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Simulation of Temperature and Rainfall Using the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) Model and Trend Analysis in Arid Regions

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ABSTRACT

This paper analyzes the temperature and rainfall data series collected by Dezful stations in a 31-year period (1986 to 2017) in order to evaluate the magnitude of these changes statistically and to forecast their behavior for the 2018-2020 period using SARIMA models. The Mann-Kendall test was used to analyze climate change in the past and future. The results show that rainfall has a decreasing trend and minimum and maximum temperatures have increasing trends. The results of the SARIMA model show that the coefficient of correlation (r) between the observed and forecasted values was 0.95, 0.9 and 0.58 for rainfall, minimum temperature, and maximum temperature and the mean absolute error (MAE) was 1.24, 1.45 and 20.24 for them, respectively. The results of trend analysis reveal that Mann-Kendall's statistics (Z-value) for the data on minimum temperature, maximum temperature and rainfall are 3.81, 1.78 and -2.71, respectively implying a descending trend for temperature and an ascending trend for rainfall. Minimum and maximum temperatures have been rising at the rates of 0.07 and 0.04°C per year, but they are forecasted to have increased by 0.084 and 0.06°C by 2020, respectively. The rate of rainfall variation will decrease from 4.4 mm to 4.85 mm per year. Improved understanding of recent climate change helps to elucidate the impacts and vulnerability of the local population in order to implement the most appropriate practices to cope with climate change and manage the changing situation in a better way.

1. Introduction

The disruption of world climate equilibrium has increased the average temperature trend of the earth. According to the 2001 report of the Intergovernmental Panel on Climate Change (IPCC), climate change and global warming are taking place (Dracup and Vicuna, 2005). This phenomenon is due to an increase in the concentration of greenhouse gases in the atmosphere (Dettinger et al., 2004). Many natural disasters are related to climate change directly and/or indirectly (Bazrafshan et al., 2017 a). According to the results of climate change studies in the Mediterranean Sea, there is a relationship between the reduction of temperature, rainfall and water shortages, and the increased risk of forest fires (Panol and Lloret, 1998). In general, two parametric and non-parametric statistical methods have been presented to investigate the existence or absence of a trend and the analysis of time series and climate change; however, the non-parametric methods have more applications (Takeuchi et al., 2003).

The temperature and rainfall trends are not the same across the world. Climate change does not necessarily mean simultaneous changes in rainfall and temperature (Carlson et al., 1970). On the other hand, proving the existence of a significant process in a rainfall time series alone cannot be a decisive factor for the occurrence of climate change in a region, but it reinforces the premise of its occurrence (Viviroli et al., 2011). Climatological studies based on time series analysis techniques have begun since the early 20th century. Examples include Jones et al. (1986), Shahid (2010), Nury et al. (2013), Mills (2014), Bazrafshan et al. (2014, 2015, 2017 a, 2017b), Graham and Mishra (2017), Rahman and Lateh (2017), Salman et al. (2017), and Nyatuame and Agodzo (2018).

Temperature is one of the most important atmospheric and climatic parameters that, along with rainfall and freezing, are exposed to climatic fluctuations. Therefore, the study of their changes in recent years can be used to plan and alleviate the impact of problems such as drought, flash floods, and so on. Using the ARIMA time series model, Nury et al. (2013) forecasted short-term minimum and maximum monthly temperature parameters. The results showed that time series models could help to set priorities for future climate changes. Mills (2014) analyzed maximum and minimum monthly temperature using the ARIMA time series model in California. The results showed that ARIMA models were suitable for forecasting

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the behavior of two variables in the future. Salman et al. (2017) applied the multiplicative time series model to analyze average monthly temperature data and forecast the temperature of the coming ten years in Erbil, Iraq. The estimation of forecast accuracy indicated the good and acceptable performance of the model.

Thus, the aim of this research is (i) to analyze the trends of monthly average minimum and maximum temperatures and monthly rainfall over the 1965–2015 period using MK tests (ii) to forecast temperature and rainfall in 2020 using multiplicative SARIMA (iii) to analyze the trend of temperature and rainfall in 2020. It is expected that The assessment of trends of rainfall and temperature can contribute to adapting public health, agriculture and water resources management as well as to improve people's well-being and development of southwestern Iran.

2. Case study

Dezful is located at the crossing of 32°22′57″ N latitude and 48°24′07″ E longitude in the north of Khuzestan province, Iran. The average rainfall and temperature are 312 mm and 24°C, respectively. It is an arid region based on the De-Martonne classification. This area is under the influence of the Sudanese precipitation system (in autumn and winter), the Mediterranean system (in spring, autumn, and winter) and Monsoon (in summer) (Hazbei et al., 2015).

Dezful is experiencing higher temperatures, lower rainfall, and more extreme weather events including dust storm. This area is highly vulnerable because it is located in a plain area and also, it is densely populated (Figure 1). As the agriculture sector is the mainstay of the economy of Dezful, its agriculture and water sectors are very sensitive to the impacts of climate change. So, this study about the trend of temperature and rainfall of Dezful in the past and future can play a key role in making the necessary plans to accommodate with the problems arising from climate change.

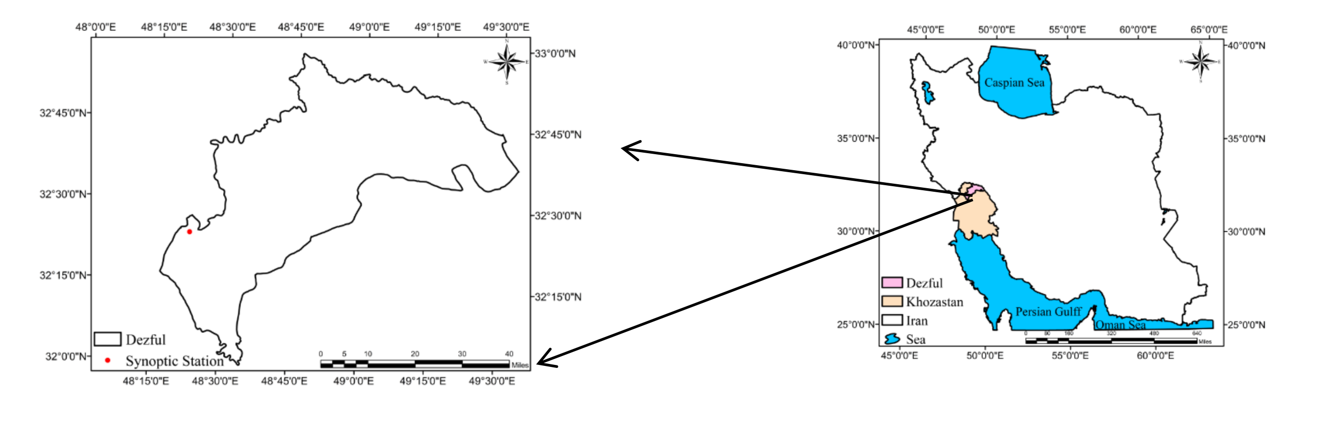

Fig. 1. Location of the case study

3. Data collection

In this study, data on average minimum and maximum monthly temperature and rainfall of Dezful synoptic station were obtained from the I.R Iran Meteorological Organization (IRIMO, 2017) for the 1986-2016 period. The adequacy (Hurst, 1951) and homogeneity tests (Hirsch, 1982) were performed on data before the inclusion in the model fitting.

4. Methods

4.1. Mann-Kendall test (MKT)

The MKT is a non-parametric test of the base order for trend analysis that was presented by Mann (1945) and Kendall (1962). The calculation steps consist of calculating the difference between the observations with each other, extracting the parameter S by Eq. 1, applying the sign function (Eq. 2), calculating the variance by Eq. 3, and calculating the Z statistic using Eq. 4.

$$S=\sum_{i=2}^{n}\sum_{j=1}^{i-1} sign(x_i-x_j) \tag{1}$$

$$sign(x_i-x_j)=\begin{Bmatrix} if \;\; (x_i-x_j)<0 & -1 \\ f \;\; (x_i-x_j)=0 & 0 \\ f \;\; (x_i-x_j)>0 & +1 \end{Bmatrix} \tag{2}$$

$$Var(s)=\frac{n(n-1)(2n+5)}{18} \tag{3}$$

$$Z=\begin{Bmatrix} \dfrac{s-1}{\sqrt{Var(s)}} & if & S>o \\ 0 & if & S>o \\ \dfrac{s+1}{\sqrt{Var(s)}} & if & S>o \end{Bmatrix} \tag{4}$$

where N is the number of data, xi and xj are the data in the time series, and Z is the standard test statistic (Kisi, 2015). According to the Chi-square test, if has the significance amount of α, the null hypothesis is accepted and there will be no trend. The positive values of the Z statistic have an ascending trend and the negative values have a descending trend (Kisi, 2015). If the Z value is within the critical range (± 1.96), it is an indication of the start of mutation and if it is beyond the critical range, it is an indication of the existence of time series at the confidence level of 95% and if it is greater than 2.61, it is significant at the 99% confidence level.

4.2. Multiplicative time series models

Autoregressive models (AR) are the simplest types of continuous models, which can be generally divided into two categories. The first is AR models with constant parameters that are common for the modeling of the annual time series. AR models have the ability to model low river flow (mostly low water) in low-water seasons that are supplied by the groundwater, but in high-water seasons (with high fluctuations), the AR modeling results can be improved by adding Moving Average (MA) model component. A combination of an AR model of the p- order and the MA model of the q-order creates an Autoregressive Moving Average of the order p and q, ARMA (p, q). The basic condition for using the ARMA model is the static time series. The base form of the ARMA models for the standardized normal variable Zt is as follows (Mishra and Desai, 2005):

$$Z_t = \sum_{i=1}^{p} \phi_i Z_{i-1} - \sum_{j=0}^{q} \theta_j \varepsilon_{t-j} \qquad for \quad \theta_0 = -1 \tag{5}$$

If a time series is not static, the time series can be made static using the differential operator. The use of the time series difference *d* and its modeling with ARMA (p, q) leads to the emergence of a new series of non-seasonal autoregressive integrated moving average (ARIMA (p, d, q)) models. The basic form of the non-seasonal ARIMA model is as follows:

$$\phi(B)(1-B)^d Z_t = \theta(B)\varepsilon_t \tag{6}$$

where ϕ (B) and θ (B) are q-order polynomial of the AR model and the-order polynomial of the MA model obtained by

$$\phi(B) = (1-\phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p) \tag{7}$$

$$\theta(B) = (1-\theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) \tag{8}$$

In the case of using the seasonal difference function with delay *w* and their fitting with the ARMA (p, q) models, the ARIMA$(P,D,Q)_w$ seasonal models are created. A combination of seasonal and non-seasonal models form models known as Multiplicative ARIMA. The basic form of Multiplicative ARIMA is as follows:

$$\Phi_P(B^w)\phi_p(B)(1-B^w)^D(1-B)^d Z_t = \Theta_Q(B^w)\theta_q(B)\varepsilon_t \tag{9}$$

where *p* is the order of non-seasonal AR model, *P* is the order of seasonal AR model, *q* is the order of unseasonal AR model, *Q* is the order of seasonal MA model, *w* is the length of the season, ε_t is the random variable (white noise), *B* is the differential operator as $B(Z_t)=Z_{t-1}$, $(1-B)^d$ is the equivalent of unseasonal difference *d* and $(1-B^w)^D$ is the equivalent of seasonal difference *d* as much as *w*. After calculating the first order of the model, the appropriate model is identified using the Akaike Information Criterion (AIC) test (Mishra and Desai, 2005).

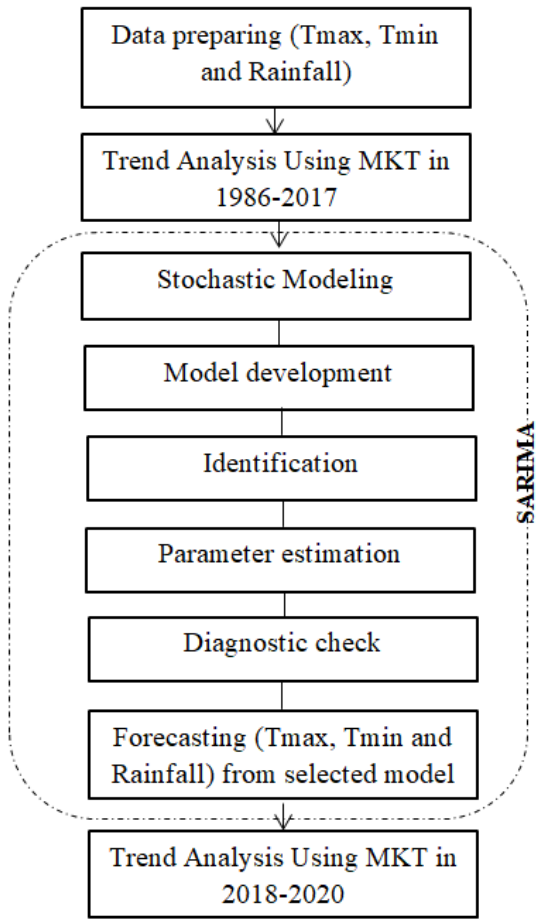

Fig. 2. The flowchart of the research methodology

4.3. Evaluation of time series models

To test the goodness of fit of the models on the variables, the Kolmogorov-Smirnov residual normality test was used. The correlation coefficients (R), root-mean-square error (RMSE) and mean absolute error (MAE) were used to examine the relationship between observed and forecasted data. Finally, the main statistical characteristics were compared between observed and forecasted values using the Z test for mean and the F test for standard deviation. Fig. 2 shows the steps of the research.

5. Results and Discussion

5.1. Multiplicative ARIMA model Development

Stochastic model development consists of model identification, parameter estimation, and diagnostic checking (Box et al., 1974; Box and Jenkins, 1976). The identification stage involves transforming the data (if necessary) to improve the normality and the stationarity of the time series and determining the general form of the model to be estimated. During the estimation stage, the model parameters are estimated using the method of moments. The diagnostic checks of the model are performed to reveal possible model inadequacies and to assist in selecting the best model. In the present study, time series of monthly rainfall and mean minimum and maximum monthly temperature data were used over the 1986-2012 period for modeling and those of the final 4-year (2013-2017) were used for model validation.

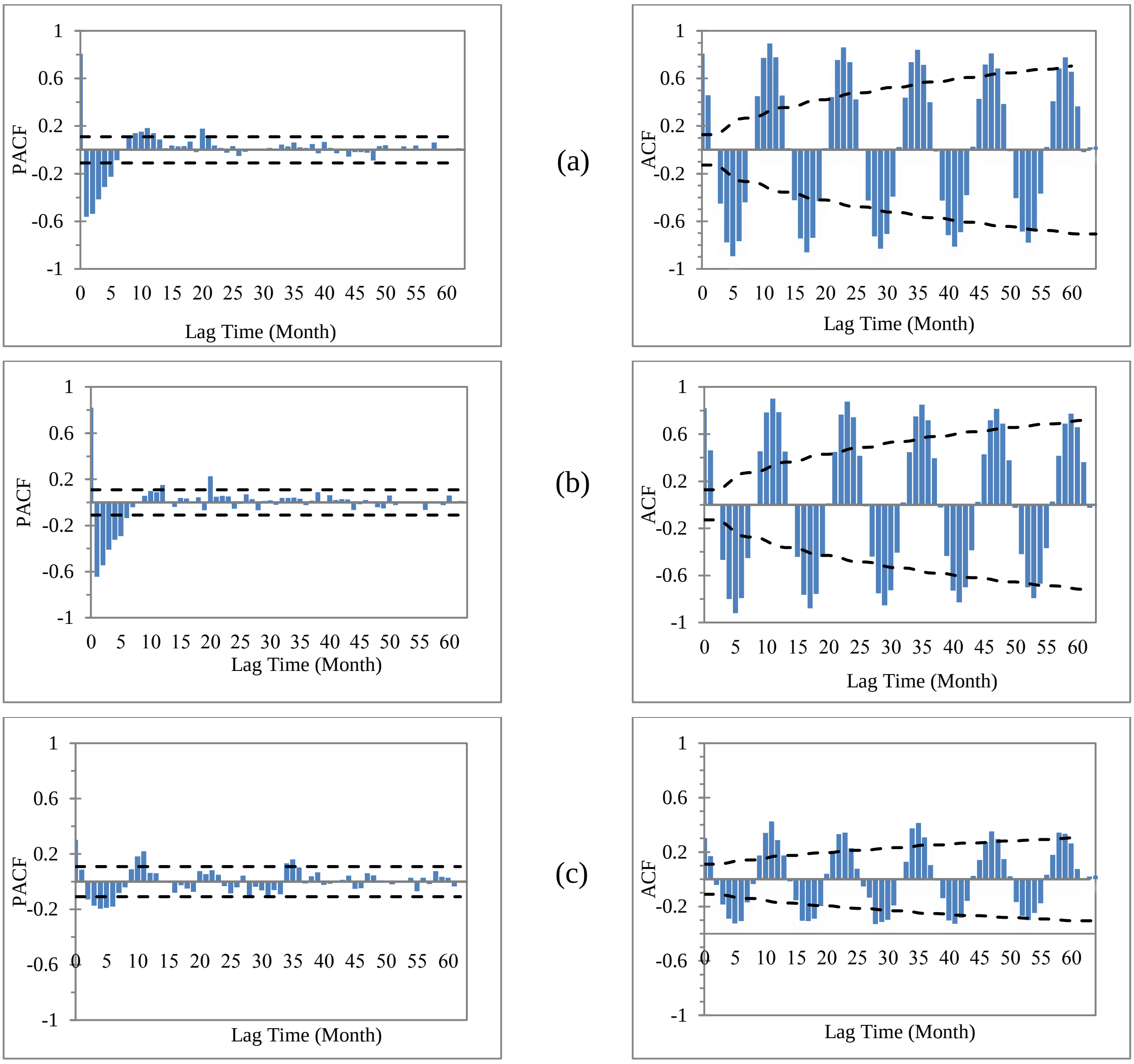

Fig. 3. ACF and PACF for minimum temperature **(a)**, maximum temperature **(b)**, and rainfall **(c)** in Dezful station.

5.1.1. Identification

Identification of the general form of a univariate model involves two steps. First, the data series is analyzed for stationarity and normality. Appropriate differencing of the series is performed (if necessary) to achieve stationarity and normality. The correlation structure of the transformed data are identified by examining its autocorrelation (ACF) and partial autocorrelation (PACF) functions. In this stage, the order model is determined using the ACF and PACF functions. Based on Fig. 3, ACF and PACF showed that the time series were not stationary. With respect to Tmax and Tmin, the first five values are significant in PACF, which indicates that the process can be modeled as a combination of both AR and MA processes. The ACF is not damping out in a sine-wave manner with significant spikes at the one-two lags. This model has manner seasonal.

This infers a possible ARIMA (p, d, q) (P,D,Q)w model with p = 1–5 and q = 1–2, d= 1,2, w=12. So, all the combinations were tried to pick the best model out of these candidate models. The minimum Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) are selected as the best model.

5.1.2. Parameter estimation

After the identification of the model using the AIC, AICC and SBC criteria, the parameters are estimated. During the estimation stage, the model estimates were calculated simultaneously for the AR and MA parameters. The selected model parameters were calculated using the MINITAB software package. The values of the selected model parameters are listed in Table 1. The standard error calculated for each of the model parameters is generally small compared to the parameters, so these parameters could be used in modeling. The t-ratio and standard error in parameters were small, so the estimates of parameters were statistically significant and these parameters were applied in the modeling.

Table 1. Parameters of the selected models.

Variable	Model	Parameter	Value	Standard error	t- ratio	P<0.05
Tmin	ARIMA $(1,0,0)(0,1,1)_{12}$	θ_1	0.23	0.05	4.4	0.00**
		Φ_1	0.8	0.04	22	0.00**
		Constant	0.06	0.01	4.2	0.00**
Tmax	ARIMA $(1,0,0)(0,1,1)_{12}$	θ_1	0.33	0.05	6.3	0.00**
		Φ_1	0.8	0.04	21.4	0.00**
		Constant	0.04	0.02	1.9	0.05*
Rainfall	ARIMA $(0,0,0)(0,1,1)_{12}$	Φ1	0.9	0.02	28.6	0.00**
		Constant	-0.38	0.2	-1.8	0.00**

** shows significance at the 99% level and * shows significance at the 95% level.

Table 2. Residual normality test using the Kolmogorov-Smirnov statistics in the selected time series models.

Variable	Model	K-S test Dcal	K-S test P value
Tmin	ARIMA(1,0,0)(0,1,1)12	0.116	0.112
Tmax	ARIMA(1,0,0)(0,1,1)12	0.162	0.115
Rainfall	ARIMA(0,0,0)(0,1,1)12	0.109	0.135

5.1.3. Diagnostic check

After the model is identified and the parameters are estimated, the diagnostic checks are applied to the fitted model to verify the adequacy of the model. For an appropriate forecasting model, the residuals left over after fitting the model should be white noise. There are different methods for diagnostic check including ACF and PACF of residual, normality test of residuals, and the Kolmogorov-Smirnov Test. In this study, we applied the K-S test. According to Table 2, the K-S test is satisfied and the residuals are normally distributed.

5.2. Forecasting from selected models

The forecast was done for 24-month lead-time using the best models from historical data. The plot between observed data and predicted data using the selected best model for all time series is shown in Fig. 4.

Basic statistical properties are compared between observed and forecasted data for one month lead time using Z-test for the means and F-test for standard. The observed and forecasted time series are compared in Table 3. The results of F and Z analyses showed the lack of any significant differences between the mean and variance of the observed and forecasted values, and the null hypothesis on the equality of variances and the means of observed and forecasted values was accepted. Therefore, the results show that stochastic models are adequately capable of maintaining the variance and mean of the observed time series and can model the relationships of phenomena well.

Table 4 shows the upper and lower limits of the forecasted values of the selected models. According to the results, the model uncertainty was estimated to be low in forecasting minimum and maximum temperature while it was very uncertain with respect to rainfall variable.

In other words, the models could provide a better forecast of minimum and maximum temperature than rainfall. The coefficients of correlation for minimum and maximum temperature and rainfall was 0.98, 0.95 and 0.59, RMSE was 2.7, 2.7 and 32.5, and MAE was 1.24, 1.45, and 24.20, respectively (Fig. 5).

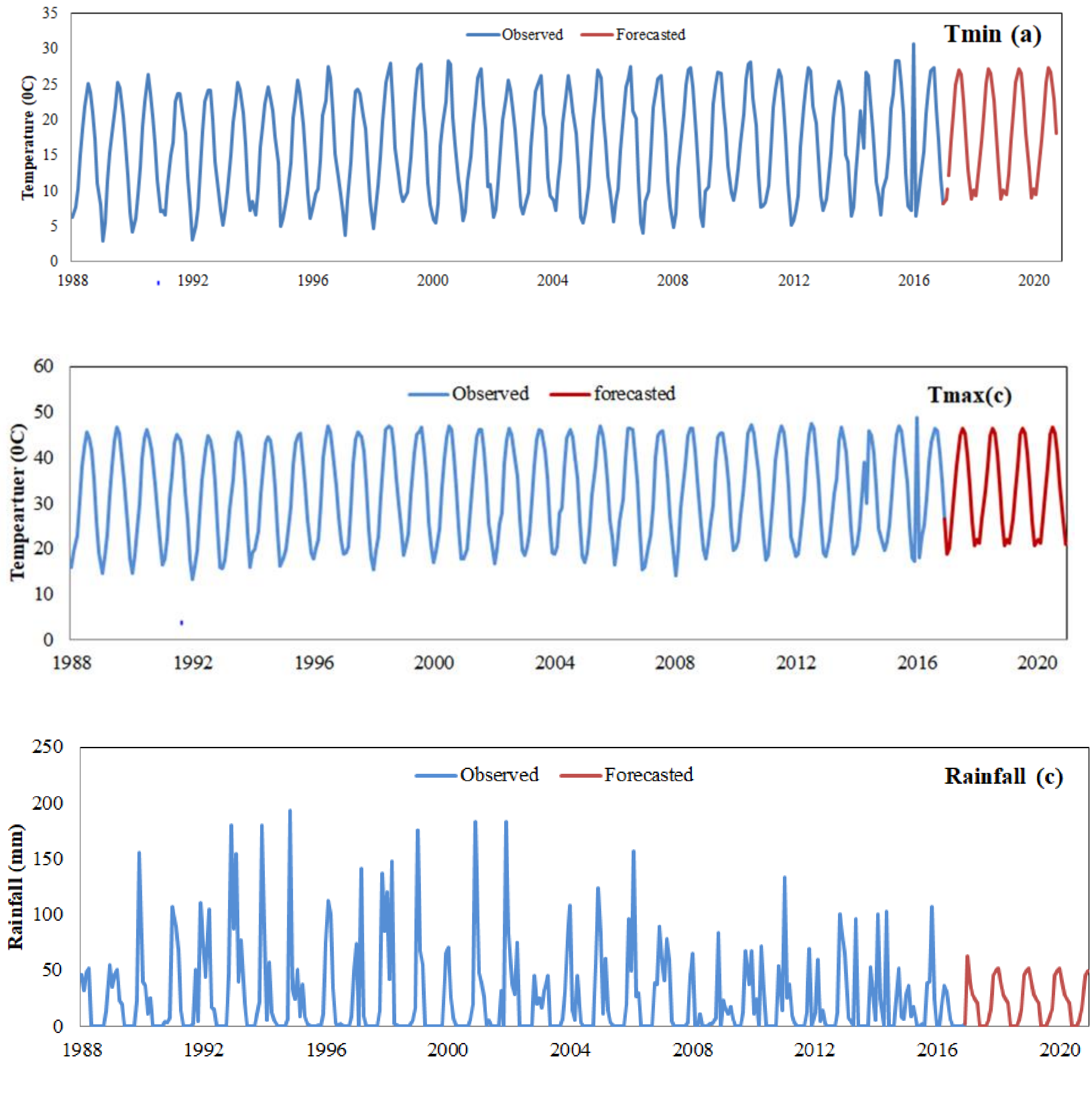

Fig. 4. The observed and the forecasted values of minimum temperature **(a)** maximum temperature **(b)**, and rainfall **(c)**

Table 3. The comparison of statistic properties of the observed and predicted data.

Variable	Variance observed	Variance forecasted	Decision $F_{cal} < F_{tab}$	Mean observed	Mean forecasted	Decision $\|Z_{cal}\| < 1.96$
Tmin	50.71	47.56	0.48	16.17	16.23	0.91
Tmax	109.88	107.73	0.85	32.3	32.3	0.98
Rainfall	1600.7	792.24	0.54	260.4	280	0.55

Table 4. The uncertainty caused by forecasting in selected time series models.

Variable	Upper limit	Lower limit	Mean	Diference Up-Lo
Tmin	31.5	4.5	17.33	8.49
Tmax	52.5	14.85	32.91	11.41
Rainfall	113.5	-69	128.9	20

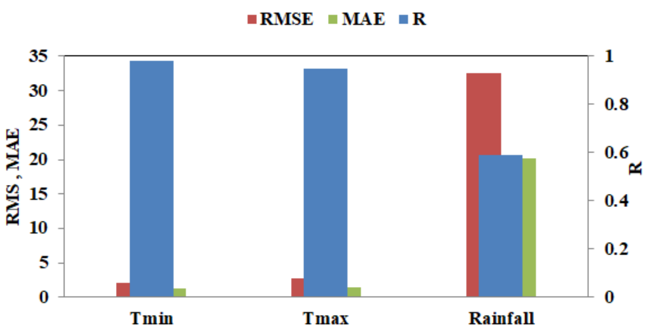

Fig. 5. The criterion of performance evaluation of time series models

5.3. Analysis of past and future trends of temperature and rainfall variables

In this research, the variables were analyzed using the Mann-Kendall method to reveal their past and future trends. Table 5 shows the results of trend analysis in the past and future for temperature and rainfall. According to the results, the minimum and maximum temperature trends with the Mann-Kendall statistics of Z= 3.81 and Z= 1.78 have increasing trends in that the minimum temperature slope is much steeper than the maximum temperature. In the case of rainfall, it has a sharp decreasing trend with a value of Z=-2.71 in that the sharpness of the slope is increased in the 2020 horizon.

Figure 6 shows the graphical Mann-Kendall test. The minimum and maximum temperatures have an increasing trend, which will continue to rise until 2020 and the decreasing trend of rainfall has begun since 2000.

Table 5. Z- statistic using Mann-Kendall trend analysis for the variables in the past and future

Variable	Past	Future
Tmin	3.81***	3.92***
Tmax	1.78*	1.95*
Rainfall	-2.71***	-2.78***

***, **, and * refer to the significance at 99, 95 and 90% confidence levels.

6. Conclusions

The purpose of this study was to forecast the changes in temperature and rainfall trends at Dezful Synoptic Station using the seasonal ARIMA model. The SARIMA time series model-based future prediction of climate change for the 2018–2020 period was evaluated and a particularly strong recent climate change was confirmed. This study also validates the SARIMA time series model for shorter timescale climate simulations and can easily be applied to more localized climate data since the SARIMA modeling focuses purely on the data rather than data generating processes.

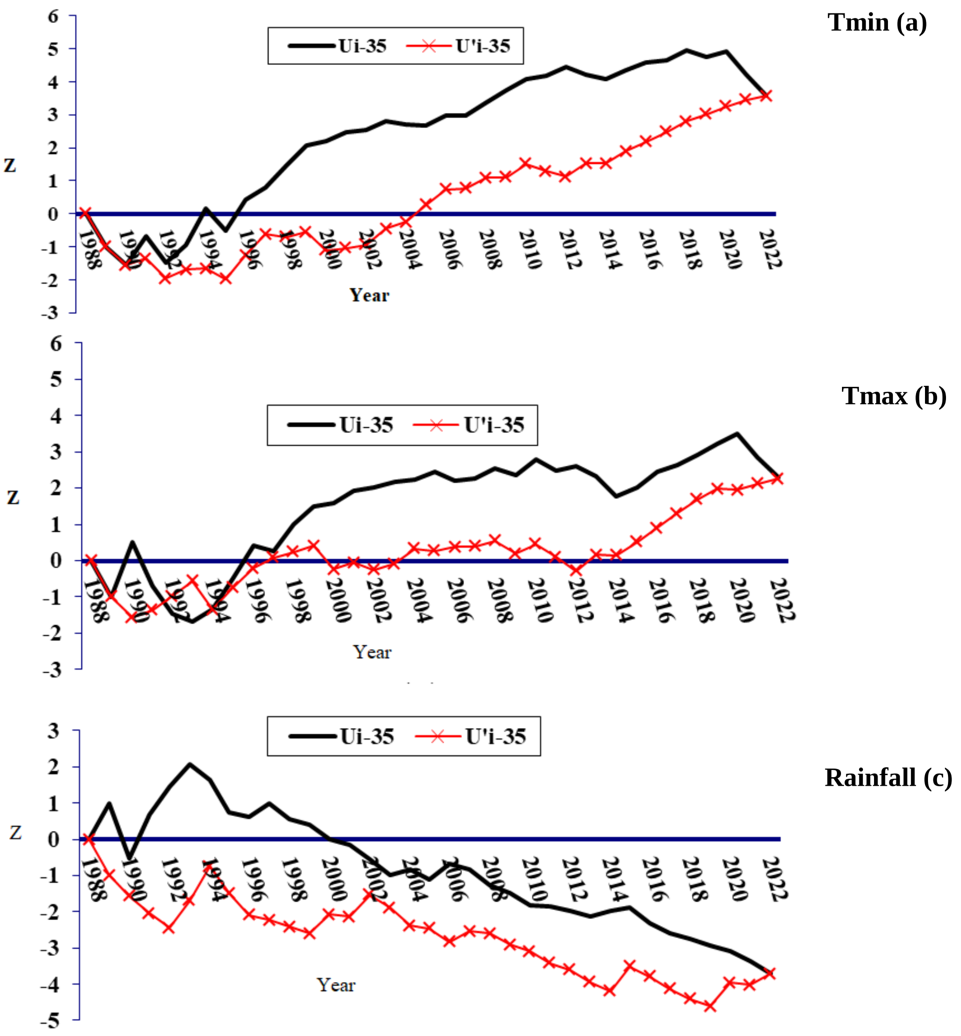

Figure 6. The Mann-Kendall graphic trend for the time series

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Based on the results, the SARIMA multiplicative model, which is a combination of seasonal and non-seasonal ARIMA, had the most suitable performance for forecasting rainfall and temperature variations. Due to the nonlinear behavior of rainfall, relative to temperature, the accuracy of the estimates was lower.

The results of rainfall trend analysis showed that rainfall has had a decreasing trend over the past 30 years at the station so that the jumping began in 1996. This trend will continue to decrease over the next 2 years to 2020 based on the forecasts. It will decrease from 4.4 mm to 4.85 mm per year.

The results of the minimum and maximum temperature trend showed that both variables are increasing in the area under study so that they will be increased by 0.084 and 0.06°C in 2020, respectively.

An understanding of recent climate change in the region can help to understand the effects and damage caused by it, so using high-accuracy models can help to manage the resulting situation.

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