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Climate Warming Prediction Using Time Series Analysis (Case Study: Western Iran)

Yaser Sabzevari[1]*, Saeid Eslamian[2]

Department of Water Science and Engineering, College of Agriculture, Isfahan University of Technology, Isfahan, Iran

ABSTRACT: One of the most important environmental challenges in today's era is climatic changes and fluctuations. The phenomenon of global warming has always affected different parts of the world. Therefore, it is necessary to investigate and predict the factors affecting it in various regions. In this study, the ARIMA time series method was used to investigate the future temperature changes in the climate of Aligoudarz Plain in western Iran. For this purpose, the monthly temperature information for the period of 1992-2023 was used from Aligoudarz station. The maximum data for 1992 is equal to 13.27 and the minimum data for 2021 is equal to 6.78. To assess the specification of time series ACF and PACF functions were used. The results showed that the time series is not Stationary. Therefore, the differentiation method was used for Stationary. The time series after one-time differentiation was Stationary, so the factor of d to 1. Results of the time series investigation showed that after evaluating different ARIMA models for the prediction of temperature, the model with the value of autocorrelation component=0, moving average=1, and differentiation=1 had the best result, so the forecasting was done with ARIMA(0,1,1) model. The forecast results showed that in the next five years (2024-2028) the temperature will decrease. In general, the results of this study showed the acceptable effectiveness of the time series model in temperature forecasting.

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1- Introduction

One of the important environmental challenges in today's era is climate change and fluctuations [1]. Our understanding of human impacts on climate variables, especially those related to warming caused by the increase of greenhouse gases, shows that many climate parameters are changing. Changes in the trend of air temperature thresholds (minimum temperature and maximum temperature) are one of the characteristics of the atmospheric cycle, which in a region has severe effects on the hydrological cycle, water resources, and as a result, on the yield and water requirement of crops. According to scientific reports, the global temperature has increased by 0.6 °C during the 20th century [2]. Therefore, investigating and predicting these variables plays an important role in the use of resources and in reducing evapotranspiration, which is one of the most important and influential components of the water balance in any region [3, 4].

To determine the trend of these changes, different methods are used. One of these methods is time series analysis. A time series is a collection of observations about a variable that are measured at discrete points of time that usually have equal intervals and are arranged by time [5, 6]. Therefore, a time series is obtained by observing a phenomenon over time. such models predict the future of climatic parameters only based on the past pattern. Unlike random samples from a population that is independent of each other, time series data are not independent of each other and are sequentially dependent on each other, and this dependence between observations has been noticed by researchers and used in forecasting [7]. Psilovikos and Elhag used ARIMA seasonal models to predict daily ET0 in the Nile River Delta and selected the appropriate model for the region [8]. Aguilera et al. combined the Arima model with the principal component model (PCA) and presented a practical model for the prediction of data on two sides of longitude. Which considers it suitable for predicting the risk of climate change phenomenon [9]. Dodangeh et al. investigated the use of time series models to determine the trend of climate parameters in the future and fitted different time series models on climate parameters and predicted the values for future years finally to investigate climate change, the trend of the predicted values was determined using the Mann-Kendall test [10]. Sabzevari and Eslamian predicted the temperature characteristics in the Khorramabad region of Iran. The results showed the high accuracy of the SARIMA model [6]. As mentioned, various researches have been conducted in the field of predicting the change process of different climate parameters. This issue shows the importance and application of this issue. Therefore, in this study, the trend of future temperature changes in the Aligoudarz region of western Iran was predicted.

*Corresponding author's email: Yasersabzevari1511@gmail.com

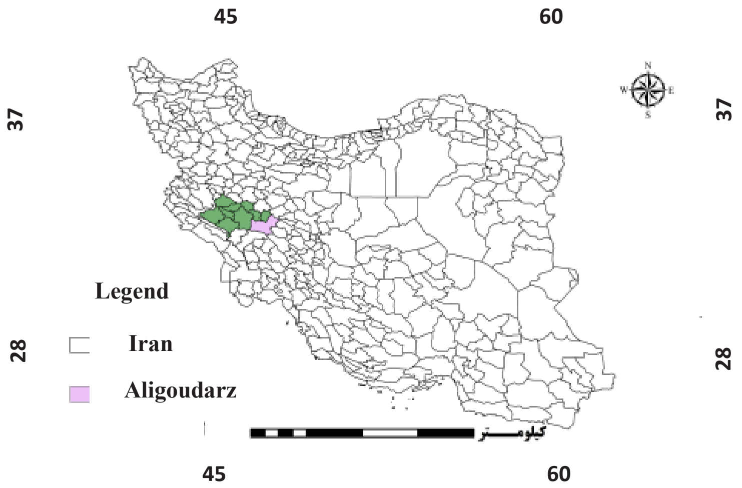

Fig. 1. Geographical location of Aligoudarz in the Iran country

2- Materials and Methods

2- 1- Study Area

Aligoudarz is located between 49 degrees and 42 minutes east longitude and 33 degrees and 24 minutes north latitude with an area of 130 hectares in the west of Iran. This area has an altitude of 2022 meters above sea level, an average rainfall of 387.7 mm, and an annual evaporation of 2048.2 mm. According to the climate classification methods of Demartin and Amberje, it has a semi-arid and arid-cold climate, with mild summer and very cold winter. Figure 1 shows the geographical location of Aligoudarz in Iran. This city has a synoptic station with north latitude of 33 degrees and 24 minutes an east longitude of 49 degrees and 42 minutes and an altitude of 2022 meters above sea level.

In this research, the temperature data of the period (1992-2023) of the Aligoudarz synoptic station was used to predict the temperature.

2- 2- Time Series

In the analysis of a time series, there may be several objectives, these objectives can be classified as description, description, prediction, control, and pattern fitting [11]. By plotting data against time, changes in a series of statistical parameters such as mean, standard deviation, and skewness can be obtained [12]. The description of the time series includes the detection of its stationarity and non-stationarity and the investigation of the autocorrelation of the series. A time series is stationary when there is no regular change in its mean and variance and strong periodic changes are removed. Non-stationary series can be transformed into stationary series by differentiating the variance [13].

2- 3- Autocorrelation Check

Autocorrelation is the dependence between consecutive values in terms of time. A function that calculates autocorrelation in terms of a time interval between observations is called an autocorrelation function. Autocorrelation can be considered as the similarity between observations. The autocorrelation function is also prepared to measure this similarity. ACF function has been used to check autocorrelation using Minitab software.

2- 4- Stationary Check

One of the main and important characteristics of time series is stationarity. A time series that has a stationary property can be analyzed. A time series is said to be stationary if its statistical properties such as mean and variance are constant over time. In time series analysis, before modeling, the series should be made stationary. For this purpose, the methods of checking the stationarity of the time series are examined in the following.

Time series models, in general, are: 1) autoregressive or autocorrelated stochastic model (p): the basis of this model is based on the Markov chain in the timing chain. 2) Moving average model (q): In this model, the variable at time t is estimated from the random value at that moment plus q equal to the random value related to the times before t. 3) Combined models. There are some processes that, in addition to having autocorrelation conditions, also have moving average characteristics. In this situation, the combined models of autocorrelation and moving average models, and cumulative moving average autocorrelation models are used [14].

$$\phi(B)Z_t = \phi(B)(1-B)Z_t = \theta(B)at \quad (1)$$

where Zt is the observed series, φ (B) is the rank of polynomial p and Θ (B) is the rank of polynomial q. For seasonal time series that are cyclical, seasonal differentiation is used, where we have the seasonal-multiplicative model:

$$\varphi_p(B)\Phi_p(B^s)\Delta^d\Delta_s^D\left(z_t - \overline{Z}\right) = \theta_q(B)\Theta_Q(B^s)a_t \quad (2)$$

where Θq: seasonal polynomial of Q and Φp: seasonal polynomial of P. The rank of seasonal-multiplicative Arima models is in the form of (p,d,q)*(P,D,Q).

2- 5- Step of Parameter Determination and Goodness of Fit Test

After determining the appropriate model, an effective estimation of the parameters should be done. Parameters must have two conditions stationarity and invertibility for moving average and autocorrelation. The parameters should be tested for significance, which is related to the error values of the estimates and the estimation of t values [15]. If Θ is a point estimate of the desired parameter and SΘ is the error of this estimate, the value of t is obtained as equation 3:

$$t = \frac{\theta}{S_\theta} \quad (3)$$

If the assumption becomes zero by considering the probability of error equal to or greater than α=0.05, then the parameter will be significant and will remain in the model.

The goodness of fit tests examines the accuracy of models using a series of tools. To check the validity of the models fitted to the data, the residuals of the model were examined for the normality of autocorrelation based on Quantile-Quantile Plot (QQ Plot), Shapiro-Wilk and Klomogrov-Smirnov tests. In this part, Minitab software was used to check the normality of the data and homogeneity, as well as T-statistics (T), P-value (P-VALUE), and Bayesian Information Criterion (BIC) to check the relationship between observational and forecasting data was used [13]. To check the appropriateness of the model, two complementary methods are used [16]:

1) Analysis of the residuals of the fitted model (in this method, the randomness or non-correlation of the residuals is proven).

2) Analysis of models with more parameters.

In the analysis of the residuals of the fitted model, the assumptions of normality of the data, constancy of the variance of the residuals, independence of the residuals, and the graph of the residuals against time are deduced, which are inferred by the Pert-Manto test. The assumption of normality of the residuals is accepted if the points are located almost around a straight line and have a uniform distribution. Pert-Manto test, which is based on the modified Box-Pierson statistic, is used as a more formal method to test the hypothesis that the residuals are uncorrelated. Pert-Manto test is written as equation 4 [7]:

$$Q(LBQ) - n(n+2)\sum_{h=1}^{k}(n-h)^{-1}\rho_h^2 \quad (4)$$

where: n is the number of observations, Q is the test statistic, which is the modified LBQ of Lejung Box. Under hypothesis H0, it has almost a Kido distribution. The first condition: If the value of the Q statistic is greater than the corresponding value in the Kido table, hypothesis H0 is rejected, which means that the data are correlated. The second condition: the value of the correction index must also be greater than the value of α.

3- Results and Discussion

The time series data in the current analysis includes 32 years of annual data as presented in Table (1). In this research, data analysis and model fitting have been done with the help of Minitab software.

The maximum data for 1992 is equal to 13.27 and the minimum data for 2021 is equal to 6.78. In this regard, the time series graph is drawn and presented in the graph of Figure (2). Since it is not easy to make predictions for non-stationary time series, it is better to remove the factors that cause the time series to go out of stationarity. In this way, the components identified in the time series should be removed, which is called "smoothing". Therefore, to check the general trend of the data and smoothing (removing the identified components), the Smoother option has been used in the software. As it is known, the data has a downward trend, which becomes more intense at the beginning of the statistical period.

3- 1- Autocorrelation Check

The autocorrelation function includes two red lines (significant upper and lower limits at the 5% level) and a blue line (autocorrelation at different time steps); At each step, when the blue line crosses the red lines, the autocorrelation is significant. In other words, wherever the T statistic is greater than 1.96 or less than -1.96, autocorrelation is significant. In the present report, according to Figure (3) and Table (2), autocorrelation is significant at the 5% level in the second step.

3- 2- Partial Autocorrelation Check

Partial correlation represents a fixed time series with its lag values. Lag means the time interval that is considered between observations.

PACF function has been used to check partial autocorrelation using Minitab software. This function, like the ACF function, includes two red lines (significant upper and lower limits at the 5% level) and a blue line (autocorrelation in different time steps); At each step, when the blue line crosses the red lines, the autocorrelation is significant. In

Table 1. The studied time series

year	(°C) Temp.	year	(°C) Temp.	year	(°C) Temp.	year	(°C) Temp.
1992	13.275	2000	8.891667	2008	8.883333	2016	**8.025**
1993	10.19167	2001	9.133333	2009	8.025	2017	**7.375**
1994	8.95	2002	9.133333	2010	8.025	2018	**8.291667**
1995	9.416667	2003	9.258333	2011	8.9	2019	**7.725**
1996	9.458333	2004	7.741667	2012	8.291667	2020	**7.141667**
1997	8.683333	2005	7.85	2013	8.125	2021	**6.783333**
1998	9.433333	2006	8.833333	2014	9.25	2022	**8.008333**
1999	8.416667	2007	7.575	2015	7.791667	2023	**7.741667**

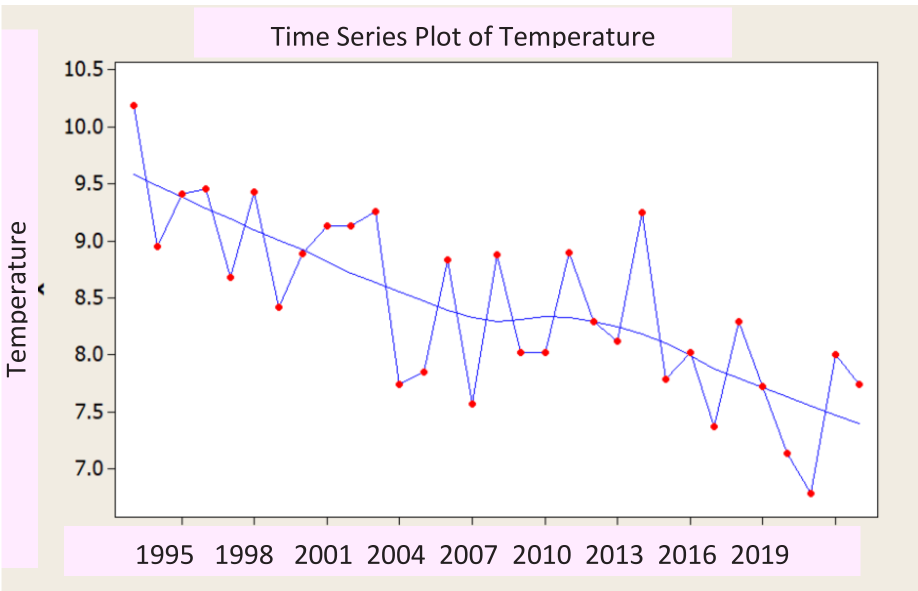

Fig. 2. Drawing a time series chart

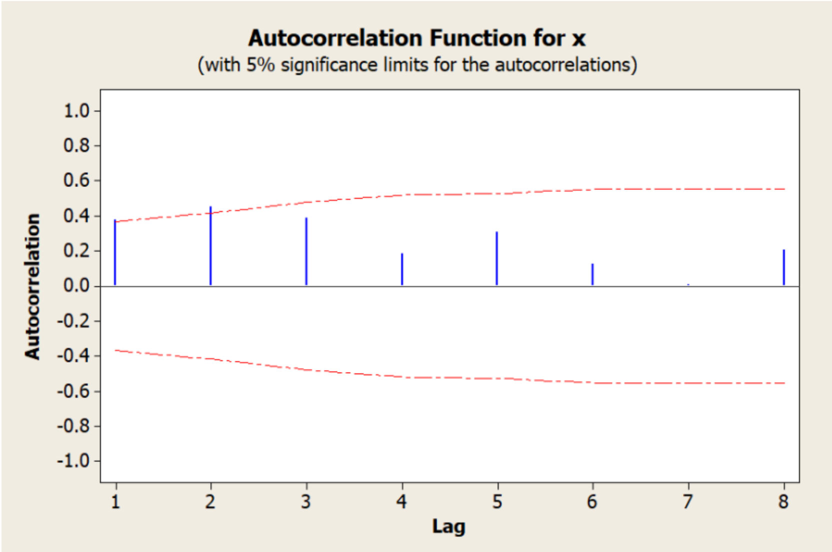

Fig. 3. Drawing the ACF function for the studied time series

Table 2. Investigating the autocorrelation of the time series in different steps based on the T statistic (Autocorrelation Function: Temperature)

Lag	ACF	T	LBQ
1	0.379244	2.11	4.90
2	0.449943	2.21	12.05
3	0.389555	1.67	17.59
4	0.183509	0.72	18.87
5	0.308346	1.20	22.61
6	0.125579	0.47	23.25
7	0.006599	0.02	23.25
8	0.207269	0.76	25.17

other words, wherever the T statistic is greater than 1.96 or less than -1.96, autocorrelation is significant. Autocorrelation according to Figure (4) and Table (3) is not significant in all steps.

3- 3- Stationary Investigation

Stationarity in Variance Checking

The stationarity of variance is checked in Minitab software using Box-Cox Plot. After drawing, if the upper and lower limits include the value of 1, the stationarity of the variance is confirmed. Otherwise, it is necessary to convert. Some of these transformations include logarithmic or exponential transformations. In the current report, the upper and lower limits include 1 and the stability of the variance can be confirmed (Figure (5)).

Stationarity in the Average Checking

To check the stationarity in the average, it is necessary to compare the data with different time steps, and after drawing, if the Smoother line shows a horizontal line, the stationarity in the average can be confirmed and the d value in the ARIMA model can also be determined. Therefore, in the current research, the stationarity of the average has been investigated in two different time steps, the results of which are presented in Figures (6) and (7). As it is known, with a time step of lag, the smoothing line becomes horizontal, and therefore, the value of d can be considered equal to 1. In the second time step, again the data has a (downward) trend and therefore the second step is not accepted.

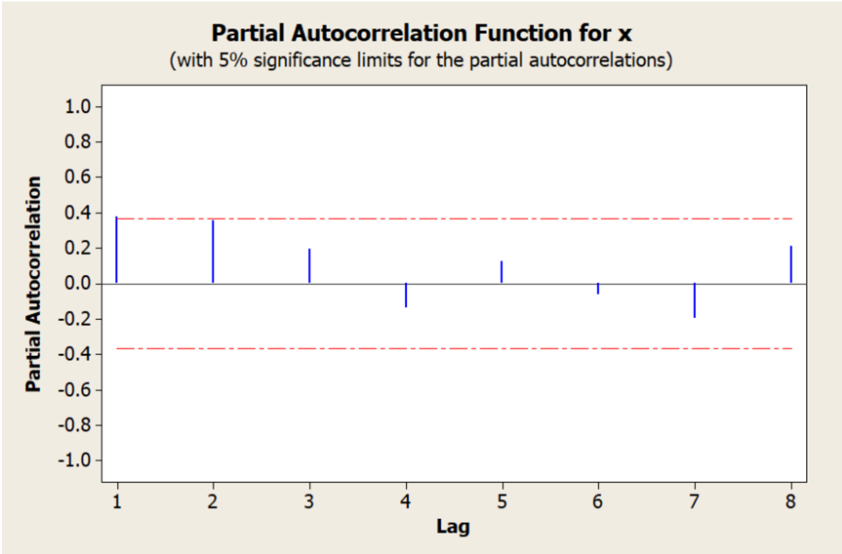

Fig. 4. Drawing PACF function for the studied time series

Table 3. Investigating partial autocorrelation of time series in different steps based on T statistic (Partial Autocorrelation Function: Temperature)

Lag	PACF	T
1	0.379244	2.11
2	0.449943	2.21
3	0.389555	1.67
4	0.183509	0.72
5	0.308346	1.20
6	0.125579	0.47
7	0.006599	0.02
8	0.207269	0.76

3- 4- Model Fit

In the first step, according to the results of the previous sections, the ARIMA (0,1,1) model was fitted and its results are presented in Table (4) (the results of the previous sections include the value of Lag = 1 to check the stationarity It has been that it includes the d value in the ARIMA model and also the autocorrelation value that significant in both the ACF function and the PACF function in the first two steps, and AR or P is considered to be equal to one (value ≤(2)).

Considering that the P-value for the moving average is less than 0.05, therefore, the model is accepted in this step and other conditions of the model are checked. Other investigated conditions are shown in Figure (8).

Uncorrelated Residual

The non-correlation of the residual has been checked with the help of Ljung-Box in Minitab software according to table (5). As it is known, the P-value values are greater than 0.05 and therefore, it can be confirmed that the residuals are uncorrelated. Also, the correlation of the residuals has been investigated with the help of the autocorrelation and partial autocorrelation function and presented in Figures (9) and (10). As it is clear, the autocorrelation line did not cross the significant upper and lower limits at the 5% confidence level at any time step.

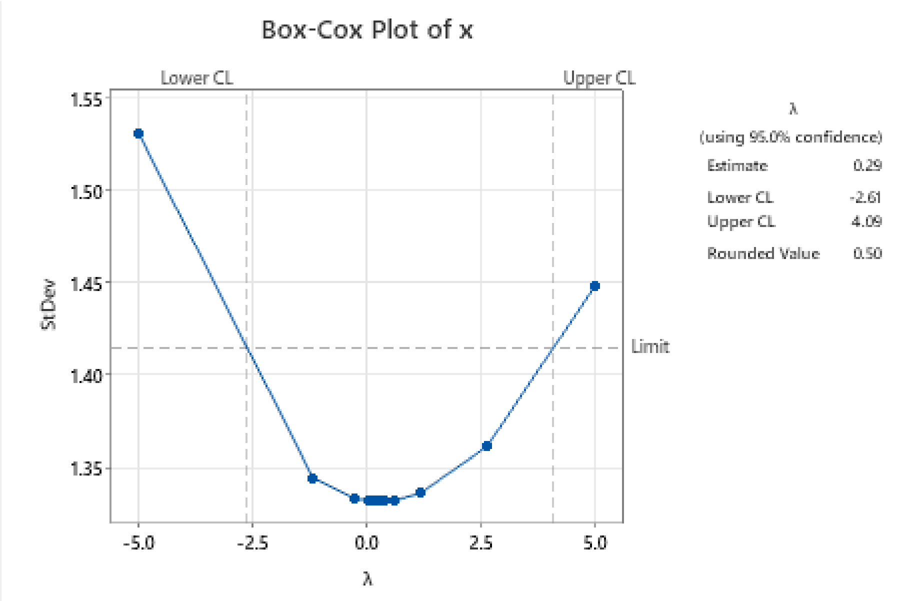

Fig. 5. Checking the stationarity of variance using Box-Cox Plot

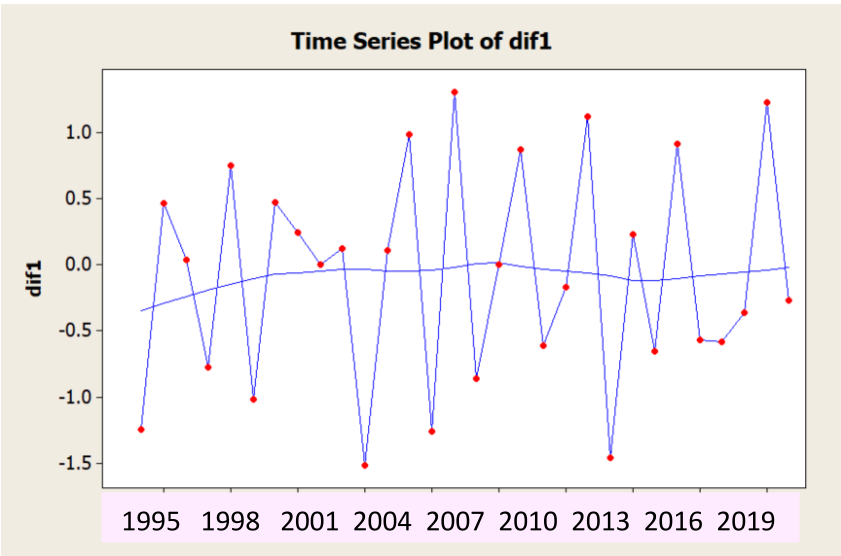

Fig. 6. Checking the stationarity in the average with a time step lag (Lag = 1)

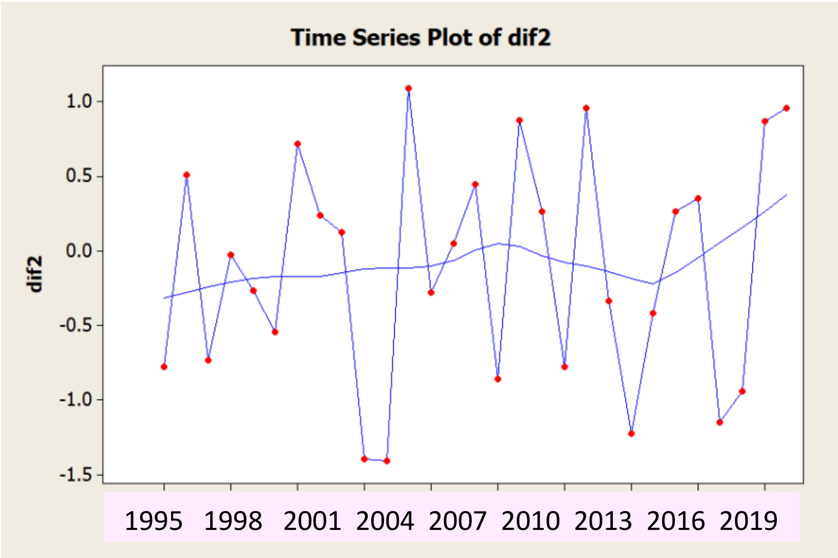

Fig. 7. Checking the stationarity in the average with two-time steps of lag (Lag = 2)

Table 4. ARIMA (0,1,1) model results (final estimation of parameters)

Type	Coef	SE Coef	T	P
AR 1	-0.5910	0.1518	-3.89	0.001
Constant	-0.1028	0.1241	-0.83	0.415

Fig. 8. Check the conditions of the fitted ARIMA (0,1,1) model

Table 5. Examination of uncorrelated residuals based on Ljung-Box (modified Box-Pierce (Ljung-Box) Chi-Square statistic)

Lag	12	24	36	48
Chi-Square	17.7	30.3	*	*
DF	10	22	*	*
P-Value	0.060	0.110	*	*

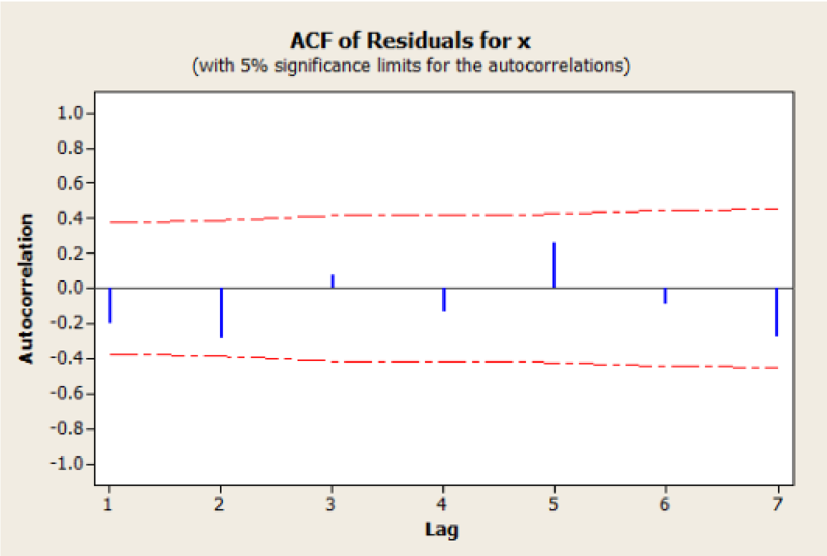

Fig. 9. Uncorrelated ness of the residuals by plotting the autocorrelation function

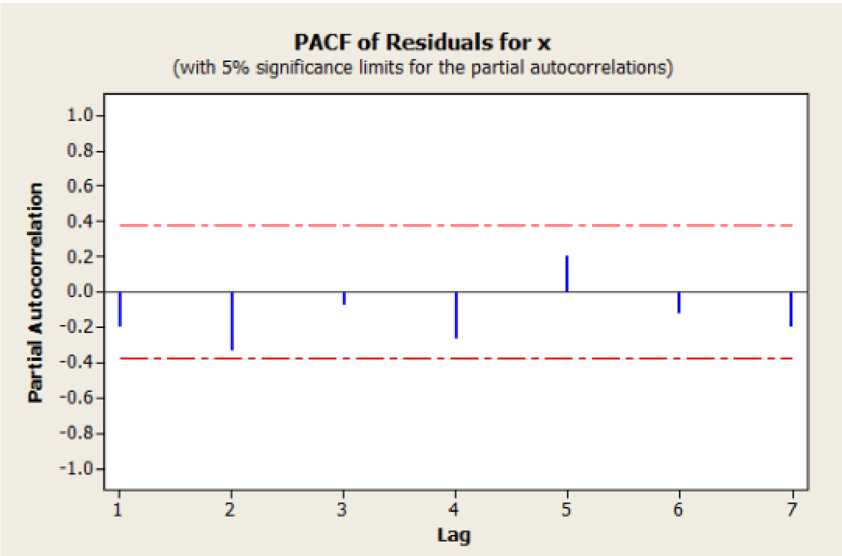

Fig. 10. Uncorrelated ness of the residuals by drawing the partial autocorrelation function

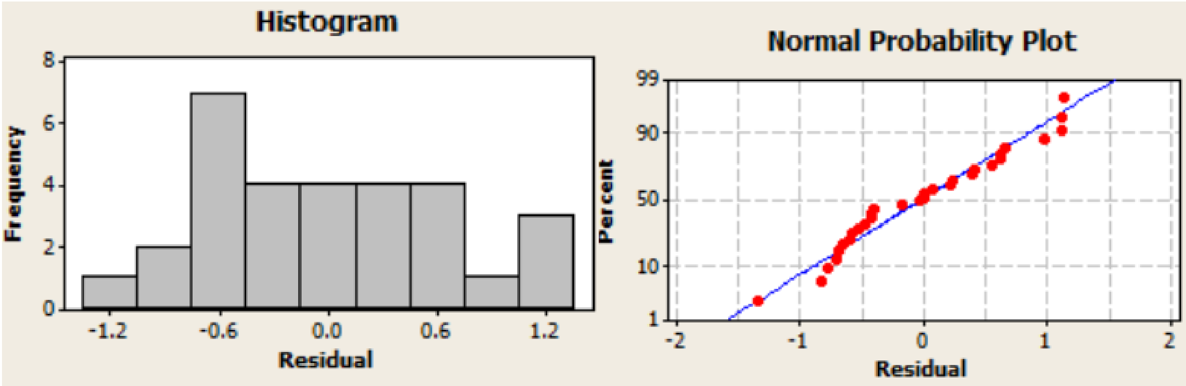

Fig. 11. Checking the normality of the residuals using the drawing method

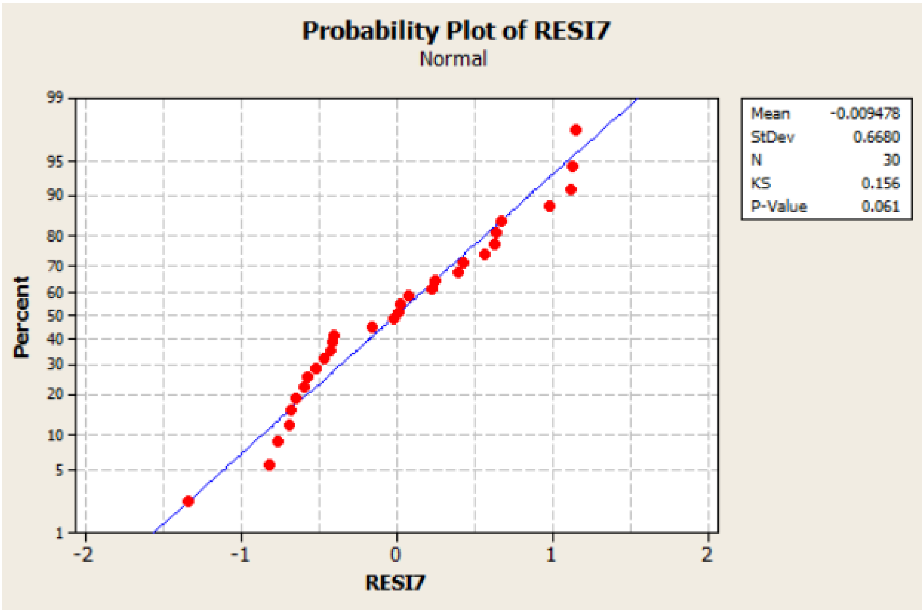

Fig. 12. Checking the normality of the residuals using the Kolmogorov-Smirnov method

Normality of Residuals

Another fitting condition of the ARIMA model is the adherence of the residuals to the normal distribution. Two methods have been used to check the normality of the distribution of residuals:

1- Drawing method using 4-1 chart, Normal Probability plot and Histogram

2- Kolmogorov-Smirnov test

Also, the Kolmogorov-Smirnov test was used to check the normality of the residuals. The Kolmogorov-Smirnov test is a non-parametric statistical test used to check the distribution of data. Statistically speaking, the Kolmogorov-Smirnov test is a type of goodness-of-fit test for comparing a theoretical distribution with an observed distribution. When checking the normality of the data, the null hypothesis based on the fact that the data distribution is normal is checked at the 5% error level. For the normality test, the statistical assumptions are set as follows:

H0: The distribution of data related to each of the variables is normal.

H1: The distribution of data related to each of the variables is not normal.

Therefore, if the larger test statistic equal to 0.05 is obtained, then there will be no reason to reject the null hypothesis. In other words, the data distribution is normal (Figure (12)).

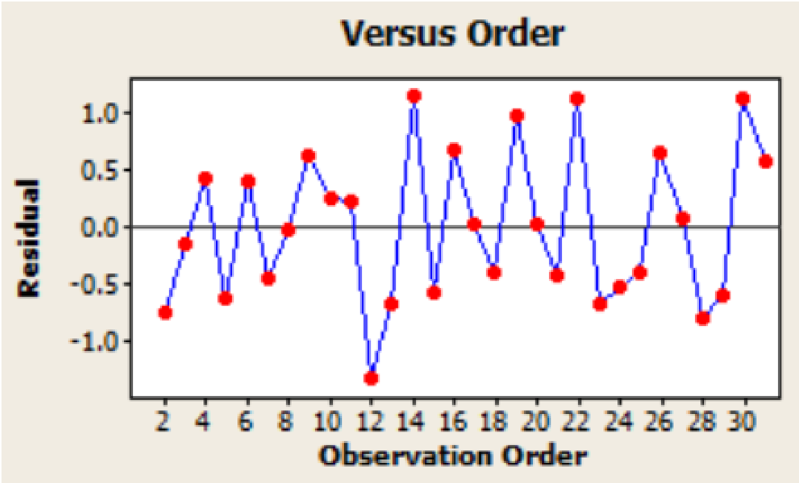

Fig. 13. Checking the randomness of the residuals using the drawing method

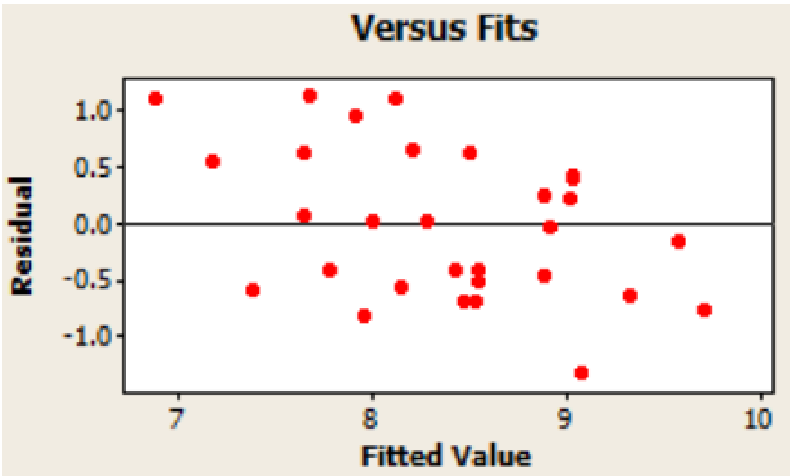

Fig. 14. Checking the stability of the variance of the residuals using the drawing method

Randomness of Residuals

4 in 1 chart is also used to check the randomness of the residuals; In this way, this chart should not show a specific pattern in the distribution. As presented in the graph (13), the data has no particular pattern in the distribution and the randomness of the residuals can be confirmed.

Variance Stability of Residuals

Residuals should also be stationary like the time series; Therefore, it is necessary to check the stability of the variance of the residuals. This task is determined by the user using the 4-1 diagram and the upper and lower limits of the drawing. As it is clear in graph (14), the horizontal lines of 1.5 are drawn as the upper and lower limits, and at no point, the residuals did not meet these limits, which can confirm the stability of the variance of the residuals.

3- 5- Prediction Using ARIMA Model

In the last step, based on the ARIMA (0,1,1) model, the data has been predicted for the next 5 years. The upper and lower red lines are presented as confidence limits and the middle red line is presented as a prediction. (Chart (15) and Table (6)). As it is known, the predicted data will have a downward trend in the next 5 years. Sabzevari and Eslamian, in their research by examining the time series of temperature in western Iran, showed that the temperature will increase in the future [6].

Table 6. EPredicted values using the ARIMA model (0,1,1)

year	Predicted value
2024	**7.42931**
2025	**7.36537**
2026	**7.30143**
2027	**7.23749**
2028	**7.17355**

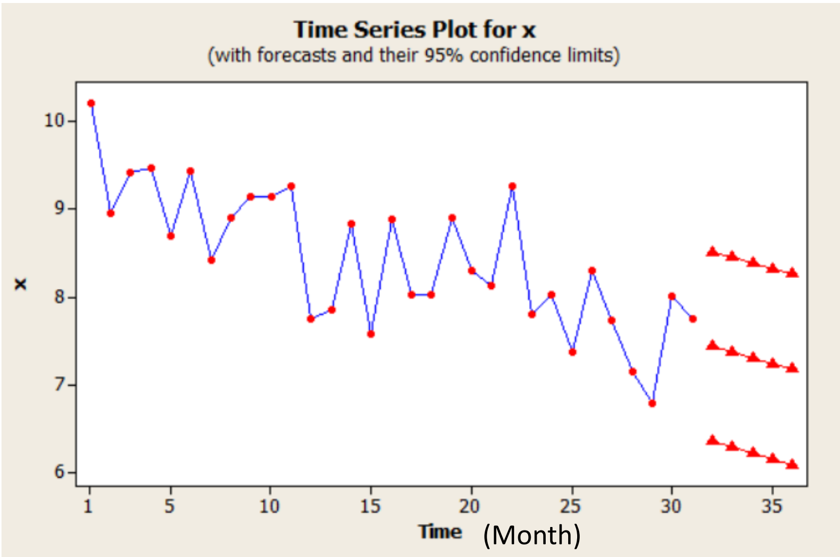

Fig. 15. Predicting using the ARIMA model for five years

4- Conclusion

This study was conducted to predict the trend of temperature parameter changes in the future period in Aligoudarz climate western Iran during the period of 1992-2023. For this purpose, ARIMA time series analysis was used. The results of this study showed that the ARIMA model has an acceptable efficiency in forecasting the temperature in the Aligoudarz climate. Based on the results of this study and after trial and error of the model with different values of the components, it was found that the ARIMA model has the best performance with the values of the autocorrelation components, moving average, and differentiation by 1. Therefore, this model was used for prediction. The result of the forecast for the next five years (2024-2028) indicated a decreasing temperature trend for the future. Despite the acceptable performance of this model in predicting the time series of temperature, this model has limitations such as the lack of user supervision, which reduces the accuracy of the prediction, and in contrast to this model, due to its user-friendliness and ability to Forecast the trend for the future period has an important role in the forecasting process.

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