 1994). In ARIMA, the future value of a variable is assumed to be a linear function of several past observations and random errors. A SARIMA model can be explained as ARIMA (p, d, q) (P, D, Q)s, where (p, d, q) is the non-seasonal part of the model and (P, D, Q)s is the seasonal part of the model in which there is non-seasonal auto-regression order, d is the number of regular differencing, that is, the order of non-seasonal MA, P is the seasonal auto-regression order, D is the number of seasonal differencing, Q is the order of seasonal MA, and s is the length of season (Faruk, 2010).

Model selection

In most of the researches carried out, Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) have been used to determine the best model. However, to enhance the accuracy of the model selection, coefficient of determination (R^2) and Akaike information criteria (AIC) have been used in this research in addition to ACF and PACF.

AIC and R^2 can be expressed as Equations (4 and 5).

$$AIC(k) = n\ln(MSE) + 2k \quad \text{Eq. (4)}$$

$$R^2 = \frac{\left[\sum_{i=1}^{n} (qi - \bar{q})(q\hat{i} - \bar{\hat{q}})\right]^2}{\sum_{i=1}^{n} (qi - \bar{q})^2 \sum_{i=1}^{n} (q\hat{i} - \bar{\hat{q}})^2} \quad \text{Eq. (5)}$$

Wherein is the number of data points (for calibration), and k is the number of free parameters used in the models. MSE represents mean square error qi, $q\hat{i}$, are observed and estimated values, while $\bar{\hat{q}}$ and $\bar{q}$ are the estimated mean values and computational model outputs, respectively. Usually, the preferred model gives higher R^2 or the smallest value of AIC.

The auto-correlation statistics as well as the corresponding 95% confidence bands from lag-0 to lag-20 were estimated for the rainfall time series (Fig. 3) (.a,b). For the rainfall data time series, the partial auto-correlation function (PACF) showed significant correlation up to lag-2 for this time series within the confidence limits as well as auto-correlation function (ACF) decreases exponentially. The study area's rainfall data behavior in Fig. 2 reveals the data of interest to be the three components (trend, seasonal and random), that were used as random components in forecasting.

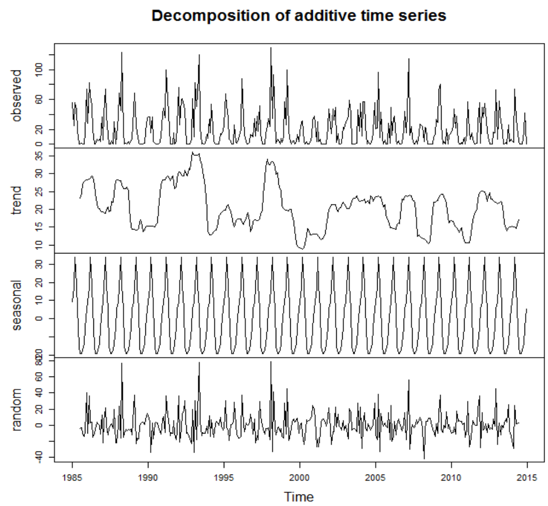

Fig. 2. Time series graphs with random, seasonal and trend components in Mashhad station.

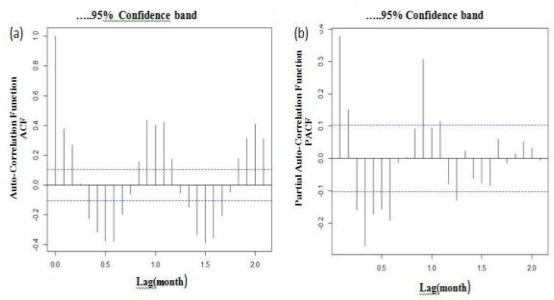

Fig. 3. (a) Auto-correlation and (b) partial auto-correlation functions of the monthly.

Meteorological drought

Meteorological drought can be explained as precipitation decreasing along time and space. (Morid *et al.*, 2006). Precipitation has commonly been used for meteorological drought analysis (Santos, 1983; Chang, 1991).

Considering drought as precipitation deficit with respect to average values, several studies have analyzed droughts using monthly precipitation data. One of the most popular tools in meteorological drought tools is SPI index.

Hayes *et al.* (1999) demonstrated how the SPI could have been used operationally at varying time scales to monitor the 1996 drought from its development to its conclusion in the southern Great Plains and southwestern USA. They concluded that 'using the SPI as a drought monitoring tool will improve the timely identification of emerging drought conditions that can trigger appropriate state and federal actions (Wu *et al.*, 2005).

Although the SPI is not a drought prediction tool, SPI methodology has been used in identifying dryness and wetness conditions, and in evaluating their impact in water resources and management (Priento-Gonzalez *et al.*, 2011).

Standardized precipitation index (SPI)

The meteorological drought index for assessing the situation in each region is calculated based on long-term rainfall record. SPI can be expressed as Equation (6):

$SPI=(X_i-\bar{X})/S$ Eq. (6).

Where SPI: Standardized Precipitation Index, Xi: rainfall in the desired year, $\bar{X}$: Long-term average annual rainfall and S is standard deviation. The SPI classes based on McKee *et al.* (1993) are presented in Table 3.

Thus, in this study, monthly rainfall data for the years 1985 to 2014 were collected from 10 synoptic stations (General Directorate of Meteorology, Mashhad). After data was prepared, R software was used to predict the height of rainfall in 10 synoptic stations (2003 to 2014) using monthly height of rainfall data (1985 to 2014) to select the optimal model to predict. Thereafter, according to the best selected model, the height of rainfall predicted from 2014 to 2024. Based on the predicted data (2014 to 2024), the drought situation was predicted and analyzed (Fig. 15a, b).

Results

The findings obtained from AR, MA, ARMA, ARIMA and SARIMA models in Ghoochan, Golmakan, Neyshaboor, Sarakhs, Sabzevar, Kashmar, Torbate Heydarieh, Torbate Jam, Gonabad and Mashhad are shown in Table 2. Also, the models performance in highest rainfall forecasting versus the observed highest rainfall are shown in Figs. 4 to 13 in Ghoochan, Golmakan, Gonabad, Kashmar, Mashhad, Neyshaboor, Sabzevar, Sarakhs, Torbate Heydarieh and Torbate Jam stations respectively.

The iso-rainfall map in 2014 and rainfall prediction in 2024 are shown in Fig. 14a, b. Consequently, the drought assessment result of 2014 and 2024 are shown in Fig. 15a, b using drought index (SPI) in 2014 and 2024 in Khorasan Razavi Province.

Table 1. Synoptic stations characteristics.

Station	Longitude	Latitude	Height (m)	Range of Values(mm/year)
Mashhad	59° 38´	36° 16´	999.2	121.4-390.2
Ghoochan	58° 30´	37°04´	1287	121.5-436.9
Golmakan	59° 17´	36° 29´	1176	108.3-319.1
Gonabad	58° 41´	34° 21´	1056	68.8-228.3
Neyshboor	58° 48´	36° 16´	1213	130-356.8
Sabzevar	57° 39´	36° 12´	972	58-295.4
Torbate H	59° 13´	35° 16´	1450	82.1-390.6
Torbate J	60° 35´	35° 15´	950	56.3-263.2
Kashmar	58° 28´	35° 12´	1109	64.7-299.1
Sarakhs	61° 10´	36° 12´	235	76.4-261

Table 2. The results of time series models performance for ten stations.

Stations / Models		Ghoochan			Golmakan			Gonabad			Kashmar			Mashhad		
		Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
AR(1)	ϕ_1	-0.0087	1836.18	0.60	0.0916	1747.85	0.60	0.0339	1716.8	0.51	-0.1040	1852.83	0.63	-0.113	1848.59	0.62
AR(2)	ϕ_1	-0.0095	1836.23	0.60	0.1049	1745.13	0.60	0.0345	1718.73	0.51	-0.1098	1854.3	0.63	-0.1107	1850.49	0.62
	ϕ_2	-0.0944			-0.1473			-0.0181			-0.0498			0.0217		
MA(1)	θ_1	-0.0108	1836.18	0.60	0.1173	1747.27	0.60	0.0344	1716.8	0.51	-0.1216	1852.5	0.63	-0.1134	1848.63	0.62
MA(2)	θ_1	-0.4384	1810.79		-0.3901	1721.74	0.60	0.031	1718.79	0.51	-0.1734	1852.42	0.63	-0.1191	1850.61	0.62
	θ_2	-0.5615		0.61	-0.6098			-0.0086			-0.1385			-0.0167		
ARMA (1,1)	ϕ_1	0.6194	1796.2	0.61	-0.2466	1748.68	0.60	0.0038	1718.8	0.51	0.6035	1815.61	0.64	-0.5655	1850.01	0.62
	θ_1	-1			0.3610			0.0307			-1			0.4615		
	ϕ_1	0.4803			0.4722			-0.5234			0.5233			-0.6042		
ARMA (1,2)	θ_1	-0.7601	1790.93		-0.6707	1698.55	0.60	0.5677	1720.26	0.51	-0.8743	1815.61	0.64	0.4956	1852	0.62
	θ_2	-0.2399		0.61	-0.3293			0.0697			-0.1257			-0.0144		
	ϕ_1	0.7550			0.8495			0.8328			0.6726			0.6741		
ARMA (2,1)	ϕ_2	-0.2223	1787.13		-0.3297	1689.67	0.59	-0.2412	1673.67	0.5	-0.1222	1814.49	0.64	-0.0969	1810.56	0.62
	θ_1	-1		0.61	-1			-1			-1			-1		
	ϕ_1	1.4591			1.4349			0.1667			1.5309			-0.3094		
ARMA (2,2)	ϕ_2	-0.6799	1765.27	***	-0.6826	1680.84	***	-0.8971	1715.6	0.5	-0.6615	1790.36	0.64	0.5694	1814.6	0.62
	θ_1	-1.8137			-1.7279			-0.1282			-1.9814			-0.0756		
	θ_2	0.8137			0.7279			1			0.9817			-0.9244		
	ϕ_1	-0.4789			-0.892			-0.0691			-0.5974			-0.5693		
ARIMA (1,1,2)	d	1	1836.01		1	1747.38	0.59	1	1717.19	0.51	1	1853.1	0.63	1	1847.99	0.62
	θ_1	-0.5032			-0.0669			-0.8947			-0.4777			-0.5318		
	θ_2	-0.4967		0.60	-0.9330			-0.1051			-0.5223			-0.4681		
	ϕ_1	-0.4526	1927.55	0.60	-0.3718	1836.63	0.60	-0.4689	1795.44	0.5	-0.5287	1943.45	0.60	-0.57	1930.71	0.62

Model		Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
ARIMA (1,2,1)	d	2			2			2			2			2		
	θ_1	-1			-1			-1			-1			-1		
	ϕ_1	-0.4473			-0.3796			-0.46			-0.5399			-0.5699		
SARIMA (1,1,0) (1,1,1)(12)	d	1			1			1			1			1		
	Φ_1	-0.0184	1864.47		0.0437	1188.33	0.57	-0.1521	1737.49	0/46	-0.0552	1883.32	0.59	-0.0038	1869.86	0.61
	D	1			1			1			1			1		
	Θ_1	-0.9390		0.58	-1			-0.8657			-1			-1		
SARIMA (1,1,1) (1,1,1)(12)	ϕ_1	-0.0169			0.0956			-0.0457			-0.1377			-0.1116		
	d	1			1			1			1			1		
	θ_1	-1	1780.82		-1	1147.87	0.57	-1	1667.46	0.49	-1	1898.22	0.62	-1	1865.37	0.61
	Φ_2	0.0604			0.006			-0.1076			0.970			-0.03		
	D	1			1			1			1			1		
	Θ_2	-0.9999		0.57	-1			-0.8599			-0.9996			-0.9673		

Table 2 (continued)

Sinoptic station / Model		Neshaboor			Sabzevar			Sarakhs			Torbate Heydarieh			Torbate Jam		
		Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2	Model coefficient	AIC	R^2
AR(1)	ϕ_1	-0.1235	1802.52	0.57	-0.0675	1808.48	0.49	-0.2533	1730.2	0.66	-0.0796	1946.62	0.58	0.0339	1716.8	0.54
AR(2)	ϕ_1	-0.1274	1804.3	0.57	-0.0721	1816.35	0.49	-0.2505	1732.17	0.66	-0.0797	1948.62	0.58	0.0345	1718.73	0.54
	ϕ_2	-0.0315			-0.0988			0.0115			-0.0023			-0.0181		
MA(1)	θ_1	-0.1346	1802.27	0.57	-0.0861	1816.18	0.49	-0.2611	1730.44	0.66	-0.0837	1946.58	0.58	0.0344	1716.8	0.54
MA(2)	θ_1	-0.155	1803.49	0.57	-0.4753	1808.48	0.49	-0.2659	1732.4	0.66	-0.1147	1948.12	0.58	-0.031	1718.79	0.54
	θ_2	-0.0952			-0.4753			-0.0182			-0.0714			-0.0086		
ARMA (1,1)	ϕ_1	0.6017	1764.2	0.57	0.6271	1816.35	0.49	-0.3482	1732.13	0.66	-0.7001	1947.66	0.58	0.0038	1718.8	0.54
	θ_1	-1			-0.9720			0.1015			0.6241			0.0307		
ARMA (1,2)	ϕ_1	0.5378			0.4727			-0.6171			-0.6904			-0.5234		
	θ_1	-0.8994	1764.97	0.57	-0.8081	1771.62	0.49	0.3573	1733.67	0.66	0.6183	1949.65	0.58	0.5677	1720.26	0.54
	θ_2	-0.1006			-0.1919			-0.0990			0.0071			0.0697		
ARMA (2,1)	ϕ_1	0.6581			0.6927			0.7115			-0.6882			0.8328		
	ϕ_2	-0.09725	1764.17	0.57	-0.1725	1769.39	0.50	-0.0906	1734	0.66	0.0049	1949.66	0.58	-0.2412	1673.67	0.54
	θ_1	-1			-1			0.4652			0.6145			-1		
ARMA (2,2)	ϕ_1	1.4823			1.5306			-0.714			-0.1397			0.1667		
	ϕ_2	-0.6576	1741.39	0.57	-0.6591	1747.38	0.49	0.393	1695.51	0.66	-0.4685	1911.09	0.58	-0.8971	1715.6	0.54
	θ_1	-1.7826			-1.9888			-0.4269			-0.2534			-0.1282		
	θ_2	0.8827			0.9891			-0.5731			-0.7466			1		
ARIMA (1,1,2)	ϕ_1	0.6095			-0.8936			-0.3739			-0.7046			-0.0691		
	d	1	1766.74	0.57	1	1817.37	0.49	1	1730.91	0.66	1	1945.14	0.58	1	1717.19	0.54
	θ_1	-1.9985			-0.1093			-0.8668			-0.3694			-0.8948		
	θ_2	0.9999			-0.8906			-0.1332			-0.6306			-0.1051		
ARIMA (1,2,1)	ϕ_1	-0.5431			-0.4851			-0.6345			-0.5425			-0.4689		
	d	2	1894.04		2	1912.54	0.49	2	1824.58	0.66	2	2029.0 2	0.53	2	1795.44	0.53
	θ_1	-1		0.54	-1			-1			-1			-1		
SARIMA (1,1,0) (1,1,1)(12)	ϕ_1	-0.5549			-0.4112			-0.6299			-0.5256			-0.46		
	d	1			1			1			1			1		
	Φ_1	0.0191	1823.05		0.004	1820.21	0.49	-0.075	1768.62	0.64	-0.0951	1962.44	0.51	-0.1521	1737.49	0.49
	D	1			1			1			1			1		
	Θ_1	-0.7675		0.41	-0.8408			-1			-0.8885			-0.8657		
SARIMA (1,1,1) (1,1,1)(12)	ϕ_1	-0.1338			-0.0673			-0.2648			-0.048			-0.0457		
	d	1			1			1			1			1		
	θ_1	-1	1738.22		-1	1763.21	0.49	-1	1682.72	0.64	-1	1885.9	0.57	-1	1667.46	0.52
	Φ_2	0.0283			0.0696			-0.0149			-0.0979			-0.1076		
	D	1			1			1			1			1		
	Θ_2	-0.7734		0.52	-1			-1			-0.8571			-0.8599		

Table 3. Classification Scale for SPI (Hayes *et al.*, 1999) and results of assessment of drought in 2014 and 2024.

SPI value	Classification	Cumulative probability 2014 %	Cumulative probability 2024 %
2.00 or more	Extremely wet	-	-
1.50 to 1.99	Very wet	-	-
1 to 1.49	Moderately wet	-	-
-0.99 to 0.99	Near normal	83.8	100
-1 to -1.49	Moderate drought	16.2	-
-1.50 to -1.99	Severe drought	-	-
-2 or Less	Extreme drought	-	-

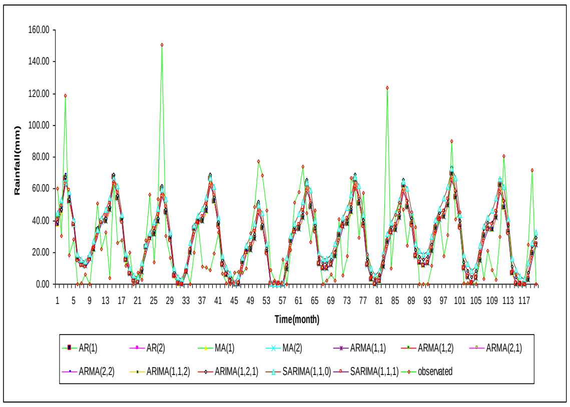

Fig. 4. Models prediction versus observed data in Ghoochan station.

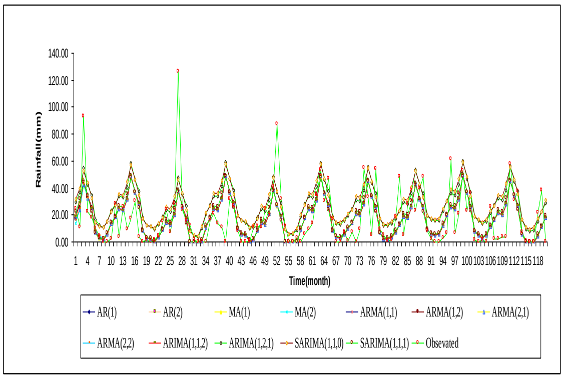

Fig. 5. Models prediction versus observed data in Golmakan station.

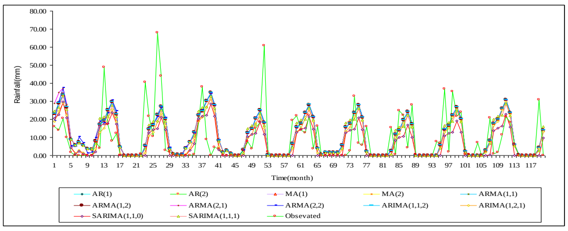

Fig. 6. Models prediction versus observed data in Gonabad station.

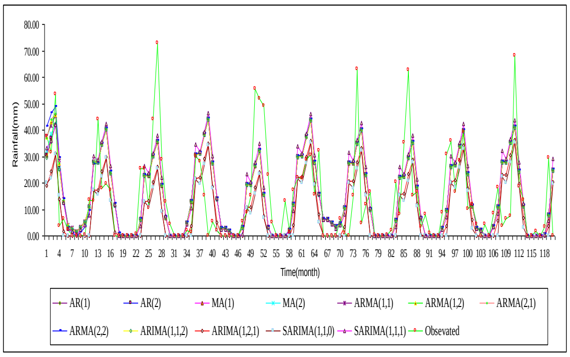

Fig. 7. Models prediction versus observed data in Kashmar station.

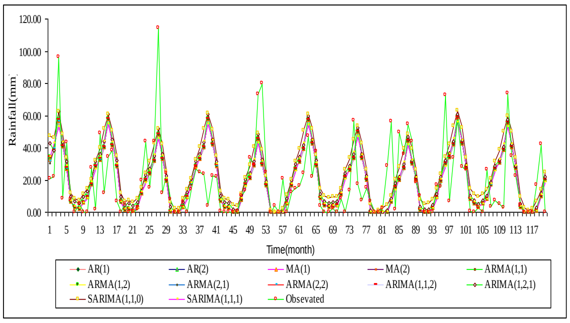

Fig. 8. Models prediction versus observed data in Mashhad station.

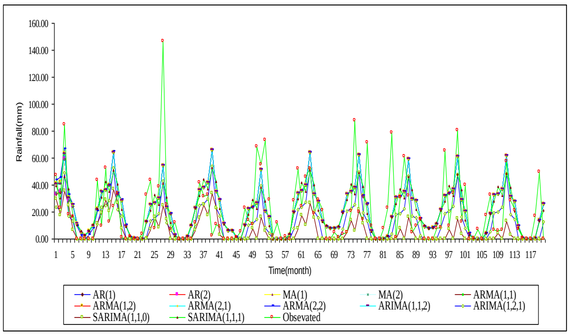

Fig. 9. Models prediction versus observed data in Nyshaboor station.

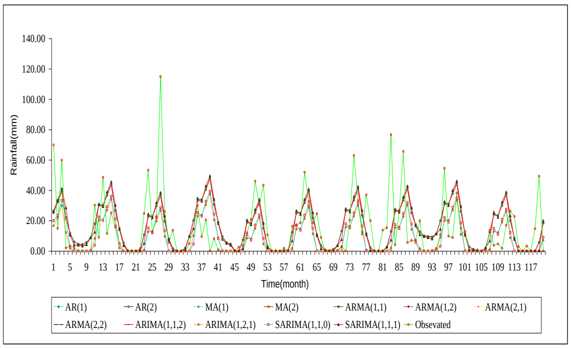

Fig. 10. Models prediction versus observed data in Sabzevar station.

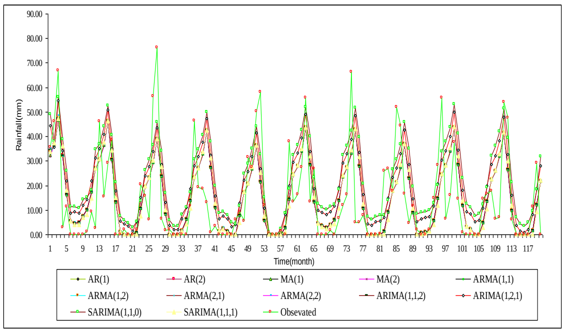

Fig. 11. Models prediction versus observed data in Sarakhs station.

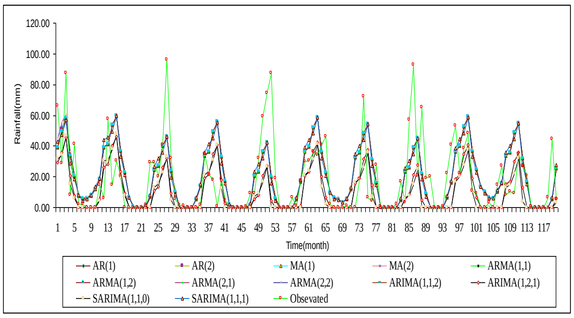

Fig. 12. Models prediction versus observed data in Torbate Hydarie station.

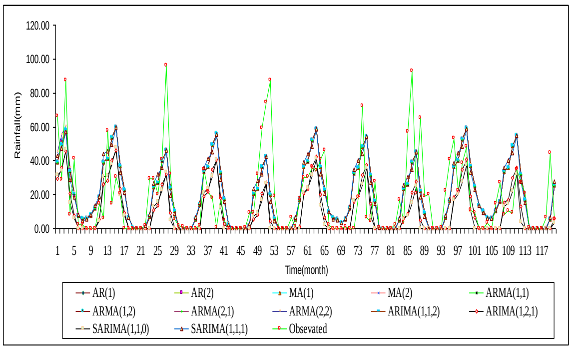

Fig. 13. Models prediction versus observed data in Torbate Jam station.

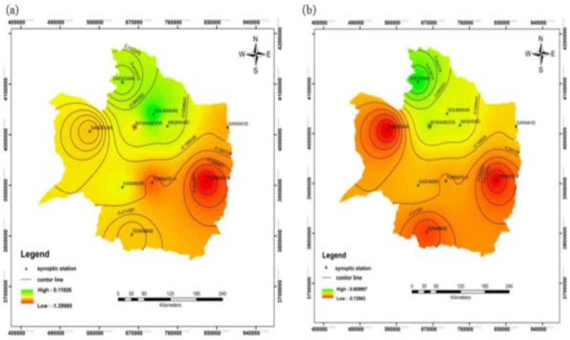

Fig. 14 (a,b). Simulated and predicted of iso- rainfall maps in 2014 and 2024.

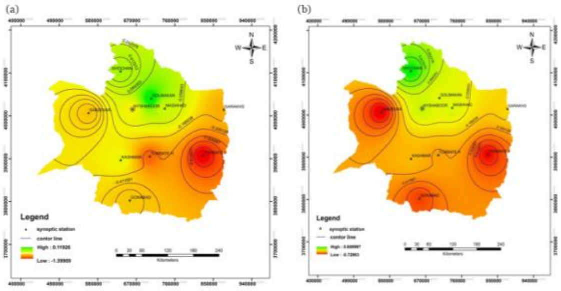

Fig. 15 (a,b). Drought simulation and prediction using SPI index in 2014 and 2024.

Discussion

The highest rainfall in 10 rain gauge stations was simulated during 2003 to 2014 using R software according to monthly highest rainfall data (1985 to 2003). Time series data have 4 components (trend, seasonal, jump and random) (Fig. 2). According to the deterministic nature of trend, seasonal and jump components, the modeling process has been run for stochastic model component at random based on AR, MA and ARMA; however, random components' modeling is a highly important hydrological modeling that uses stochastic models especially for AR, MA and ARMA. Thus, there was a decomposition of the time series and a modeling of the random component in these models. Nevertheless, for ARIMA and SARIMA, models fitted the original time series.

In this study, five (5) models with 12 different structures were examined. According to the results, the highest rainfall data showed a seasonal trend before removal of deterministic components of the data (Fig. 2). From the research by Nirmala and Sundaram (2010), it is possible to determine the best model using ACF and PACF (Fig. 3a, b), however for a more accurate prediction, the Akaike criterion and correlation coefficient were also used for model selection. The ACF and PACF of selected series showed the seasonal behavior of the monthly rainfall. The observations revealed that in Ghoochan, Golmakan, Gonabad, Kashmar, Mashhad, Neyshaboor, Sabzevar and Torbate Jam stations, the ARMA (2,1) model displayed better performance than the other models, however, for Sarakhs and Torbate Heydarieh the ARMA(2,2) shows a more suitable results (more square R and low AIC) (Table 2 and Figs. 4 to 13). In determining the best models, some of the models were eliminated due to violation of model parameters from absolute value (Table 2). Based on the results these models show a low R^2 in comparison to the other models. To ascertain the best models in time series, it is imperative that the models are assessed based on Akaike and correlation coefficient using the ACF and PACF graph. The studies show a wide range of results for determining the best time series model as the data used varies (Saeidian and Ebadi, 2004; Soltani *et al.*, 2007; Javidi Sabbaghian and Sharifi, 2009; Khadar *et al.*, 2011; Mansour *et al.*, 2011; Schaars *et al.*, 2012 ; Poormohammadi *et al.*, 2013; Said *et al.*, 2013; Mirzavand and Ghazavi, 2015). Hence, it is essential that the all-time series models for any area and any hydrological parameters are assessed in the course of determining the best model for our subjects. Finally, it can be expressed that the time series models can be used in forecasting the highest rainfall up to the next 120 months (2014 to 2024) with an acceptable accuracy (as presented in Figs. 4 to 13). It is also possible that the assertion that time series models are fast to compute, easier to model, easier to identify changes in trends, random, jumps and seasonal components of rainfall is correct. Based on the simulation and prediction of rainfall for 2014 and 2024, iso-rainfall maps were drawn (Fig. 14a, b). To assess cases of future drought in Khorasan Razavi province, the SPI index was used. The SPI index for 2014 revealed that 83.8% of the area has near normal situation while 16.2% are experiencing moderate drought situation (Table 3).

However, according to the forecasted time series data in 2024 obtained by means of stochastic models, the SPI index was used and the result revealed that 100% of the area is in near normal situation (Table 3). This means that by the end of 2024 there will have been considerable decrease in severity of drought in some areas. Consequently, according to the results, prediction of future drought situation with time series prediction using SPI, could help to better understand and make informed decisions for management of water resources in such areas in the future.

Conclusion

This research aimed to assess use of the time series models (AR, MA, ARMA, ARIMA and SARIMA) in predicting future rainfall as well as assessment of drought situation in the future using SPI index. The results reveal that the best model for forecasting rainfall in the next 120 months is ARMA (2,1) (in 80% of data). With use of the SPI index, drought severity will have decreased considerably by the end of 2024 than in 2014. The use of time series model for rainfall prediction and assessment of drought situation according to the predicted rainfall data could furnish a water resources manager with better understanding and management of water resources in the future especially in arid and semi-arid environments.

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