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Predicting the Effect of Temperature Changes on Reference Evapotranspiration by Means of Time Series Modeling (Case Study: Khorramabad Basin)

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Abstract

Global warming phenomenon has affected the hydrologic balance, especially in the arid and semi-arid regions of the world. Therefore, it seems necessary to study these effects to achieve better water resources management system. In this study, maximum and minimum temperature information at the period of 1992-2017 of Khorramabad synoptic station were assessed. the changes of these two characteristics and reference evapotranspiration of Khorramabad plain were investigated by time series analysis. MSE, RMSE and R^2 indices were used to validate the models. The results has shown that both maximum and minimum temperature series are static and abnormal, so for normalization, the square root for the minimum data and the squared conversion for the maximum temperature data were used. The ACF chart of both series reaches its local peak at time intervals of multiples of 12, indicating a seasonal trend with a period of 12 months. Finally, the ARIMA model (0,0,4) (0,1,1) for the minimum temperature and the ARIMA model (0,0,1) (0,1,1) for the maximum temperature were the best chosen models. The values of R^2, RMSE and MSE for the selected maximum temperature model were 0.971, 1.656 and 0.991, respectively, and for the minimum temperature model 0.965, 1.304 and 0.991, respectively, which indicates the acceptable accuracy of the proposed models. Forecasts indicate an increase in the minimum and maximum temperatures in the whole future period compared to the base period. The peak of this increase occurs in June, July and August for the minimum and maximum temperatures respectively for Tmin: 2.03, 1.54, 1.75, and for Tmax: 1.91, 2.03, 1.77 Celsius. In the next period, the reference evapotranspiration will increase on average compared to the base period, with most of this increase occurring in March, April, and May.

Introduction

One of the major environmental challenges in the current century is climate change (Hulme et al., 1999). Warming is due to an increment in greenhouse gases, indicating that a number of climatic parameters are changing. Changes in the trend of air temperature thresholds (minimum temperature and maximum temperature) is one of the characteristics of the atmospheric cycle that in a region has severe

effects on hydrological cycle, water resources and consequently on the yield and water requirement of crops. According to scientific reports, the temperature of the Earth has increased by 0.6 ° C during the twentieth century, which is expected to have an increasing rate of evaporation (Esmaeilpour and Dinpazhooh, 2012, Farshi and Emdad, 1999). Therefore, studying and predicting these variables play an important role in the better use of resources and reducing evapotranspiration, which is one of the most important and effective components of water balance in each region (Feng et al., 2017; Shabani et al., 2016; Zarei and Moghimi, 2016).

Various methods are used to determine the trend of these changes. One of these methods is time series analysis. Time series is a set of observations about a variable that are measured at discrete points in time, usually at equal distances, and arranged in time (date and magnitude, 2007). Thus, a time serie is obtained from observing a phenomenon over time, in which such models predict their future based on the past pattern of climatic parameters. Unlike random examples of a community that are independent, time series data are not independent of and are consistently related to each other, and this relationship between observations has been considered by researchers and used in forecasting (Abdolahnezhad, 2015). Gotham and Cena analyzed the ET0 time series for the Bukarra and Jahrkhand regions of India. The results showed that, ARIMA (0,1,1) (0,1,4) had the best results compared to other models (Gautam and Sinha, 2016). Using ARIMA models, Psilovikos and Alhaq predicted the daily ET0 season in the Nile Delta and selected the appropriate model for the region (Psilovikos and Elhag, 2013). Aguilera et al. (2008) combined the ARIMA model with the principal component model (PCA) and provided a practical model for predicting longitudinal data from both sides. Which considers it suitable for predicting the risk of climate change.

Lucas et al. (2020) forecasted Reference evapotranspiration using time series with ensemble of convolutional neural networks. The results showed the feasibility of the CNN models for forecasting and that ensemble models were better than the well-known Seasonal ARIMA and Seasonal Naive and improved predictions. Patra (2017) assessed time series analysis of reference evapotranspiration using soft computing techniques for Ganjam District, Odisha, India. The reliability of these computational models was analysed in light of simulation results and it was found that SVM model produces better results in comparison with the three others. The future research should be routed to extend the validation data set and to check the validity of our results on different areas with hybrid intelligence techniques. Manikumari et al. (2017) used time Series in forecasting daily reference evapotranspiration by neural network ensemble learning for irrigation system. Among the ensemble models, Boosted-NN reduces the forecasting errors compared to Bagged-NN and individual NNs. Regression co-efficient, mean absolute deviation, mean absolute percentage error and root mean square error also ascertain that Boosted-NN lead to improved ET0 forecasting performance. Soltani Gardfaramarzi et al. (2017) determined the best time series model in predicting the annual rainfall of selected stations in West Azerbaijan province. The results showed that the (1,0,0) ARIMA, (0,1,1) ARIMA and (0,1,1) ARIMA models for Urmia stations, Mako and Mahabad respectively, are the most suitable models. Gheisoori et al. (2018) investigated and predicted the trend of changes in the parameters affecting the discharge in Godarkhosh watershed. The results of this study showed that the SARIMA (0,1,1) (1,0,0) model had the best accuracy in prediction among different models. Zarei and Moghimi (2016) in their research predicted and studied the average monthly temperature using time series models. The results showed that the best model the best fits the model data (1,26) AR was derived from Burg method with an acai index of 2609.91. Babamiri et al. (2017) modeled and predicted the ET0 time series for Tabriz station using ARIMA and SARIMA models. The results showed that the output of the two models are not significantly different

 Vol. 45, No. 2, 2022, pp. 125-138

from each other. Shabani et al. (2016) predicted changes in water requirement of some agricultural products in Mashhad plain due to changes in temperature. The results showed that the minimum and maximum temperatures will increase by 1.4 and 1 ° C in the future and the changes of evapotranspiration of the reference source are more affected by the maximum temperature. As mentioned, various studies have been conducted to predict the trend of changes in various climatic parameters. However, little research has shown the effect of these changes on different sectors that are affected by climate. The purpose of this study is to predict the trend of changes in minimum and maximum temperature characteristics and its effects on water requirement of crops in Khorramabad plain. For this purpose, the appropriate time series model is selected first and then minimum and maximum temperature forecasting is done. Using forecasted information, evapotranspiration is calculated and analyzed for the future.

Materials and methods

Study area

Khorramabad plain with an area of about 2500 square kilometers at an altitude of 1147.8 meters above sea level and at 48 degrees and 21 minutes east longitude and 33 degrees and 29 minutes north latitude is located in the center of Lorestan province. Based on the Dumarten coefficient, this plain is considered as a semi-arid region in terms of climate, and is excepted to be a semi-arid region based on the Amberje climogram.

Average total annual rainfall in this region is about 508 mm, of which 54% is received in winter, 28.5% in autumn and 17.3% in spring (Azizi, 2000). Figure (1) shows the location of the plain and Khorramabad station.

In this study, monthly minimum and maximum temperature characteristics of the time period (1992-2016) of Khorramabad synoptic station were used to predict the temperature characteristics. The geographical location of this station is given in table (1).

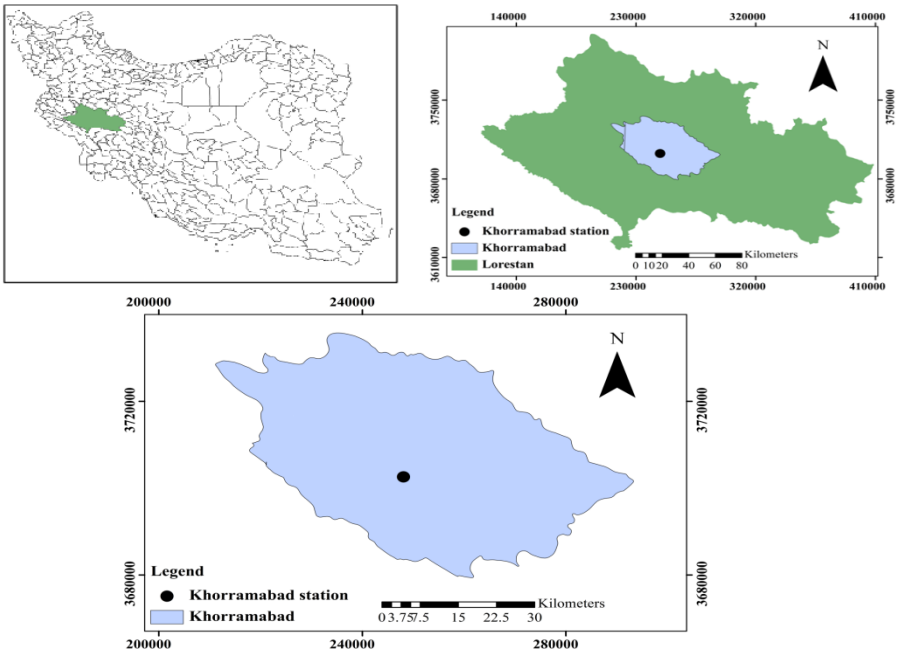

Fig. 1- Geographical location of Khorramabad in Lorestan and the country

Table 1- Geographical location of Khorramabad synoptic station

station	longitude	latitude	altitude
Khoramabad	48 17 E	33 26 N	1147.8

Time series

In the analysis of a time series, several goals may exist. These goals include: Described, predicted, controlled, and fitted the classification model (Chatfield, 1996). By plotting the data with respect to time, changes in statistical parameters of the series such as mean, standard deviation and skewness can be obtained (Daniel et al., 2005; Niroumand, 2012). Description of time series including static diagnosis and its instability and the study of self-correlation. The time series is static when there is no regular change in the mean and variance and strict periodic changes are omitted. Non-static series can be converted to static series by differentiating variance (Brockwell and Davis, 1996).

Time series models are generally as follows: 1) Autoregressive stochastic model (p): The basis of this model is based on the Markov chain in the time chain. 2) Moving average model (q): In this model, the variable at time t is estimated from the random value of the moment plus q equal to the random value of the times before t. 3) Combined models. There are some processes that, in addition to having autocorrelation conditions, also have moving average properties. In these conditions, a combination of autoregression and moving average models and cumulative moving average autoregression models are used (Soltani-Gardfaramarzi et al., 2017).

Self-correlated model - integrated moving average ARIMA (p, d, q).

In this type of models, the best time series model for fitting on the data is determined through two functions, ACF autocorrelation and PACF partial autocorrelation, and according to these two functions, the seasonal properties and static nature of the data are investigated. One of the most freqently used of these models is the ARIMA model (Box et al., 2015). The two general forms of ARIMA model include non-seasonal ARIMA (p, d, q) and multiplicative seasonal ARIMA (p, d, q) * (P, D, Q) that q and p are the autoregressive parameters and the non-seasonal moving average, respectively, and P and Q are the parameters and the seasonal moving average. The two other parameters, d and D, are differential parameters for static time series. The differential operators used for the dynamic time series are $\Delta^d = (1-B)^d$ and $\Delta = (1-B)$ (B is the backward jump operator). This form of non-seasonal ARIMA models as Equation (1):

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

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

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

Where Θq: seasonal polynomials Q and Φp: seasonal polynomials P. The order of seasonal-multiplicative ARIMA models is (p, d, q) * (P, D, Q) (Box et al., 2015).

Parameter determination stage and good fit test

After determining the appropriate model, an effective estimate of the parameters should be performed. The parameters must have two conditions of static and inverse for the moving average and autoregression. The parameters should be tested for significance that is related to the error values of the estimates and the estimation of the t values (Box et al., 2015). If Θ is the point estimation of the desired parameter and SΘ is the error of this estimation, the value of t is obtained as Equation 3:

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

If the assumption of error equals or becomes greater than α = 0.05 is assumed to be zero, then the parameter will be significant and will remain in the model.

Good fit tests investigate accuracy of models using a variety of tools. To evaluate the accuracy of the models fitted to the data, the model residues were examined for normal correlation based on Q-Q Plot, Shapiro-Wilk and Klomogorov-Smirnov tests. In this section, SPSS and minitab software were used to check the normality of data and homogeneity, as well as T (T) and P-VALUE statistics and Bayesian information criterion (BIC) were used to investigate the relationship between observational and predicted data (Niroumand and Bozorgnia, 1994). To evaluate the suitability of the model, two methods that are complementary are used (Box et al., 2015).

1- Analysis of the residuals of the fitted model (in this method, the residuals are proved to be random or uncorrelated).

2- Analysis of models with more parameters.

In the residual analysis of the fitted model, the assumptions of data normality, residual variance constant, residual independence and residual diagram against time are inferred pert-Manto test is done. The assumption that the residuals are normal is accepted if the points are approximately around a straight line and have a uniform distribution. Pert Manto test, which is based on a modified Box-Pearson statistic, is used as a more formal method in testing the residual correlation hypothesis. Pert Manto test is written as equation 4 (Abdolahnezhad, 2015):

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

Where: n is the number of observations, Q is the test statistic whose modified LBQ is Lejangbox. Assuming H0 has an almost Kido distribution. First condition: If the value of Q statistic is more than the corresponding value in Kido table, the assumption H0 is rejected and it means that the data are correlated. Second condition: The value of the correction index must also be greater than the value of α.

Checking the accuracy of the selected model: For this purpose, the indicators of error measurement, mean absolute error value (MSE), root mean square error (RMSE) and coefficient of determination (R^2) are used.

$$MAE = \frac{\sum_{t=1}^{n}\left|x_t - \bar{x}_t\right|}{n} \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(x_t - \bar{x}_t\right)^2}{n}} \quad (6)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)\right]^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \quad (7)$$

After reviewing different models and comparing their accuracy, a suitable model was determined and predicted for the next ten years, and the average minimum and maximum temperatures of different months for the next period (2027-2017) and the base period (1992-2016) were compared and the amount of changes in these parameters for the future period compared to the base period was calculated. In this study, to investigate the effect of changes in temperature characteristics on the evapotranspiration rate of the reference plant, the reference evapotranspiration was calculated by Hargreaves method (Hargreaves, 1994).

$$ET_0 = 0.0023R_a(T_{mean} + 17.8)\sqrt{TR} \quad (8)$$

In this regard, T_{mean}: average daily temperature in the desired period (Celsius), T_R: average range of daily temperature changes (difference between maximum and minimum temperature) in the period, ET_0: Reference evapotranspiration of grass and R_a: External radiation R_a value is obtained for different

geographical offerings for each month. According to the latitude of Khorramabad, the values of R_a for the months of the year are as shown in Table (2) (Hargreaves, 1994).

Results and discussion

The first step in modeling is to check the normality of the data used in modelig (Table 3). Q-Q Plot, Shapiro-Wilk and Klomogorov-Smirnov tests were used to check the normality of the data. The results showed that the data need to be normalized. For this purpose, the square root conversion was used for the minimum temperature data and the squared conversion was used for the maximum temperature data and then the outlet data was deleted. The results of the normality tests for both the minimum and maximum temperature models are given in Table (3) and the Q-Q plot diagram of the maximum and minimum temperature data in Figures 2). Based on the tests performed, the significance level (sig) at the 99% confidence level was significant, indicating the normal autocorrelation for the remaining data, and according to the Q-Q Plot data They have a normal distribution around the mean line.

The next step is to identify the model based on the characteristics of the observational series. Therefore, as the second stage of forecasting, the data trend chart was drawn. Figure(3) shows the trend diagram of the maximum temperature and minimum temperature parameters. According to these diagrams, it was found that the existing series are static.

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Table 2- R_a value for different months of the year for Khorramabad basin

month	Dec	Nov	Oct	Sep	Aug	Jul	Jun	May	Apr	Mar	Feb	Jan
R_a (Mj/m^2.day)	7.1	8.1	10.4	13.1	15.3	16.6	16.9	16.3	14.7	12.2	9.6	7.7

Table 3- Results of Kolmogorov-Smirnov and Shapiro-Wilk tests

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	df	Sig.
min	0.085	252	0.84	0.953	252	0.21
max	0.118	252	0.2	0.914	252	0.11

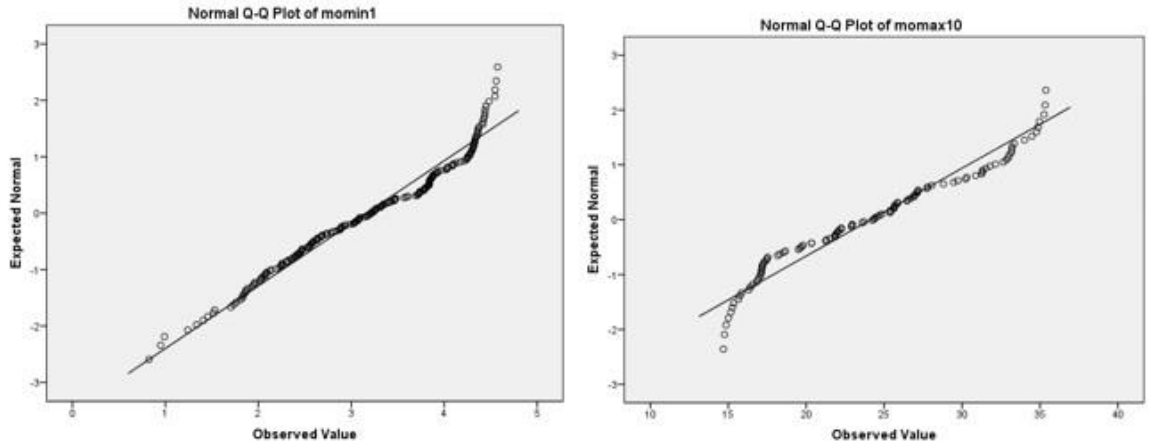

Fig. 2- Q-Q plot diagram for minimum and maximum temperatures normalization

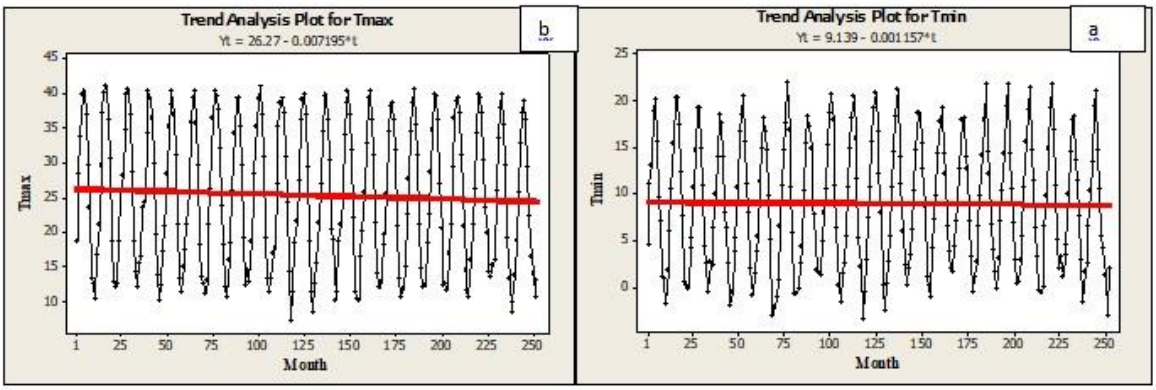

Fig. 3-A- diagram of minimum temperature trend and 3-B- diagram of maximum temperature trend

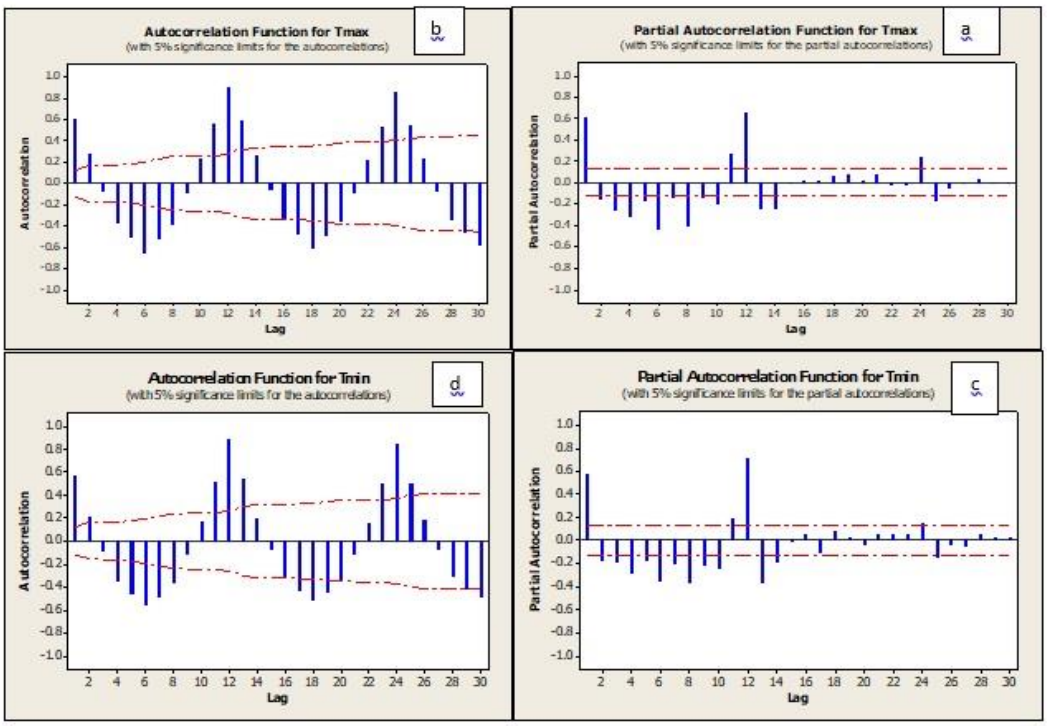

Fig. 4- Self-correlation and partial self-correlation for minimum and maximum temperatures

An important method for studying periodic or seasonal behavior and selecting the appropriate model and the appropriate coefficients of the model is to draw autocorrelation (ACF) and partial autocorrelation (PACF) diagrams. The number of steps in mapping these functions according to the recommendation Hipel et al, (1977) is between 20 and 40 steps, of which 30 steps were considered in this study. Figure (4) shows the ACF and PACF diagrams of the time series of maximum temperature (a and b) and minimum temperature (c and d) (at 95% confidence level). As can be seen from the ACF functions, the series reaches its local peak at time intervals of multiples of 12, which indicates a seasonal trend with period 12, so for modeling and forecasting the model SARIMA is used.

Finally, the ARIMA model (0,0,4) (0,1,1) for the time series of minimum Temperature and ARIMA model (0,0,1) (0,1,1) for the maximum temperature time series were identified as the best models based on the

statistics of the models. The results for model fit is given in table (4), including MA (Moving Average), SMA (Season Moving Average) and BIC (Bayesian Information Criterion). According to the results of the table, the absolute value of T statistic in most parameters was more than 2 and P-value was less than 0.05.

Checking the appropriateness and accuracy of the model

Residual autocorrelation results according to Pert Manto statistics is shown in table 5 for selected models ARIMA (4,0,0) (0,1,1) and ARIMA (1,0, 0) (0,1,1). According to the P-VALUE part of the table, in most delays, the χ^2 test is greater than 0.05, these results indicate the autocorrelation of the residuals. In this test, the purpose of delays is to investigate the partial correlation between different delays and confirm the H0 hypothesis in the selected model (Figure 5). The graph of these functions shows that the residues are in the zero range. Therefore, the assumption of data independence and randomness is acceptable.

Table 4- Fitting results of minimum and maximum temperature models

BIC	T	P-VALUE	parameter	model
	3.13	0.002	MA1	
	2.53	0.012	MA2	
0.622	2.96	0.036	MA3	ARIMA (0,0,4) (0,1,1)
	2.72	0.007	MA4	
	25.81	0.000	SMA12	
	4.62	0.000	MA1	
	5.61	0.008	MA2	
1.054	2.14	0.015	MA3	ARIMA (0,0,1) (0,1,1)
	3.35	0.030	MA4	
	23.05	0.000	SMA12	

Table 5- Results of Pert manto test in suitable models at minimum and maximum temperatures

For Tmin ARIMA (0,0,4) (0,1,1)				
Lag time	12	24	36	48
$\chi 2$	3.4	1.17	5.27	37
Freedom degree	6	18	30	42
P-VALUE	636.0	516.0	594.0	689.0
For Tmax ARIMA (0,0,1) (0,1,1)				
Lag time	12	24	36	48
$\chi 2$	10.7	27.7	48.7	71.1
Freedom degree	6	18	30	42
P-VALUE	0.099	0.067	0.017	0.003

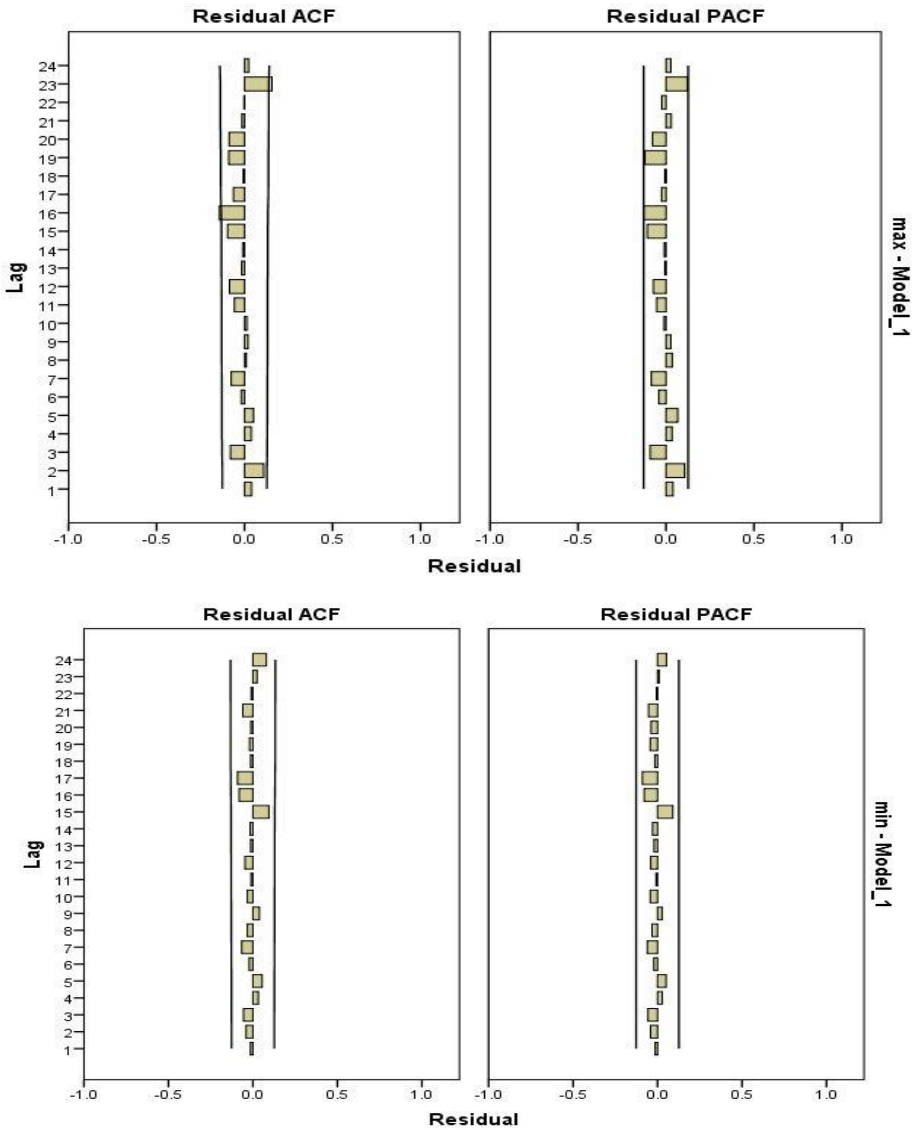

Fig 5- ACF and PACF for a- Minimum temperature data based on ARIMA model (0,0,4) (0,1,1) and b- Maximum temperature data based on ARIMA model (0,0,1) (0,1,1)

Table 6- Accuracy index of minimum and maximum temperatures models

	R^2	RMSE	MAE
ARIMA (0,0,4) (0,1,1)	0.965	1.304	0.991
ARIMA (0,0,1) (0,1,1)	0.971	1.656	1.233

Table (6) contains the results of examining accuracy of final models for minimum and maximum temperatures in Khorramabad. Relatively low values of error indicators and high coefficient of determination confirm the acceptable accuracy of the minimum and maximum temperatures models.

According to the fitted models on the minimum and maximum temperatures data, observed and forecasted maximum and minimum temperatures are shown for 10 statistical years (2017-2026).The series shows the minimum (a) and maximum (b) temperatures.

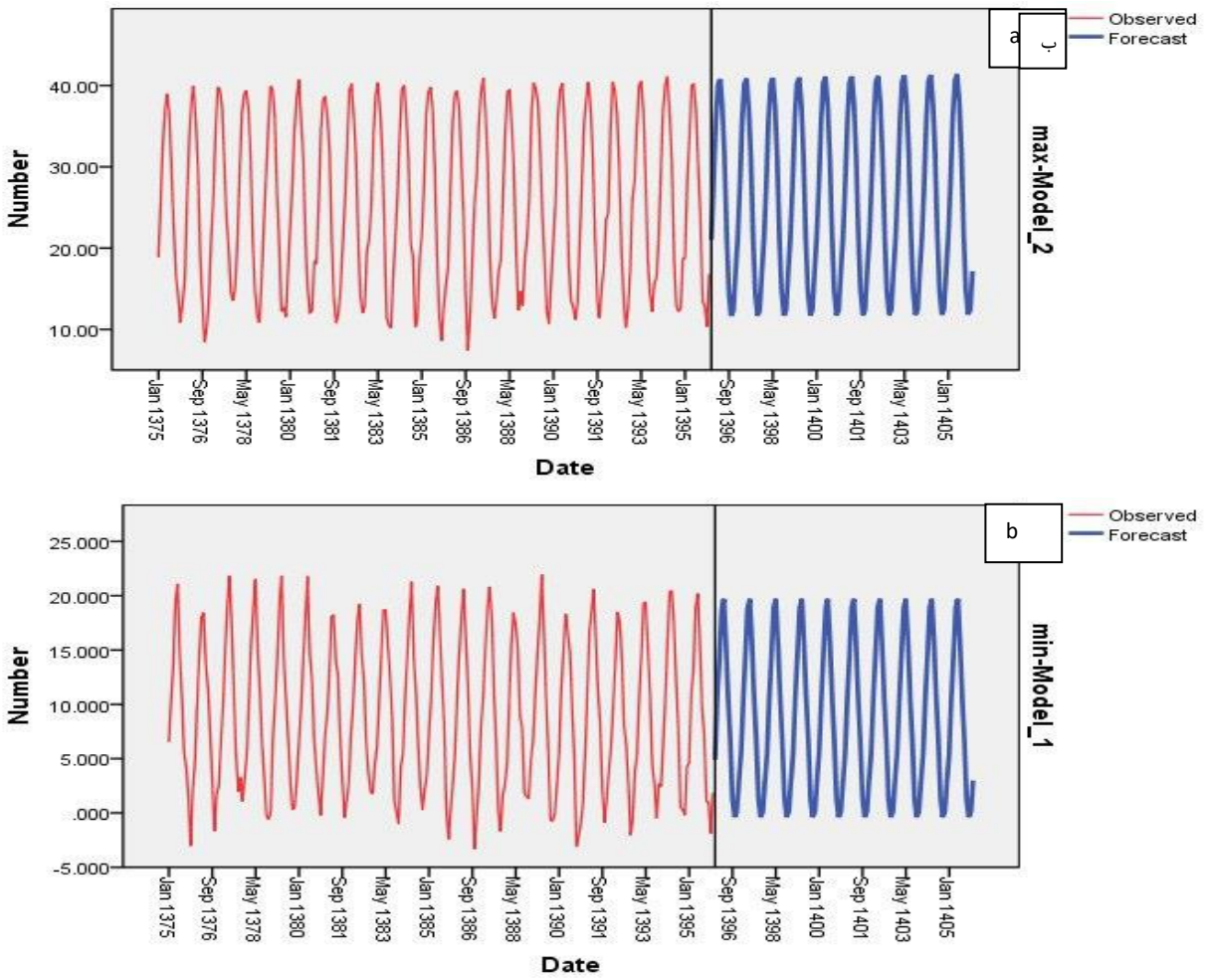

Fig 6 – a- Predicted and observed values for maximum temperature data based on ARIMA model (0,0,1) (0,1,1) and b - Minimum data Temperature based on ARIMA model (0,0,4) (0,1,1)

Predicting the trend of temperature characteristics

The minimum and maximum temperatures in the next ten years (2017-2026) were finally predicted and compared with the base period (1996-2016) After reviewing different models and selecting the final model. Table (7) contains the values for minimum temperature, maximum temperature and reference evapotranspiration in the predicted period (2026-2017) and base period (1996-2016). Figure (7) depicts the changes in the monthly average minimum temperature for the periods (2026-2017) and (2016-1996). As it can be seen from this figure, in the whole future period, the minimum temperature will increase compared to the base period, and most of these changes occur in the warm seasons of the year. The peak of this increase is seen in June, July and August at 2.03, 1.54 and 1.75, respectively. Figure (8) shows the changes in the average monthly maximum temperature in the period (2017-2026) compared to the period (1996-2016). As shown in this figure, the average maximum temperature in the next period will change significantly compared to the base period. These changes will be much more tangible in the warmer months of the year. In this chart, similar to the minimum temperature chart, we see the highest value of this increase in June, July and August at 1.91, 2.03 and 1.77, respectively.

Table 7- Values of minimum temperature, maximum temperature and reference evapotranspiration for basic and predicted periods

month	ET_0-base	ET_0-forecast	T_{max}-base	T_{max}-forecast	T_{min}-base	T_{min}-forcast
Jan	2.14	2.20	20.92	21.01	6.4	7.29
Feb	3.29	3.38	27.03	28.01	10.4	11.68
Mar	5.12	5.97	34.8	35.83	14.7	15.56
Apr	7.16	7.36	39.23	40.37	18.7	1997
Mey	7.98	8.43	39.91	41.54	20.0	21.21
Jun	7.70	7.85	36.52	38.43	15.4	17.39
Jul	6.45	6.58	30.32	32.36	11.1	12.61
Aug	4.18	4.29	20.87	22.65	6.6	8.37
Sep	2.75	2.79	14.34	15.81	1.9	2.28
Oct	1.93	1.94	11.56	12.88	-0.2	1.05
Nov	1.53	1.55	12.10	13.45	0.3	1.11
Dec	1.67	1.67	16.66	17.90	2.9	3.98
total	4.32	4.50	25.36	26.68	9.0	10.21

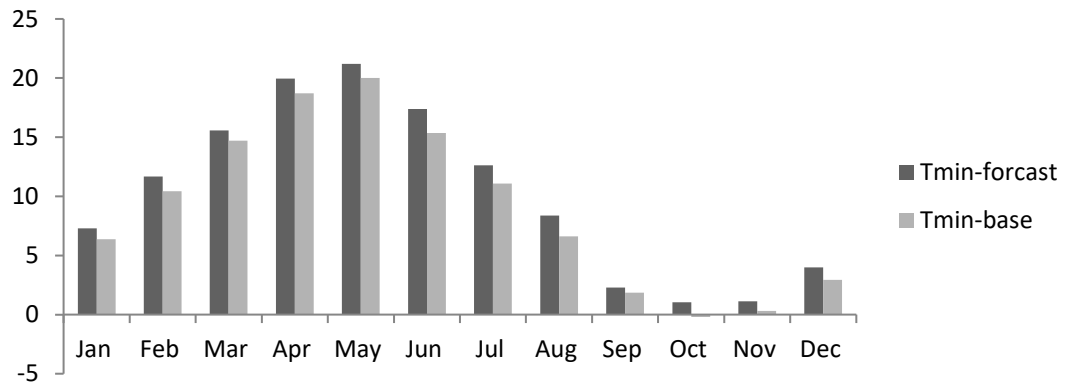

Fig 7- Changes in the average predicted minimum temperature (2026-2017) compared to the base period (1996-2016)

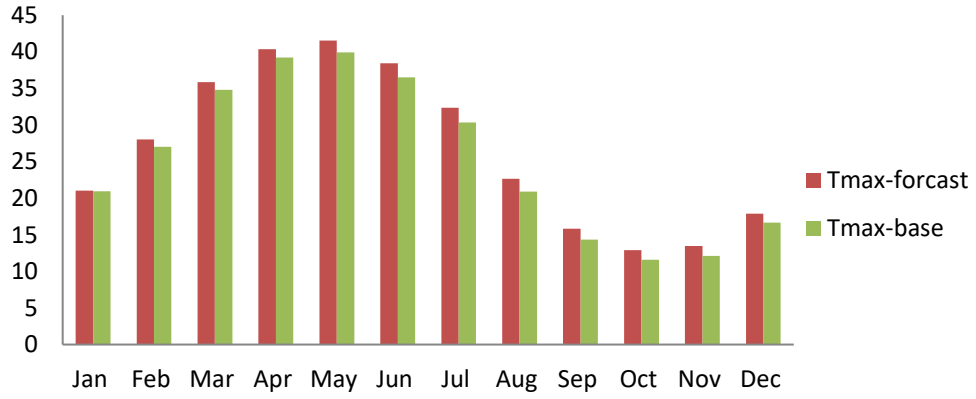

Fig 8- Changes in the average predicted maximum temperature (2026-2017) compared to the base period (1996-2016)

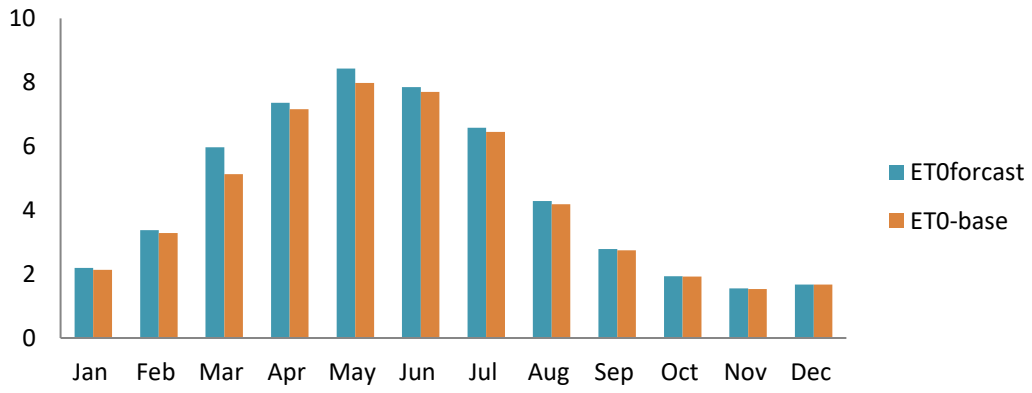

Fig 9- Changes in the average reference evapotranspiration of the predicted reference (2026-2017) compared to the base period (1996-2016)

Investigating the effect of air temperature changes on reference evapotranspiration

Figure (9) shows the reference evapotranspiration fluctuations that are affected by temperature changes in the next decade. It can be seen that in the next period, the reference evapotranspiration will increase on average compared to the base period, most of which will be in March, April and May. This increase is in the months that coincide with the spring planting season. This indicates that due to the increase in both minimum and maximum temperature characteristics, especially the maximum temperature in this period of the year, the changes of reference evapotranspiration are more affected by the maximum temperature, which increases water consumption in agriculture sector.

Conclusion

In this research, time series modeling was used to predict the minimum and maximum temperatures. For this purpose, the box-Jenkins ARIMA model was used. The results represent high capability of ARIMA models in predicting climatic and hydrological parameters. After static analysis of the data, a normality test was performed for the remaining autocorrelation data. Bayesian information criterion was extracted from a combination of different models of the best model. The significance of the parameters was investigated by the least squares method, which in most cases, their significance was confirmed ($P < 0.05$). Then the independence of the residues was examined and confirmed by Jang-Box statistic ($P > 0.05$). Finally, the accuracy of the models was determined using different statistical indices. The reason for using multiple statistical indices was to obtain high reliability and trust in the accuracy of the selected models. To validate the model, the mean square error (RMSE), mean absolute error (MAE) and coefficient of determination (R^2) were used and the model ARIMA (0,0,4) (0,1,1) was used for minimum temperature and model ARIMA (0,0,1) (0,1,1) for maximum temperature due to low error and appropriateness of other statistical indices were selected, and minimum temperature and maximum temperature prediction from 2017 to 2026 was performed using selected models. The use of the obtained models can be a guide for setting priorities and determining basic strategies in the country's water resources management. After implementing the prediction and according to the results, the effect of global warming can be observed in the Khorramabad basib, and the increase in the maximum and minimum temperature parameters, especially in the warm seasons of the year, indicates that we will have warmer days ahead in the coming years. Following the temperature characteristics prediction, plants evapotranspiration was predicted based on the forecast of air temperature using the Hargreaves model equation. The results of this prediction has shown an increment in evapotranspiration in Khorramabad basin. The phenomenon of warming and consequently

increasing the water requirement of plants in the future, the proper management of water consumption, especially in the agricultural sector would be inevitable.

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