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Rainfall forecast of Kashan in Iran using time series models

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Abstract. The most important part of the hydrological cycle is precipitation. The study aimed to forecast rainfall with a time series model. Many studies have been done, but we want to predict annual rainfall in Kashan. Annual rainfall of 53 years was collected from Kashan (office of Meteorology) from spring 1967 to winter 2019. We predicted the amount of annual rainfall from 2020 to 2023. The method of data analysis is that the time series models are fitted to the data using statistical package for the social science (SPSS) statistical software (also, we used R and MINITAB software). The average annual rainfall is 133.70mm with a standard deviation of 49.32mm. The best model is $ARIMA(0,0,1)$. In the selected model, the AIC and BIC are equal to 564.64 and 570.55, respectively. Our prediction results show a significant drop in rainfall in these four years. Since Kashan is one of the arid and semi-arid regions, we will face the problem of water shortage, so water consumption must be saved.

Keywords: Environmental Sciences, Prediction, Hydrological Variables, The ARIMA Models, Water Shortage.

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1. Introduction

Many of the most important applications of time series methods have been to problems in the environmental sciences. More modern research may focus on whether warming is present in global temperature measurements or whether pollution levels may affect daily mortality in a particular country. Precipitation is the foremost fundamental portion of the hydrology cycle [27]. It is the result of many complex physical processes that persuade particular features and make its observation complex [2]. The investigation and analysis of precipitation are so necessary for the prediction of meteorological data [26], and accurate anticipation of rainfall is vital to better management of water resources, especially in the arid environment [31].

Iran is in the mid-latitude belt of arid and semi-arid areas of the Earth. The arid and semi-arid regions cover more than 60% of the country. In this agropastoral transition region, the rains are highly variable in time, space, amount, and duration, and water is the most critical limiting factor for biological and agricultural activities. Seasonal changes in rainfall patterns may alter the hydrological cycle and environmental processes [9] as well as the vegetation and the entire ecosystem [18, 25].

Being in arid and desert areas has caused the amount of rainfall in some periods to be lower than the long-time annual average, so that in 13 of the last 23 years, this situation has occurred in the country. In the Kashan plain, due to the prevailing dry and semi-arid climate, the plain is prone to drought and floods. The occurrence of prolonged and intermittent droughts and high climatic fluctuations are the leading causes of water scarcity, especially surface water resources, which puts additional pressure on groundwater resources [14].

In the last decades, many techniques have been used as suitable tools for modeling and forecasting meteorological information, such as precipitation [8, 31, 34]. In these techniques, time series modeling is an essential technique in simulation, prediction, and decision making of hydrology cycle components [10, 16, 28, 34]. A time series is an observation of a variable at discrete time periods (usually equal distances) that measured and sorted according to time [25]. This technique is used to explain data using statistical and graphical methods, to select the best statistical models to explain the data generating process, to predict the future amounts of a series and, to control a given process [6].

Tularam and Ilahee [36], applied time series analysis for rainfall and temperature interactions in coastal catchments of Queensland, Australia. They suggested that, the ARIMA model is appropriate for the prediction of these series. Eni [12], applied the SARIMA modeling for the forecast of rainfall in Warri town, Nigeria. The $ARIMA(1,1,1)(0,1,1)$, 12 models fitted to this series with an AIC value of 281. Model adequacy checks showed that the model was appropriate. The coefficient of the fitted model was finalized by the residual tests. Wang et al. [37], used the improved the ARIMA model to predict the monthly precipitation at the Lanzhou station in Lanzhou, China. The results showed that the accuracy of the improved model is significantly higher than the seasonal model. Mahsin [21], used Box-Jenkins methodology [5] to build a SARIMA model for monthly rainfall data taken for Dhaka station for the period 1981-2010 with a total of 354 readings. Mirmousavi et al. [22], studied precipitation behavior in Khoi meteorological stations using statistical methods. They found that the $ARIMA(1,1,0)$ model was the best fitted to annual precipitation. Based on this model, annual precipitation was predicted at a 95 percent level by 2016 in this station. During recent decades, several researchers have developed methods of analyzing stochastic characteristics of rainfall time series [1, 3, 29, 34, 35].

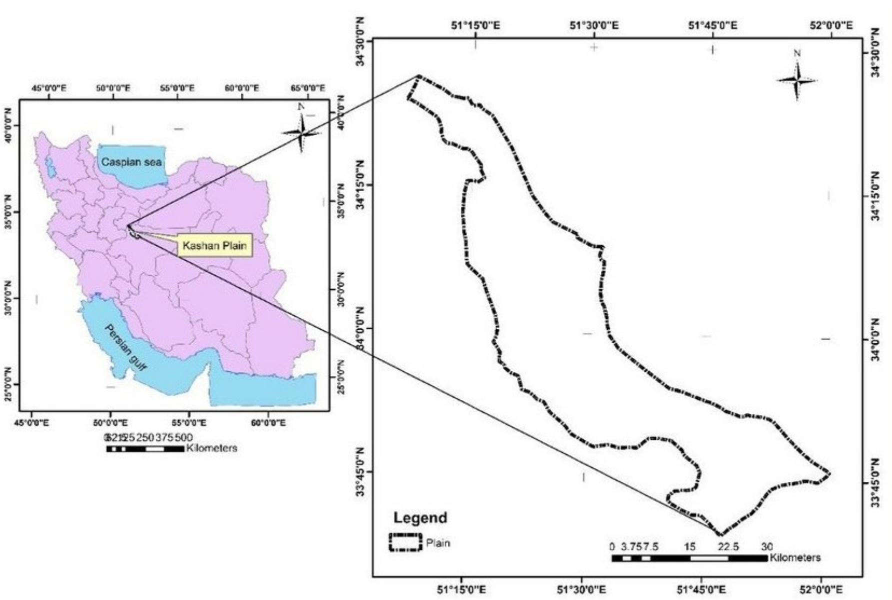

Figure 1. Spatial location of the selected rainfall station

Many studies have been done, but we want to predict annual rainfall in Kashan. The objective of this study was modeling and prediction of the annual rainfall data of Kashan in Iran by stochastic the ARIMA model using Box-Jenkins approach [5] to predict future rainfall values by the best ARIMA model and identify whether the annual rainfall had significantly changed during the period 2020 to 2023. Besides, the ARIMA models, which were found adequate, were used to predict the seasonal rainfall for the coming four years to help decision-makers to establish priorities in terms of water demand management.

2. Study area

Kashan territory is found within the northern portion of Isfahan area, Iran, with geographical longitude: 51.4100°E, and geographical latitude: 33.9850°N (Figure

Table 1. The amount of annual rainfall from 1967 to 2019

Years	Rainfall(mm)				
	Spring	Summer	Fall	Winter	Annual
1967	23.90	0.60	7.20	72.60	104.30
1968	58.20	0.30	44.30	122.50	225.30
1969	25.80	4.60	9.80	86.40	126.60
1970	27.00	0.00	19.00	33.90	79.90
1971	32.00	0.40	67.10	126.00	225.50
1972	106.40	5.00	18.00	37.50	166.90
1973	6.40	0.00	4.00	128.00	138.40
1974	47.00	2.00	20.80	25.00	94.80
1975	32.90	0.00	50.00	57.10	140.00
1976	71.00	0.00	31.30	68.30	170.60
1977	92.10	1.20	25.50	37.20	156.00
1978	5.20	0.00	65.10	38.60	108.90
1979	41.40	2.00	32.50	178.60	254.50
1980	3.30	0.00	33.10	42.70	79.10
1981	22.00	1.00	0.40	41.60	65.00
1982	31.20	0.00	88.40	90.00	209.60
1983	51.00	0.00	31.80	62.40	145.20
1984	19.20	0.20	22.30	36.00	77.70
1985	11.60	0.00	25.90	105.00	142.50
1986	67.00	4.70	56.30	13.70	141.70
1987	42.30	4.10	26.50	60.10	133.00
1988	27.90	2.00	6.90	62.60	99.40
1989	10.20	0.00	36.90	61.30	108.40
1990	5.10	0.20	2.30	53.50	61.10
1991	25.00	0.00	26.40	112.60	164.00
1992	107.00	0.30	21.30	86.30	214.90
1993	57.60	0.00	17.70	38.90	114.20
1994	39.90	0.00	25.20	23.10	88.20
1995	58.20	1.00	8..20	141.70	209.10
1996	68.50	5.70	4.00	39.50	117.70
1997	16.30	0.80	31.50	97.60	146.20
1998	41.20	4.80	8.40	96.60	151.00
1999	18.00	2.40	38.20	10.70	69.30
2000	2.60	0.00	121.30	53.50	177.40
2001	12.90	3.00	27.00	21.90	64.80
2002	139.40	0.00	43.50	60.30	243.20
2003	65.50	0.00	19.80	64.00	149.30
2004	61.90	3.10	19.40	67.00	151.40
2005	22.20	0.00	16.80	39.30	78.30
2006	31.50	1.80	50.80	20.90	105.00
2007	70.70	12.90	6.20	53.00	142.80
2008	20.00	0.30	45.30	47.90	113.50
2009	78.40	3.20	31.40	32.60	145.60
2010	35.80	0.00	10.90	87.30	134.00
2011	24.70	2.60	55.50	12.30	95.10
2012	46.30	4.00	49.80	59.40	159.50
2013	17.80	4.60	49.10	87.10	158.60
2014	30.30	0.00	20.50	38.50	89.30
2015	25.70	4.20	36.40	14.00	80.30
2016	25.40	2.00	12.40	40.70	80.50
2017	33.70	1.10	1.40	29.20	65.40
2018	83.74	0.00	32.00	71.80	187.54
2019	44.00	0.00	48.50	43.50	136.00

1). The Kashan has an zone of $86{,}082 km^2$. The ponder region features a semi-arid climate condition. The cruel yearly temperature is almost $28°C$, and the yearly precipitation primarily $116mm$. In arrange to plan information for modeling, every year precipitation information were collected from precipitation stations in Kashan territory (Northeast portion of Isfahan, Iran) from 1967 to 2019 (Table 1), redressed the measurable deformity and after that typicality test information on the residuals of each fitted show utilizing the Kolmogorov–Smirnov test [17] was done.

Figure 2, shows the trend of rainfall from 1967 to 2019 in Kashan. As you can see, the data has no trend and has been stationary. Also, the highest amount of rainfall was in 1979.

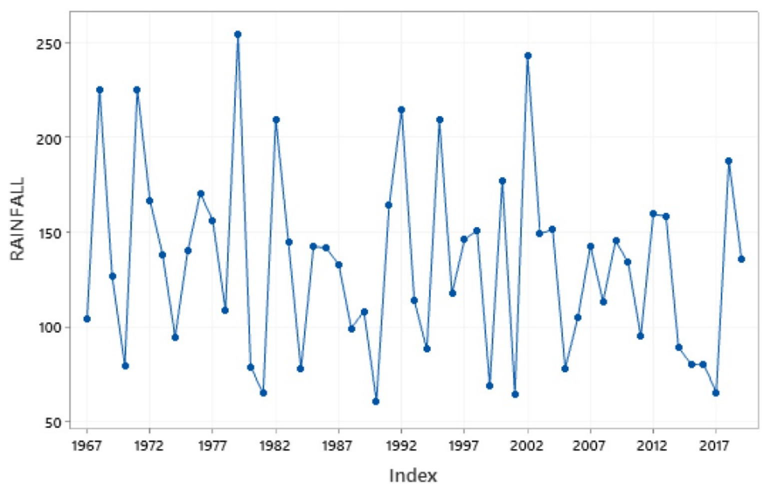

Figure 2. Time series plot of original data

3. Statistical analysis

Time series models: Time series is basically a measurement of data taken in chronological order within a certain time [19]. The purpose of the time series is to determine the regularity and identify its behavior to predict the future. Time series analysis and prediction have become a major tool in different applications in meteorological and hydrological phenomena, such as rainfall, temperature, evaporation, flood, drought, etc. The first step in any time series analysis involves a careful examination of the recorded data plotted over time. This scrutiny often suggests methods of analysis as well as statistics that will be helpful in summarizing the information contained in the data. We start by linearly regressing the current value of a time series on its own past values and the past values of other time series. This modeling leads to the use of the results of the time domain approach as a forecasting tool, and for this reason it is particularly popular among economists.

Generally, the models for time series data can have different forms and represent different non-deterministic processes [23, 33]. Most modeling of time series takes place based on a linear technique. The AR, MA, and ARMA models have a linear base [23]. In this research, the ARIMA models based on trial and error were examined and used to assess these models' ability in annual rainfall prediction. One approach, advocated in the work of Box and Jenkins (1970) [5] develops a systematic class of models called the ARIMA models to handle time-correlated modeling and forecasting. The defining characteristic of these models is that they are multiplicative models, which means that the observed data are assumed to be products of the factors of the differential or difference equation operators that respond to the white noise input.

The AR (Autoregressive) model: Time series data is related to data that are not independent and are successive. For example, the value of $(t+1)^{th}$ period depends on the present t^{th} period of the previous, and then for such a series, the observed sequences $X_1, X_2, ..., X_t$ are used to fit an AR model. The AR model can be expressed as (3.1):

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ...\phi_p X_{t-p} + Z_t \tag{3.1}$$

where $\phi_1, \phi_2, ..., \phi_p$ are model parameters and coefficient and Z_t is the random component of the data that follows a normal distribution with mean 0 and finite variance [7]. A random process $\{Z_t\}$, which is a sequence of uncorrelated variables, is also called white noise [6].

The MA (Moving Average) model: The MA models are simple covariance stationary and ergodic models that can use for a wide variety of autocorrelation patterns [6]. The MA model can be expressed as (3.2):

$$X_t = \theta_1 Z_{t-1} + \theta_2 Z_{t-2} + ...\theta_q Z_{t-q} + Z_t \tag{3.2}$$

where $\theta_1, \theta_2, ...\theta_q$ are model parameters and coefficient and Z_t is the random component of the data that follows a normal distribution with mean 0 and finite variance [7].

The ARMA (Autoregressive Moving Average) model: The ARMA model is a synthesis of an AR and a MA model. The ARMA model forms a type of linear models which are widely applicable and parsimonious in parameterization. The $ARMA(p,q)$ model can be expressed as (3.3):

$$X_t = \delta + \sum_{i=1}^{p} \phi_i X_{t-i} + \sum_{j=1}^{q} \theta_j Z_{t-j} + Z_t \tag{3.3}$$

where δ is the stationary part of the ARMA model, ϕ_i points out the i^{th}, the AR coefficient, θ_j is the j^{th}, the MA coefficient, it shows the error part at time period t, X_t refers the value of rainfall observed or predicted at time period t and Z_t is the random component of the data that follows a normal distribution with mean 0 and finite variance [13].

The ARIMA (Autoregressive Integrated Moving Average) models: A process X_t is said to be $ARIMA(p,d,q)$, if

$$\nabla^d X_t = (1-B)^d X_t$$

is $ARMA(p,q)$ as (3.3) where B is a backshift operator defined as $BX_t = X_{t-1}$ and extend it to $B^k X_t = X_{t-k}$. The first difference is denoted as $\nabla X_t = X_t - X_{t-1}$. It is clear that $\nabla X_t = (1-B)X_t$. Also differences of order d are defined as $\nabla^d = (1-B)^d$. Thus in general, we will write the ARIMA model as

$$\Phi(B)(1-B)^d X_t = \delta + \Theta(B) Z_t \tag{3.4}$$

where $\Phi(B) = 1 - \sum_{i=1}^{p} \phi_i B^i$ and $\Theta(B) = 1 + \sum_{j=1}^{q} \theta_j B^j$ [6]. The ARIMA models are one of the well-known linear models for time series modeling and predicting [23]. The ARIMA models have been originated from the synthesis of the AR and MA models. The ARIMA is used to model time series data behavior and to make predictions [32]. The ARIMA modeling uses correlational methods and could be used to model arrays that may not be observable in plotted data [15, 23]. In the ARIMA model, the future amount of a parameter is assumed to be a linear function of past observations and random errors [4].

The SARIMA (Seasonal Autoregressive Integerated Moving Average) models: A SARIMA model can be explained as

$$SARIMA(p,d,q)(P,D,Q)_s$$

where (p,d,q) is the non-seasonal component of the model and $(P,D,Q)_s$ is the seasonal component of the model in which p is the order of non-seasonal autoregression, d is the number of regular differencing, q is the order of non-seasonal MA, P is the order of seasonal AR, D is the number of seasonal differencing, Q is the order of seasonal MA, and s is the length of the season [15, 23]. Thus in general, we will write the $ARIMA(p,d,q)(P,D,Q)_s$ model as

$$\Phi_P(B^s)\Phi(B)\nabla_s^D \nabla^d X_t = \delta + \Theta_Q(B^s)\Theta(B) Z_t \tag{3.5}$$

where the operators

$$\Phi_P(B^s) = 1 - \sum_{i=1}^{P} \phi_i B^{is},$$
$$\Theta_Q(B^s) = 1 + \sum_{j=1}^{Q} \theta_j B^{js}$$

are the seasonal autoregressive operator and the seasonal moving average operator of orders P and Q, respectively, with seasonal period s [6]. Also ordinary and seasonal difference components are represented by $\nabla^d = (1-B)^d$ and $\nabla_s^D = (1-B^s)^D$.

The BIC (Bayesian information criteria): The BIC or Schwarz information criterion (SIC), (also the SBC (Schwarz-Bayesian Criteria) and the SBIC (Schwarz-Bayesian Information Criteria)) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function, and it is closely related to the AIC. The BIC can be expressed as (3.6):

$$BIC \ = \ k\ln(n) \ - \ 2\ln(\hat{L}). \tag{3.6}$$

$\hat{L}$ is the maximized value of the likelihood function of the model M, i.e., $\hat{L} = p(x|\hat{\theta}, M)$, where $\hat{\theta}$ are the parameter value that maximizes the likelihood function;

x is the observed data; n is the number of data points in x; k is the number of parameters estimated by the model [30].

The AIC (Akaike information criterion): The AIC were used to evaluate the performances of models, and model selection. The AIC can be expressed as (3.7):

$$\mathrm{AIC(k)} = 2k - 2\ln(\hat{L}) \tag{3.7}$$

where k represents the number of model parameters and $\hat{L}$ is the same as mentioned above [6].

Box-Jenkins: The Box-Jenkins approach [5] to time series analysis, forecasting and control, is a new, powerful but rather complicated procedure which is yet relatively untried. The methods are potentially useful in many types of situations that involve the building of models for discrete time series and dynamic systems. Finding appropriate models for time series is a nontrivial task. We will develop a multistep model-building strategy espoused so well by Box and Jenkins [5]. There are three main steps in the process, each of which may be used several times [7]:

1. model specification (or identification),
2. model fitting,
3. model diagnostics.

Chi-square Test: Chi-square independent test is a test method to detect the independence of two or more random variables [17].

Dickey-Fuller Test: The Dickey-Fuller test tests the null hypothesis that a unit root is present in an AR model. The alternative hypothesis is different depending on which version of the test is used but is usually stationarity or trend-stationarity. It is named after the statisticians Dickey and Fuller [11], who developed the test in 1979.

4. Materials and models

Our research method has a statistical basis and is based on the use of time series models. Because climatic elements such as precipitation occur with respect to time and the evidence shows that there is a relationship (dependence) between the previous values of the data and the later values (it should be noted that we also performed a Chi-square test and showed that the data is dependent), so the best option for data analysis is to choose time series methods. In Figure 2, it was clear that the data had no trend and was stationary. The Dickey-Fuller test [11] showed that the original data were stationary and there was no need to differentiate the data. In this paper, first, all models were fitted, and finally, we came to the conclusion that the best model is the ARIMA model. We have fitted the rain data and predicted the amount of rain for the years 2020 to 2023.

The statistical population includes the amount of rainfall in Kashan city station and the volume of sample rainfall data for a period of 53 years from 1976 to 2019. The method of data analysis is that the time series models are fitted to the data

Table 2. Model selection using AIC and BIC

Model Statistics		
Model	**Model Fit statistics**	
	AIC	**BIC**
ARIMA(0,0,0)	566.65	570.59
ARIMA(0,0,1)	564.64	570.55
ARIMA(1,0,0)	566.22	572.13
ARIMA(1,0,1)	566.05	573.93
ARIMA(2,0,1)	566.59	576.44
ARIMA(1,0,2)	566.85	576.70
ARIMA(2,0,2)	568.58	580.40
ARIMA(3,0,1)	568.59	580.41
ARIMA(3,0,2)	570.57	584.36
ARIMA(3,0,3)	572.56	588.32
ARIMA(1,0,3)	568.58	580.41
ARIMA(2,0,3)	570.56	584.35

using statistical package for the social science (SPSS) statistical software (also, we used R and MINITAB software), and in the end, after testing the existing models, the best method for rainfall prediction is selected, or in other words, based on data from the years 1976-2019, we predict the amount of rainfall for the years 2020-2023.

5. Model selection

The sample ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) provide effective tools for identifying pure the $AR(p)$ or the $MA(q)$ models. However, for a mixed ARMA model, its theoretical ACF and PACF have infinitely many nonzero values, making it is difficult to identify mixed models from the sample ACF and PACF [7].

The main tool for model identification is to plot the ACF and PACF and match them to the patterns of the ARIMA model. In most of the carried out research, in order to determine the best model, we need to use PACF and ACF [10]. Also, we use the AIC and BIC for model selection.

6. Results

In the present study, we had 53 years of rainfall. The average annual rainfall is $133.70mm$ with a standard deviation of $49.32mm$. The best model is the $ARIMA(0,0,1)$ (or the $MA(1)$). For the selected model, the AIC and BIC are equal to 564.64 and 570.55, respectively (Table 2).

Table 3. Final estimates of parameters for $\mathbf{ARIMA(0,0,1)}$

Type	Coef	SE Coef	T-Value	P-Value
MA(1)	0.333	0.132	2.52	0.015
Constant	133.65	4.39	30.42	$p \leq 0.001$
Mean	133.65	4.39		

The $ARIMA(0,0,1)$ model is the same as the MA model with parameter 1. The $MA(1)$ process, i.e., $X_t = \theta_1 Z_{t-1} + Z_t + \delta$ is always stationary, but for the process to be inverted, the roots of the $\psi(B) = 1 + \theta_1 B$ are greater than the unit in absolute value, which results $|\theta_1| < 1$. The following output is from Minitab, which indicates that the coefficients are significant. Finally, estimates of parameters the $ARIMA(0,0,1)$ model (Table 3). So, the $MA(1)$ model can be expressed a $X_t = 0.333Z_{t-1} + Z_t + 133.65$.

An ARIMA model can be explained as $ARIMA(p,d,q)$, where (p,d,q) is the non-seasonal component of the model which p is the order of the non-seasonal AR, d is the number of regular differencing, q is the order of the non-seasonal MA. We conducted a a stationary test. The data was stationary and there was no need to differencing, so the parameter d is equal to zero.

In Figure 3, the ACF diagram is interrupted from delay one onwards, and the PACF diagram is sinusoidally reduced to zero. So we conclude our model $ARIMA(0,0,1)$ or in other words $MA(1)$.

In the following diagrams (Figure 4), it is assumed that the residues are independent of each other and are random. The ACF and PACF charts for the residuals are used to illustrate this situation. As can be seen, these correlation coefficients, are small and without a trend, the autocorrelation between the residuals changes at different lags. Therefore, the evaluation of the model diagnosis is appropriate.

After fitting the model, the last step is to check the residue. White noise was examined by the ACF and PACF, which showed that the delays tended to zero (Figure 4). Also, according to the diagram below, the residues almost follow the normal distribution (Figure 5).

In Table 4, we compare the forecast amount with the actual annual rainfall. As you can see from Table 4, they are very different, but he has predicted the last one very well. Because the residuals are normal, this difference is due to the model error, so the model is appropriate.

The first column in Table 5, is the annual period from 2020 to 2023. The second column shows the predicted values, which are predicted based on the $ARIMA(0,0,1)$ according to the previous 53 year. Prediction of annual values from 2020 to 2023 according to the previous values of 204 periods. The third and fourth columns show the lower and upper bounds of 95% confidence interval.

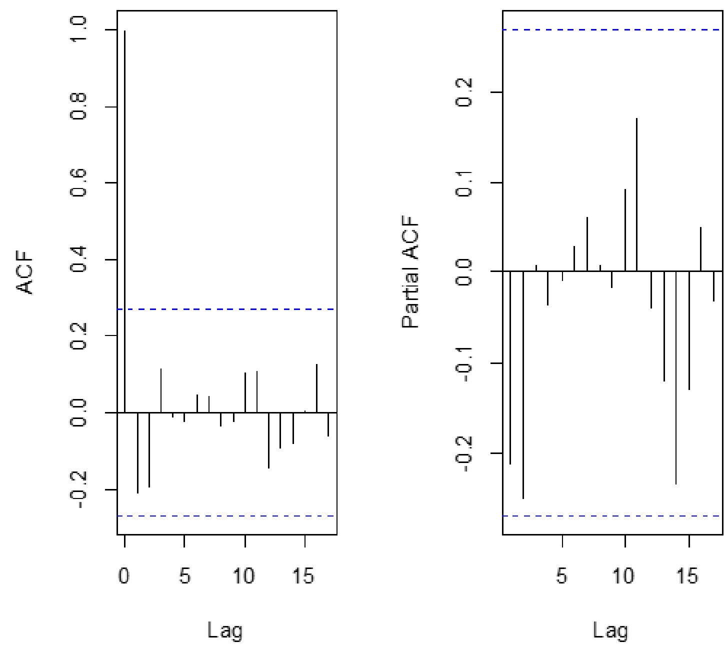

FIGURE 3. Plot ACF and PACF of rainfall

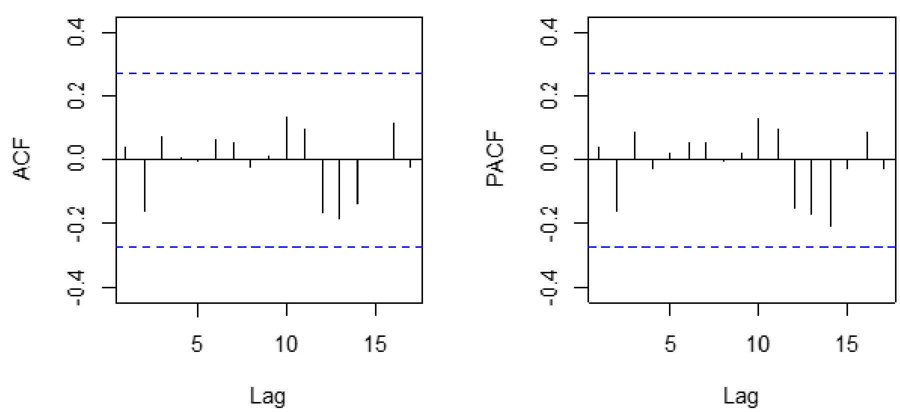

FIGURE 4. Plot ACF, PACF of residues for $\mathbf{ARIMA(0,0,1)}$

To evaluate the model, we delete the last 4 data, that is, from 2016 to 2019, and we predict with the same model that we have chosen. In Figure 6, we show a graph comparing the actual and forecast values of rainfall.

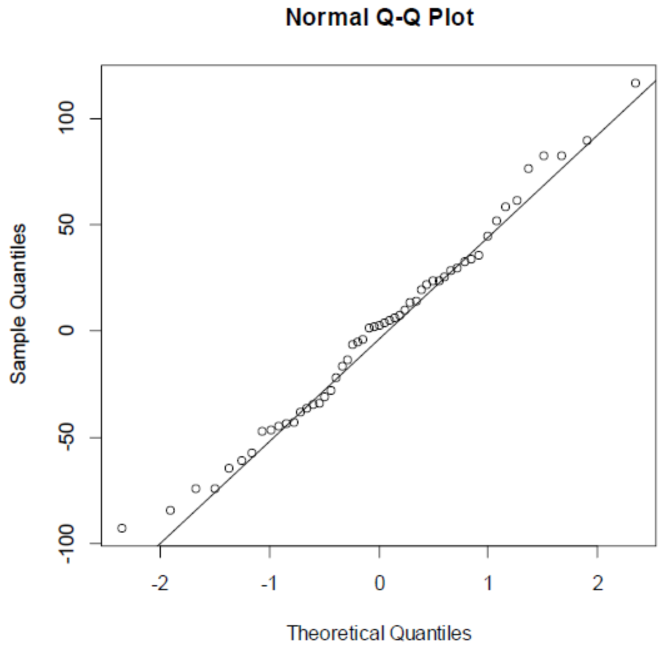

Figure 5. Q-Q plot of residues for $\mathbf{ARIMA(0,0,1)}$

Table 4. Compare the forecast amount with the actual annual rainfall

		95% Limits		
Period	**Forecast(mm)**	**Lower**	**Upper**	**Actual(mm)**
2016	170.695	80.3926	260.997	80.50
2017	135.666	35.2729	236.058	65.40
2018	135.666	35.2729	236.058	187.54
2019	135.666	35.2729	236.058	136

Table 5. Forecasts from period 53

		95% Limits	
Period	**Forecast(mm)**	**Lower**	**Upper**
2020	130.327	36.3954	224.258
2021	133.648	34.6389	232.657
2022	133.648	34.6389	232.657
2023	133.648	34.6389	232.657

7. Discussion & Conclusions

Rainfall prediction is crucial for making important decisions and performing strategic planning. The ability to predict rainfall quantitatively guides the management

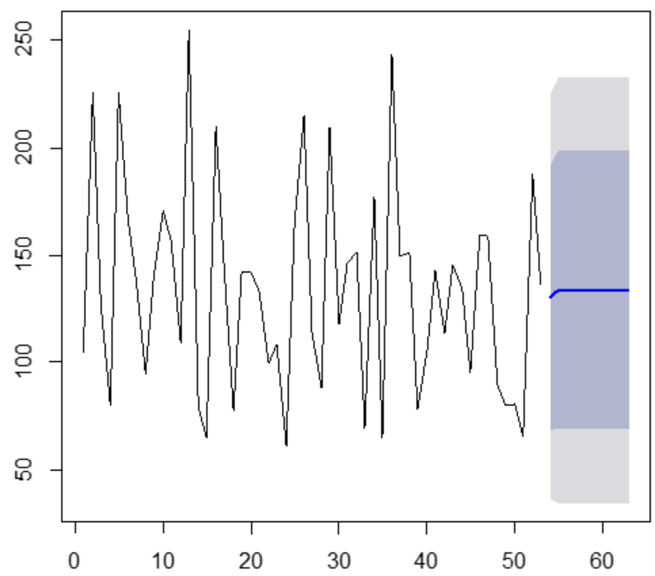

FIGURE 6. Forecasts from $\mathbf{ARIMA(0,0,1)}$ with non-zero mean

of water-related problems such as extreme rainfall conditions such as floods and droughts, among other issues. Therefore, the prediction of hydrological variables such as rainfall, flood stream, and runoff flow as probabilistic events is a key issue in water resources planning. These hydrological variables are usually measured longitudinally across time, making time series analysis of their occurrences in discrete-time appropriate for monitoring and simulating their hydrological behavior. Rainfall is among the sophisticated and challenging components of the hydrological cycle to modelling and prediction because of various dynamic and environmental factors and random variations, both spatially and temporally [20].

The objective of this study in this article, is to analyse the annual rainfall forecast from 2020 to 2023. This was predicted according to previous data. Using time series models, the best model according to the AIC and BIC was the ARIMA model, where the non-seasonal parameters of this model are $AR = [0]$, $DIFF = [0]$ and $MA = [1]$. As you can see from Table 3, the forecasted rainfall is lower than the average rainfall of previous years. Since Kashan is one of the arid and semi-arid regions, we will face the problem of water shortage, so water consumption must be saved. The limitation of this study is that the results cannot be generalized to the whole of Iran. It seems necessary to conduct this research in all geographical areas. It is suggested that in future studies, the factors affecting rainfall in Kashan in the future should be studied.

El Nino and La Nina are among the phenomena affecting the global climate, it is possible that there will be a climate anomaly in the environment of every country and every year that exceeds the limits of the natural range of its environment, and events and anomalies often arouse the curiosity of people and societies and take care of them. Especially in cases where what is happening is not natural [24]. Climate is not a fixed region and changes under the influence of two groups of factors:

1. Factors that cause annual climate change.
2. Factors that create long-time change trends.

El Nino, LA Nina and NAO are the main causes of short-time global climate change. While long-time global climate change (on a scale of 10 to 1000 years) is influenced by two main factors, namely the change in energy input from the sun and global warming due to the intensification of the effects of greenhouse. Rising sea levels and changes in climate thresholds are the consequences of climate change. Climate change and increasing global warming are causing droughts, uneven rainfall distribution, and economic problems for the global economy. The cause of low rainfall is the negative phase of LA Nina. In other words, in this situation, the water of the oceans, which are the source of moisture for autumn rains, has become colder, and as a result, they will not have evaporation and will not have clouds and rain. Agricultural water management requires culture building and proper management of managers.

8. Compliance with ethical standards

Conflict of interest: The authors declare that they have no conflict of interest.

Data Availability: Datasets published in the literature.

Ethical standard: This article does not contain any studies with human participants or animals performed by the authors.

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