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# Comparative Study Among Different Time Series Models for Monthly Rainfall Forecasting in Shiraz Synoptic Station, Iran

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## Abstract
In this research, monthly rainfall of Shiraz synoptic station from March 1971 to February 2016 was studied using different time series models by ITSM Software. Results showed that the ARMA (1,12) model based on Hannan-Rissanen method was the best model which fitted to the data. Then, to assess the verification and accuracy of the model, the monthly rainfall for 60 months (from March 2011 to February 2016) was forecasted and compared with the observed rainfall values in this period. The determination coefficient of 99.86 percent ($R^2$=0.9986) and positive correlation ($P<0.05$) between the observed data and the predicted values by the ARMA (1,12) model illustrates the goodness of this model in prediction. Finally, based on this model, monthly rainfall values were predicted for the next 60 months that the model had not been trained. Results showed the forecasting ability of the chosen model. So, it can conclude that the ARMA (1,12) model is the best-fitted model overall.

**Keywords:** ARMA, Forecasting, Rainfall, Shiraz, Time Series.

## 1. Introduction
Assessment and prediction of various weather and climatic parameters are vital in irrigation scheduling. Due to climate change, understanding of changes in evaporation, rainfall, drought, etc. is critical for long term agricultural and environmental planning (Hooshmand et al. 2013; Salari et al. 2015; Bahrami et al. 2018). Rainfall is the result of many complex physical processes inducing particular features and make its observation complex. The investigation and analysis of precipitation is so essential for climatic information forecast (Radhakrishnan and Dinesh 2006; Bahrami et al. 2014), and accurate forecasting of precipitation is extremely important for proper mitigation and management of floods, droughts, environmental flows, water demand by different sectors, maintaining reservoir levels, and disasters, particularly in arid environment (Feng et al. 2015; Sadeghian et al. 2016).

In recent decades, several methods which have been used as suitable tools for modeling and forecasting the climatic information such as precipitation were basically linear, conceptual and statistical models (Dastorani et al. 2016). Among the methods, time series modeling is an important method in simulation, prediction and decision making of hydrology cycle components (Dastorani et al. 2016).

A time series is a set of observations x, each one being recorded at a specific time t. A discrete-time time series is one in which the set

$T_0$ of times at which observations are made is a discrete set, as is the case, for example, when observations are made at fixed time intervals.

This method is used to describe data using graphical and statistical techniques, to designate the best statistical models to describe the data generating process, to predict the future amounts of a series and controlling a given process (Dastorani et al. 2016).

Time series models building contains three steps: identification, assessment and error detection (Shirmohammadi et al. 2013).

The assumption in time series analysis is that data consists of a systematic pattern (usually an identifiable component set) and random noise (error) which usually makes the pattern difficult to identify. Time series analysis methods usually import some method of filtering out noise in order to make the pattern more salient (Meher and Jha 2013).

Many scientists have used time series theory to address hydrological problems (Gorman and Toman 1966; Salas et al. 1980; Bras and Rodriguez- Iturbe (1985); Galeati 1990; Lin and Lee 1992; Lall and Bosworth 1993; Hsu et al. 1995; Dastorani et al. 2016; Davidson et al. 2003).

Meher and Jha (2013) developed a univariate time series autoregressive integrated moving average (ARIMA) model for (a) simulating and forecasting mean rainfall over the Mahanadi River Basin in India at 38 rain-gauge stations in district towns across the basin.

Farajzadeh et al. (2014) used Feed-forward Neural Network and Autocorrelation Regressive Integrated Moving Average (ARIMA) models to forecast the monthly rainfall in Urmia lake basin.

Mirzavand and Ghazavi (2015) used several time series models to find the best model to forecast the ground-water level fluctuation.

Dastorani et al. (2016) investigated the ability of different time series models including autoregressive (AR), moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), and seasonal autoregressive integrated moving average (SARIMA) in forecasting monthly rainfall for nine rainfall stations in North Khorasan province.

Weesakul and Lowanichchai (2005) applied the ARIMA model to forecast annual rainfall at 31 rainfall stations in Thailand. Mahsin et al. (2012) used a seasonal ARIMA model to forecast monthly rainfall in the Dhaka Division of Bangladesh.

Modeling the climatic time series based on statistical models has confirmed by many researchers because these models are the appropriate selection for the area where nothing but the meteorological time series data is available (Dastorani et al. 2016). Statistical models like the Markov, Box-Jenkins (BJ), SARIMA, ARMA, periodic autoregressive (PAR), transfer function-noise (TFN) and periodic transfer function-noise (PTFN) are used for these aims (Box 1994; Brockwell and Davis 2010; Mirzavand and Ghazavi 2015; Dastorani et al. 2016). Several usages of these approaches have been accepted to be very beneficial techniques to forecast the rainfall data over time in many types of research (Radhakrishnan and Dinesh 2006; Soltani et al. 2007; Willems 2009; Mair and Fares 2011; Dutta et al. 2012; Dastorani et al. 2016). The selection of an appropriate method for modeling and forecasting a phenomenon depends on various parameters such as data accuracy, time, cost, easiness of application of the model's results, explanation of results and etc. (Mondal and Wasimi 2007; Dastorani et al. 2016).

In many studies, the time series models applied to simulate and forecast the precipitation but comparison of statistical time series models like AR, MA, ARMA, ARIMA, and SARIMA for rainfall forecasting was not reported. Therefore, the main goal of this research was to evaluate these models capability for rainfall forecasting in a semi-arid climate condition.

## 2. Materials and Methods

### Study Area

Shiraz station located in the south of Iran with geographical longitude: $52^{o}$ 36′ E, geographical latitude: $29^{o}$ 32′ N, and altitude:

1484 m (Fig. 1). Shiraz County has an area of 1268 km$^2$. According to De Martonne aridity index, the climate of the study area is semi-arid. The mean annual temperature is about 18 degrees Celsius and the annual rainfall is 346 mm, which is mostly concentrated in the winter months. In order to provide the data for modeling, monthly rainfall data of the station gathered from 1971 to 2016. We made time series plots and computed basic statistics to understand the statistical variations, trends, and seasonality at the synoptic station (Fig. 2).

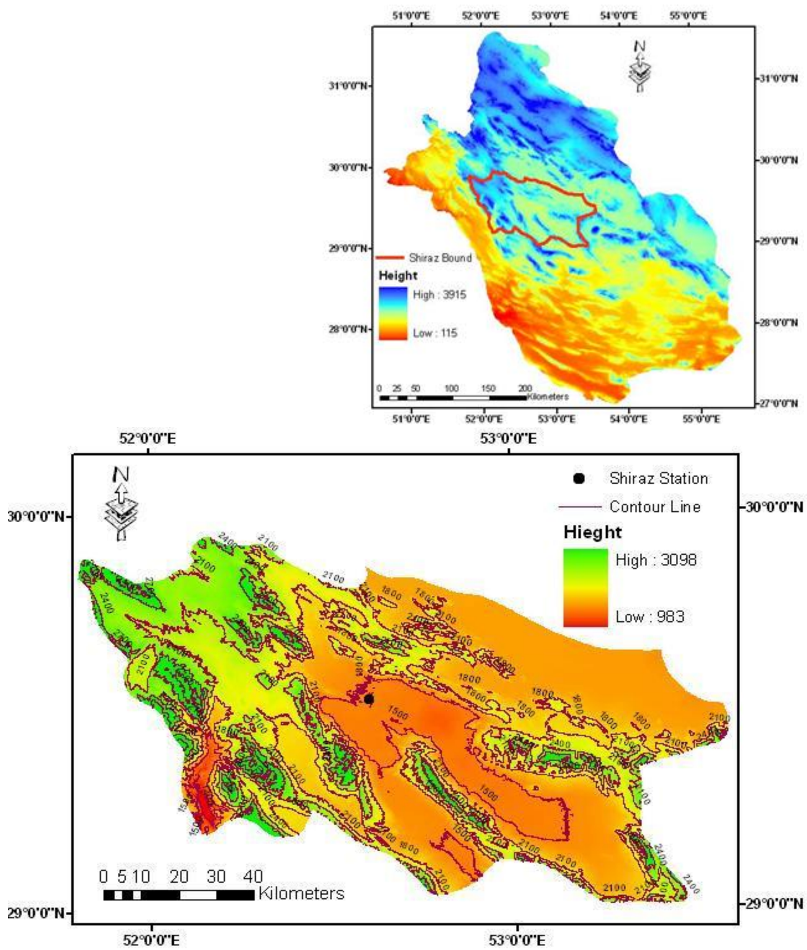


**Fig. 1.** A schematic map of the selected rainfall station

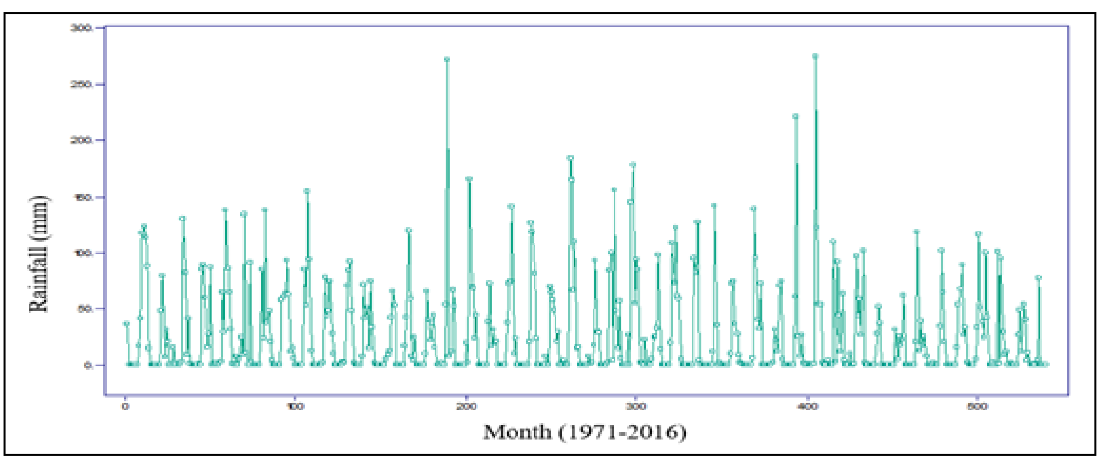


**Fig. 2.** Monthly rainfall data for Shiraz synoptic station

## Time series models

Universally, the data of time series models can have various shapes and represent various non-deterministic processes (Dastorani et al. 2016). Utmost modeling of time series happens based on a linear method. AR, MA, and ARMA methods have a linear basis (Mirzavand and Ghazavi 2015; Dastorani et al. 2016). In the present study, AR, MA, and ARMA models tested and applied to evaluate the capability of these models in monthly rainfall forecasting using ITSM Software.

## AR model

In the series where continuity is existent, that is the event outcome of $(t+1)^{th}$ the period is dependent on the existent $t^{th}$ period value and those past magnitudes, then for such a series, the observed sequences $X_1, X_2, \ldots, X_t$ is applied to fit an AR model.

Autoregressive model represented as Eq. (1):

$$X_t = \varnothing_1 X_{t-1} + \varnothing_2 X_{t-2} + \ldots + \varnothing_p X_{t-p} + Z_t \quad (1)$$

Where $\varnothing_1, \varnothing_2, \ldots, \varnothing_p$ are model coefficients and $Z_t$ is the random component of the data that pursues a random distribution with mean equal 0. Also, $Z_t$ is uncorrelated with $\{X_s: s < t\}$. (Dastorani et al. 2016).

## MA model

Moving average model is simple covariance stationary and ergodic model can be used for a vast diversity of autocorrelation patterns (Dastorani et al. 2016). Moving Average model represented as Eq. (2):

$$X_t = Z_t + \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + \ldots + \theta_q Z_{t-q} \quad (2)$$

Where $\theta_1, \theta_2, \ldots, \theta_q$ are model coefficients and $Z_t$ is the random component of the data that pursues a random distribution with mean equal 0 (Mirzavand and Ghazavi 2015; Dastorani et al. 2016).

## ARMA model

The ARMA model is a combination of an AR and an MA model. ARMA model forms a type of linear models, which are vastly suitable and advantageous in parameterization. ARMA $(p, q)$ model represented as Eq. (3):

$$X_t = \varnothing_1 X_{t-1} + \varnothing_2 X_{t-2} + \ldots + \varnothing_p X_{t-p} + Z_t + \theta_1 Z_{t-1} + Z_2 \theta_{t-2} + \ldots + \theta_q Z_{t-q} \quad (3)$$

Where $\varnothing_i$ is the $i^{th}$ autoregressive coefficient, $\theta_j$ is the $j^{th}$ moving average coefficient, it demonstrates the error part at time period $t$, and $Z_t$ refers the magnitude of rainfall observed or forecasted at time period $t$ (Mirzavand and Ghazavi 2015; Dastorani et al. 2016).

There are four phases in identifying patterns of time series data. The first is to analyze and represent the properties of time series data, the second is to calculate and represent the properties of time series models, and the third is to synthesize these functions in order to fit models to data. The last phase contains controlling that the properties of the fitted model collate those of the data in a proper status. After finding an appropriate model, we used it in conjunction with the data to predict the future values of the series.

## Model selection

To specify the best model among the class of plausible models, we used partial autocorrelation function (PACF), autocorrelation function (ACF) (Mirzavand and Ghazavi 2015), the Corrected Akaike Information Criterion (AICC) proposed by Akaike (1974), and coefficient of determination ($R^2$). After consideration of ACF and PACF values, the model which had the minimum AICC value was considered as the best model for the Shiraz rainfall analysis. Also, there are some other model-choosing statistics in ITSM 2000, such as BIC statistic. Actually, the BIC statistic (Schwarz 1978) is a Bayesian modification of the AICC statistic. The BIC is considered at the same time and applied in the same way as the AICC. Each information statistic represented as:

$$\mathrm{AICC}_{p,q} = \mathrm{N} \log \hat{\sigma}_{\varepsilon}^2 + \frac{2rN}{(N-r-1)} \quad (4)$$

$$BIC_{p,q} = N \log \hat{\sigma}_{\varepsilon}^{2} + r \log N \tag{5}$$

Where $\hat{\sigma}_{\varepsilon}^{2}$ is the maximum likelihood estimator of $\sigma_{\varepsilon}^{2}$, and $r = p+q+1$ is the number of parameters estimated in the model, including a constant term. The second term in the first two equations is a penalty for increasing $r$. Therefore, the best model is the model adequately describes data and has fewest parameters.

## 3. Results and Discussion

Total of 540 samples obtained during the period of 1971- 2016 were used for the time series analysis of the Shiraz mean rainfall. Fig. 2 shows that the variance of data is not stable. Also, the ACF and PACF plots of the original data, as presented in Fig. 3, indicates that the rainfall data reflects a seasonal cycle of period 12.

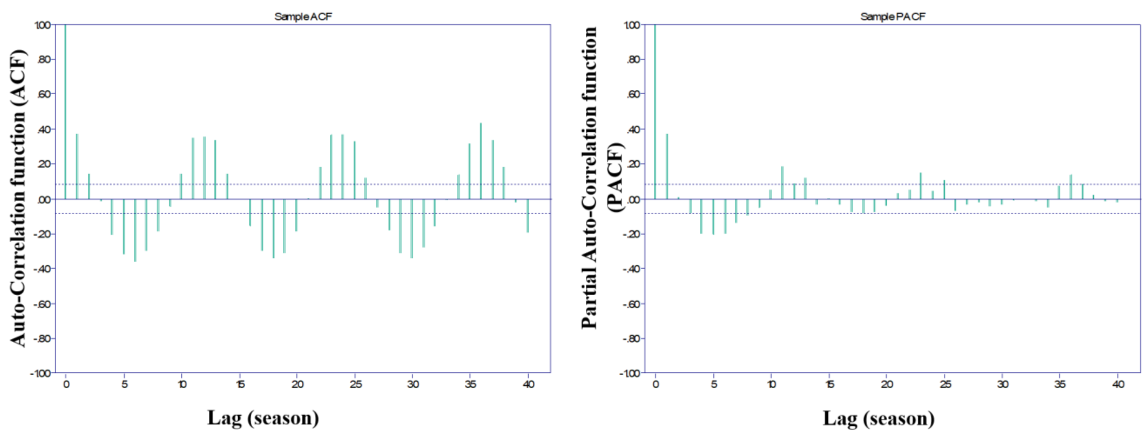


**Fig. 3.** (Left): Autocorrelation (ACF); (Right): Partial Autocorrelation (PACF) for original rainfall data

In order to fit time series models, a stationary series is needed. If a time series has stable variance and do not have trend and seasonality components, it will be stationary. Because of non-stationarity, we tried to transform the original dataset to a stationary time series. A Box-Cox power transformation ($\lambda$=-0.9) was used to the dataset to establish the stability of the variance of the time series. Also, to remove the seasonality component of period 12, the difference operator of lag 12 ($\nabla_{12}$, were defined by $\nabla_{12} W_t = W_t - W_{t-12}$) was done.

The ACF and PACF plots for the differenced series were obtained again to investigate the stationary (Fig. 4). The figure confirms that the ACF and PACF plots for the differenced and deseasonalized rainfall data were nearly stable.

To choose the best model among the AR, MA, and ARMA models, the AICC and BIC were used. The results gained from time series models with minimum AICC and BIC in Shiraz synoptic station are shown in Table (1).

According to the results in Table (1), and regarding to the principle of parsimony, by which the best model is the one which has fewest parameters among all models that fit the data, the ARMA (1,12) model which had the low AICC and BIC values and also is the one which has fewest parameters among all models that fit the data was considered as the best model for Shiraz synoptic station rainfall analysis.

Then to make sure that ARMA (1,12) model is representative for the studied data and could be applied to predict the upcoming rainfall data, the goodness of fit was evaluated for this model using different indices. For this purpose, homogeneity, residuals randomness, model validation to forecast, and comparing ACF and PACF of original and fitted data were investigated.

The result of the Ljung-Box statistic test (p>0.05) implies the randomness and homogeneity of residuals. According to Fig. (5), the maximum 5% of the amount of ACF /

PACF remaining outside the scope of zero (dotted lines) which indicates the suitability of the selected model.

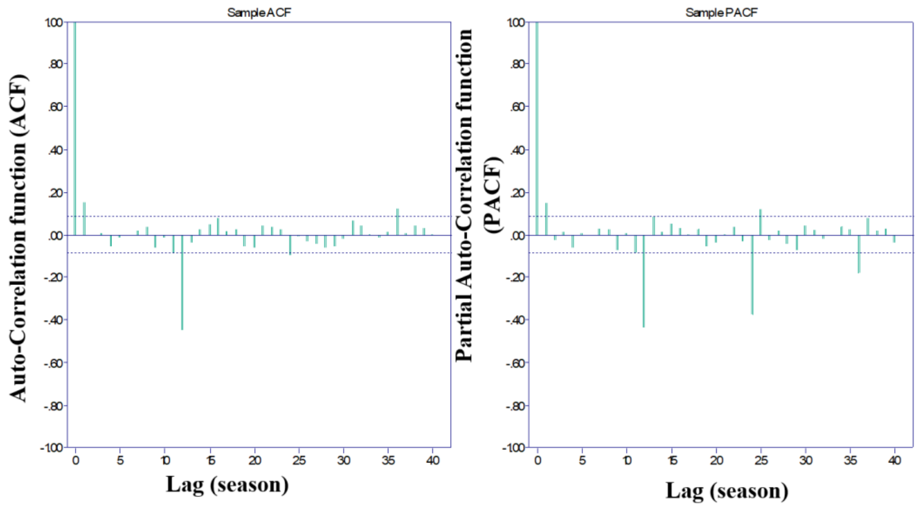


**Fig. 4.** ACF (left) and PACF (right) plots after transformation and differencing

**Table 1.** Time series models with minimum AICC and BIC

| Model | Method | Order | Equation | AICC | BIC |
|---|---|---|---|---|---|
| AR | Y-W | 25 | X(t) = 0.1670 X(t-1) - 0.6626 X(t-12) + 0.1244 X(t-13) - 0.4214 X(t-24) + 0.09345 X(t-25) + Z(t) | -2062.33 | -2056.63 |
| | Burg | 25 | X(t) = 0.1675 X(t-1) - 0.6623 X(t-12) + 0.1251 X(t-13) - 0.4212 X(t-24) + 0.09395 X(t-25) + Z(t) | -2062.33E | -2056.62 |
| MA | H-R | 12 | X(t) = Z(t) + 0.1332 Z(t-1) - 0.9612 Z(t-12) | -2095.16 | -2231.32 |
| | I | 12 | X(t) = Z(t) + 0.1332 Z(t-1) - 0.9613 Z(t-12) | -2095.16 | -2231.36 |
| **ARMA** | H-R | (1,1) | X(t) = 0.1515 X(t-1) + Z(t) - 0.004359 Z(t-1) | -1846.87 | -1849.47 |
| | I | (1,1) | X(t) = 0.006144 X(t-1) + Z(t) + 0.1472 Z(t-1) | -1847.26 | -1849.47 |
| | **H-R** | **(1,12)** | **X(t) = 0.1681 X(t-1) + Z(t) - 1.000 Z(t-12)** | **-2102.40** | **-2253.15** |
| | H-R | (1,13) | X(t) = Z(t) – 1.000 Z(t-12) | -2089.44 | -2244.28 |
| | H-R | (1,24) | X(t)=0.1774 X(t-1)+Z(t)- 0.07345 Z(t-6)- 1.180 Z(t-12)+ 0.1176 Z(t-24) | -2144.40 | -2266.30 |
| | H-R | (1,25) | X(t)= 0.1729 X(t-1)+ Z(t) + 0.07487 Z(t-6)- 0.9936 Z(t-12)+ 0.03467 Z(t-20) + 0.03402 Z(t-24) | -2144.71 | -2177.96 |
| | H-R | (2,1) | X(t) = 0.1503 X(t-1) +Z(t) | -1848.91 | -1849.47 |
| | I | (2,1) | X(t) = - 0.4203 X(t-1) + 0.06454 X(t-2) + Z(t)+0.5736 Z(t-1) | -1845.73 | -1849.47 |
| | H-R | (2,12) | X(t) = Z(t) – 1.000 Z(t-12) | -2089.44 | -2244.28 |
| | H-R | (2,13) | X(t)= Z(t) – 1.000 Z(t-12) | -2089.44 | -2244.28 |
| | H-R | (2,24) | X(t) = 0.1772 X(t-1) + Z(t) - 0.07237 Z(t-6) – 1.182 Z(t-12) + 0.1184 Z(t-24) | -2144.40 | -2266.99 |
| | H-R | (2,25) | X(t) = 0.1779 X(t-1) +Z(t) - 1.144 Z(t-12) +0.1441 Z(t-24) | -2139.30 | -2244.11 |

Y-W: Yule-Walker; H-R: Hannan-Rissanen; I: Innovations

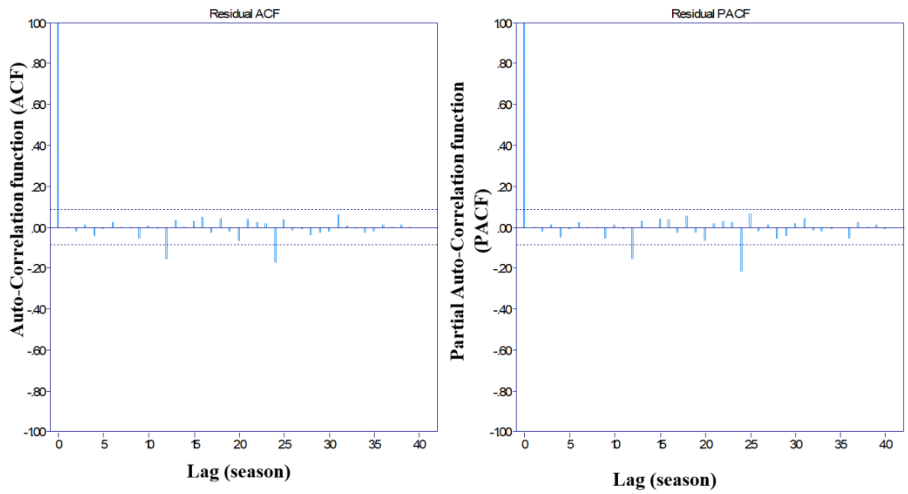


**Fig. 5.** (a): Autocorrelation (ACF) (b): Partial Autocorrelation (PACF) for residual errors resulted from ARMA (1,12) model

Also, the ACF / PACF plots of original and fitted data are very close together, which confirms the goodness of fit (Fig. 6).

These conclude that ARMA (1,12) model is proper to demonstrate the studied data and could be applied to predict the upcoming rainfall data.

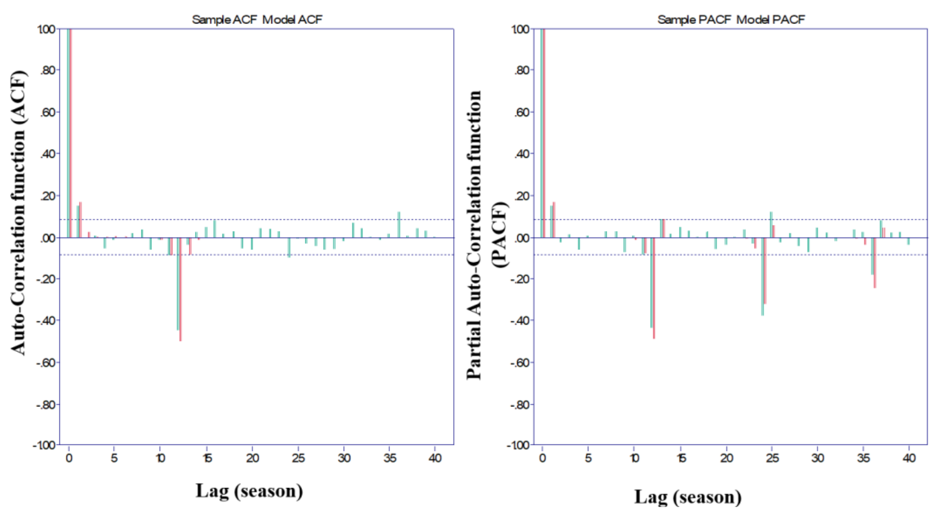


**Fig. 6.** Comparison of autocorrelation (ACF) and partial autocorrelation (PACF) plots of data sets and ARMA (1, 12) model

So, the ARMA (1,12) model was tested for its validity. The fitted model was applied to predict the last 60 observations (March 2011 to February 2016) based on the previous 480 observations (March 1971 to February 2011). The results obtained using the fitted model are shown in Fig. (7-8).

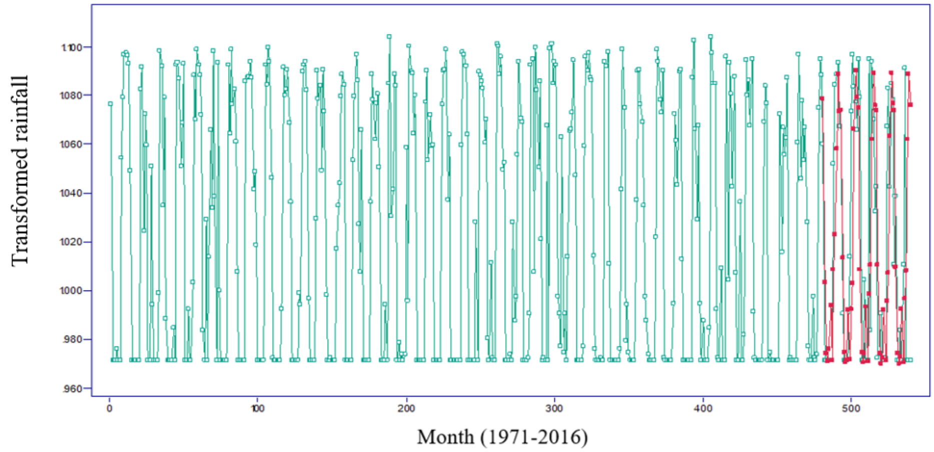


**Fig. 7.** Forecasting of transformed rainfall using ARMA (1, 12) model

Coefficient of determination value of 99.86 percent ($R^2$ = 0.9986) and positive correlation ($P$<0.05) between the original data and predicted values indicate the appropriateness of the model to forecast (Fig. 8).

From the results presented in this study, it is apparent that the chosen model should be sufficiently accurate to forecast rainfall in this region.

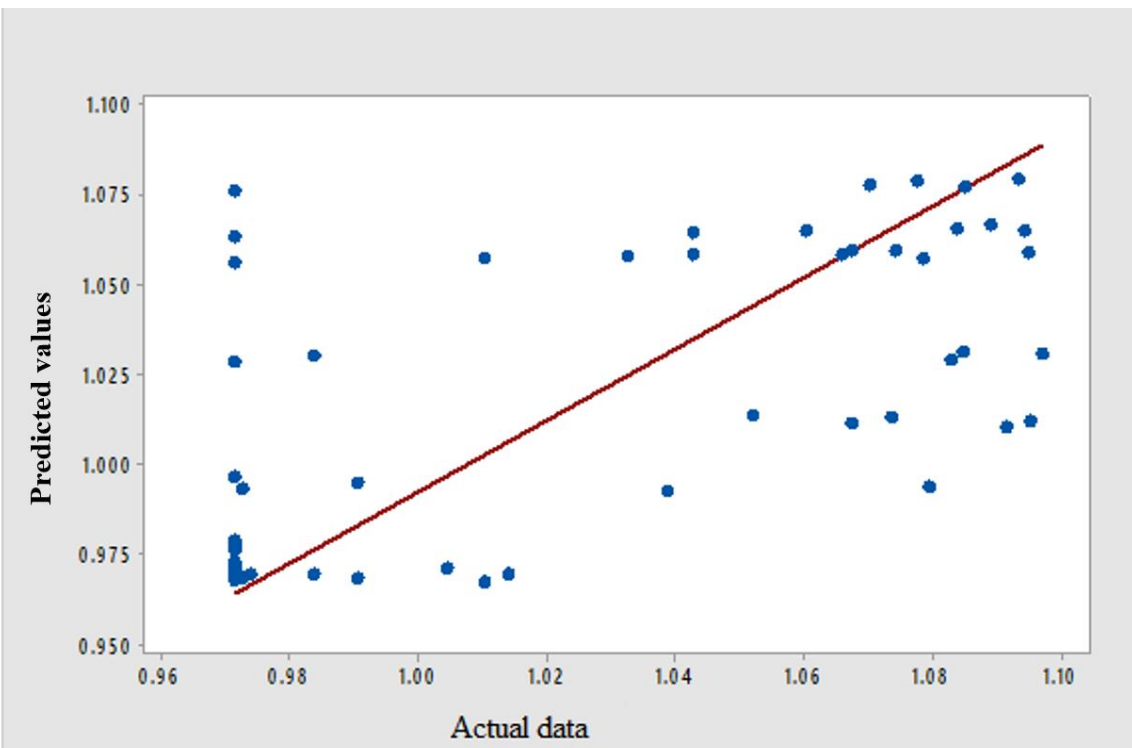


**Fig. 8.** Comparison of original data and predicted values by ARMA (1,12) model

Finally, based on the ARMA (1,12) model, the values for the next 60 months (March 2016 to February 2021) were forecasted. The obtained results in Fig. (9) and Table (2) show that the seasonal drought seasons in 50% of the predicted normal conditions, 29 percent moderate and 21 percent seasons wet weather conditions will be mild drought conditions.

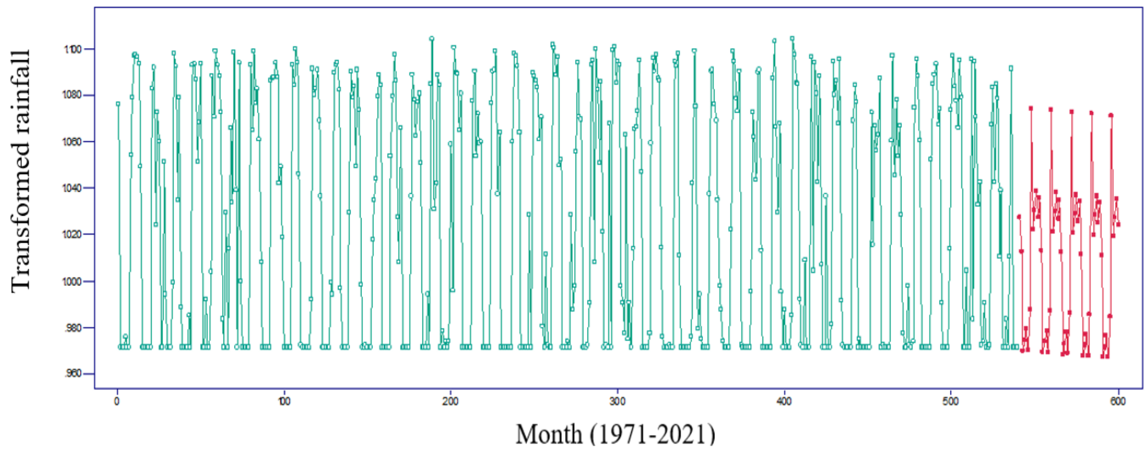


**Fig. 9.** Forecasting transformed monthly rainfall in Shiraz synoptic station from March 2016 to February 2021

**Table 2.** The predicted monthly rainfall using the ARMA (1,12) in 2016-2021

| Month and Year | Prediction (mm) | Month and Year | Prediction (mm) | Month and Year | Prediction (mm) | Month and Year | Prediction (mm) |
|---|---|---|---|---|---|---|---|
| Mar 2016 | 7.6 | Jun 2017 | 0.2 | Sep 2018 | 1.3 | Dec 2019 | 7.9 |
| Apr 2016 | 4.7 | Jul 2017 | 0.6 | Oct 2018 | 31.8 | Jan 2020 | 10.0 |
| May 2016 | -0.1 | Aug 2017 | -0.1 | Nov 2018 | 6.2 | Feb 2020 | 7.1 |
| Jun 2016 | 0.3 | Sep 2017 | 1.4 | Dec 2018 | 8.1 | Mar 2020 | 9.3 |
| Jul 2016 | 0.7 | Oct 2017 | 32.8 | Jan 2019 | 10.3 | Apr 2020 | 4.5 |
| Aug 2016 | -0.1 | Nov 2017 | 6.4 | Feb 2019 | 7.3 | May 2020 | -0.3 |
| Sep 2016 | 1.5 | Dec 2017 | 8.3 | Mar 2019 | 9.5 | Jun 2020 | 0.0 |
| Oct 2016 | 33.8 | Jan 2018 | 10.5 | Apr 2019 | 4.6 | Jul 2020 | 0.4 |
| Nov 2016 | 6.5 | Feb 2018 | 7.5 | May 2019 | -0.3 | Aug 2020 | -0.3 |
| Dec 2016 | 8.4 | Mar 2018 | 9.7 | Jun 2019 | 0.1 | Sep 2020 | 1.2 |
| Jan 2017 | 10.7 | Apr 2018 | 4.7 | Jul 2019 | 0.5 | Oct 2020 | 30.1 |
| Feb 2017 | 7.7 | May 2018 | -0.2 | Aug 2019 | -0.3 | Nov 2020 | 5.9 |
| Mar 2017 | 9.9 | Jun 2018 | 0.1 | Sep 2019 | 1.3 | Dec 2020 | 7.7 |
| Apr 2017 | 4.9 | Jul 2018 | 0.5 | Oct 2019 | 31.0 | Jan 2021 | 9.8 |
| May 2017 | -0.2 | Aug 2018 | -0.2 | Nov 2019 | 6.1 | Feb 2021 | 7.0 |

## 4. Conclusion

A method of forecasting the future monthly rainfall by applying time series modeling method was presented in this research. A dataset occurred from 1971 to 2016 were used for time series analysis. Model validation results based on 60 months obtained for the years 2011-2016 were successful for the proposed method. Then, the forecasting results for the upcoming 60 months during the years 2017 to 2021 were considered to be excellent and accurate. Therefore, we conclude that the ARMA (1,12) model is the best-fitted model overall. This will certainly assist policy makers and decision makers to establish strategies, priorities and proper use of water resources in Shiraz.

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