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Research Article

Monitoring annual precipitation changes in Dezful plain with statistical analysis and time series

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ABSTRACT

Background and objective: Predicting and studying the trend of climate variables in the future plays an important role in the optimal management of water resources**.** Different methods are used to determine the trend of change. One of the most common methods of trend change analysis is time series analysis. Time series is a set of observations about a variable that is measured at discrete points in time, usually at equal distances, and arranged in chronological order.
Materials and methods: In the present study, the trend of precipitation changes in Dezful plain during 32 years was investigated and by selecting the appropriate time series model, a forecast was made for the next ten years. Man-Kendall's non-parametric test was used to investigate the trend of precipitation changes.
Results and conclusion: The result of this test showed that the annual precipitation of Dezful had a decreasing trend due to having a Man-Kendall statistic of -1.6. To select the appropriate time series model, data preparation (trend elimination and normalization) was performed first. Data stagnation was assessed with autocorrelation (ACF) and partial autocorrelation (PACF) charts. Using the differentiation method, the data became static (eliminating the mean trend) by applying one-time differentiation. By static data, random models were used to predict the average annual precipitation. Then, by fitting different Arima models and considering the criteria of T, P-VALUE less than 0.05 and Bayesian information criterion (BIC), the Arima model (3,1,1) was selected as the most appropriate model and to verify this the model was predicted for the period 2011 to 2018. The validation results showed that the prediction of this model is acceptable according to the actual values. Then, based on this model, a forecast was made for the next ten years from 2019 to 2028, which is predicted that the precipitation trend will decrease for the next period.

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1. Introduction

One of the most important problems in the world which will affect human life in the future is the problem of water shortage and the lack of proper distribution of water resources. Predicting and studying the trend of climate variables in the future plays an important role in the optimal management of water resources (Wang et al., 2000). One of the climatic variables that is predicted to help achieve appropriate harvest patterns from water resources, crop management, especially rainfed cultivation, and reduction of irreparable damage due to droughts and floods is precipitation (Ouma et al., 2022). Different methods are used to determine the trend of change. One of the most common methods of trend change analysis is time series analysis (Rhif et al., 2019). Time series is a set of observations about a variable that is measured at discrete points in time, usually at equal distances, and arranged in chronological order (Khorrami & Bozorgnia, 2017; Ghaderpour et al., 2021).

Thus, a time series is obtained by observing a phenomenon over time. Time series models predict their future based on the past pattern of climate variables. Time series data can be discrete or continuous (Salas, 1996). Unlike random examples of a community that is independent of each other, time-series data are not independent of each other and are consistently interdependent, and this relationship between observations is considered by researchers and used in forecasting (Abdullah Nejad, 2015). These experimental models are a powerful tool for simulating and predicting the random behavior of hydrological systems such as precipitation (Nail & Momani, 2009; Jamali et al. 2020; Mishra et al., 2021). Precipitation predicting for the future years will play an effective role in better management of water resources in agriculture and other water consumption sectors. Also, since hydrological variables such as discharge, runoff and precipitation from precipitation are affected by this climatic characteristic, so it is important to know the extent and trend of changes in drought management, flood control, sediment, and groundwater.

It is important to note that predicting means determining the amount of precipitation with the highest probability of occurrence and does not in any way imply an accurate prediction of precipitation. However, researchers believe that the projected values will play an important role in the management of water resources despite uncertainty. Shahid (2010) investigated spatial patterns of seasonal and annual precipitation in Bangladesh from 1957 to 2007. The results showed a significant trend of increasing annual precipitation. Veisipour et al., (2010) used the Arima model to predict precipitation and temperature in Kermanshah province of Iran. The results showed that for predicting precipitation on a ten-day scale, only ten-day precipitation and using monthly data on a monthly and annual scale are more accurate.

Abdullah Nejad, (2015) used autoregressive time series models, moving average and combined autoregressive models with moving average and seasonal models to select the most appropriate method for estimating total precipitation during the statistical period 1976 to 2012 in Hashemabad station of Gorgan in Iran. The results showed that the Sarima model has better performance than other time series models and simulates the process of time-series changes with the least error. Momani and Naill, (2009) modeled the precipitation time-series of the Jordan region and selected the Arima model (1,1,0) (0,0,1) as the appropriate model. Ruhf and Cutrim, (2003) analyzed the precipitation time series in southern Michigan and proposed the Arima model. Borland and Montana, (1996) used Arima models to predict hourly precipitation at the time of occurrence Compared with precipitation gauge data.

They concluded that as the precipitation duration increased, the forecasts had a more accurate trend, and as it shortened, the difference between the forecast precipitation and the corresponding actual amount was greater. Studying different researches in time-series analyzing of rainfall can find that, studying future changes in rainfall is necessary. Considering the importance and necessity of studying the trend of precipitation changes and awareness of its future changes, which is important in water resources, the purpose of this study is to investigate the trend of 32-year annual precipitation changes in Dezful station, selecting the appropriate time series model and Validation of the selected model based on real data that has not been done in other studies and it is assumed that this step will lead to better model selection and then prediction the annual precipitation for the next 10 years is based on the selected model.

2. Material and Methods

Dezful city is one of the cities of Khuzestan province in southwestern Iran. Dezful city with an area of about 4762 square kilometers is located between 48 degrees and 20 minutes to 48 degrees and 31 minutes east of the Greenwich meridian and between 32 degrees and 75 minutes north latitude of the equator and at an altitude of 140 meters above sea level. This city is limited to Lorestan province from the north, Andimeshk city from the west, Chaharmahal Bakhtiari province from the east, Masjed Soleiman from the southeast, Shushtar and Gotvand from the south and Shush from the southwest. The highest point of this city is the mountain hall with a height of more than 2600 meters. Fig. 1 shows the geographical position of Dezful plain. In this study, to predict the annual precipitation, the information of Dezful synoptic station was used its geographical location of it, is given in Table 1.

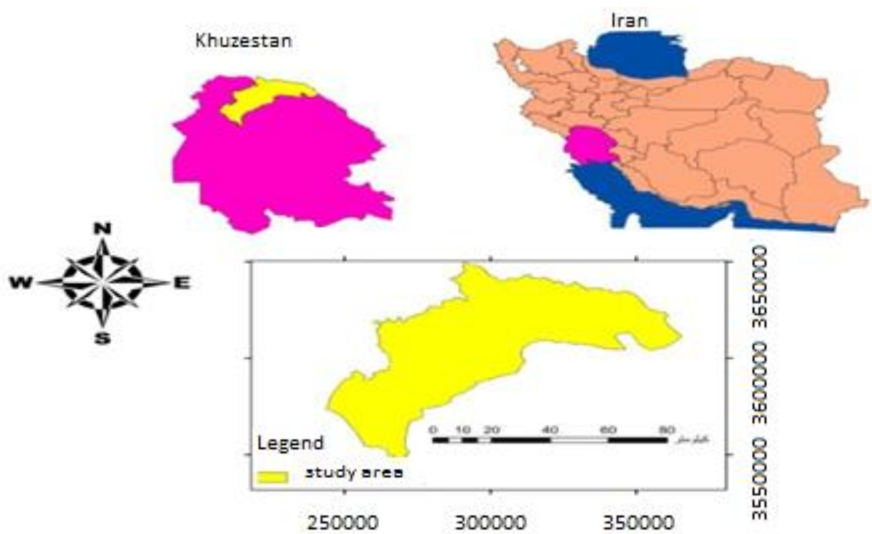

Fig. 1- geographical position of Dezful plain in Iran

Table 1- geografical position of Dezful synoptic station

altitude	latitude	longitude	station
82.9	16" N° 32	25° "48 E	**Dezful**

Time series trend analysis is one of the methods that can be used to study precipitation changes in the past and present at different time scales (Khalili & Bazrafshan, 2004). Statistical methods are one of the most common methods for analyzing time series, examining the presence or absence of trends in them. Mann-Kendall test is one of the non-parametric methods in the analysis of time series trends (Pasquini et al., 2006) which was used in this study for investigating of 32-years trend of annual precipitation.

1.2. Mann – Kendall test

The Mann-Kendall test is used to check the time trend for each set of data. The results of this test show whether there is a significant increase or decrease trend in a certain level of confidence in the parameter time series trend or not. Using the non-parametric Mann-Kendall test is not sensitive to the normality of the data. The Mann-Kendall test was first developed by Mann (1945) and then developed by Kendall (1975). The use of this method was recommended by the World Meteorological Organization (Soltani Gordfaramarzi et al., 2017). One of the strengths of the Mann-Kendall method is that it is suitable for time series that do not follow a specific distribution. This method is used to examine the flow of data. In this method, the S statistic for the gth month and the kth station is calculated as follows.

$$S_{gk} = \sum_{i}^{n-1} \sum_{j=i+1}^{n-1} sgn\,(X_{jgk} - X_{igk}), \forall \leq i<j\leq n \quad (1)$$

Where n is the number of series data and sgnθ is a function of the sign and θ is the difference between the two observations in each of the parameters studied in different years i and j, which is defined as follows:

$$gn(\theta) = \begin{cases} 1 & if \quad \theta > 0 \\ 0 & if \quad \theta = 0 \\ -1 & if \quad \theta < 0 \end{cases} \quad (2)$$

Kendall and Mann showed that when n ≤ 10 is 10, the S statistic is distributed almost normally and has a mean of 0 and the following standard deviation:

$$(\sigma_{gg})_k = \frac{[n(n-1)(2n+5) - \sum d(d-1)(2d+5)]}{18} \quad (3)$$

Where d is the same number of data in the time series. In this method, Sgk is normalized as follows:

$$S'_{gk} = S_{gk} - sgn(S_{gk}) \quad (4)$$

Then the standardized test statistic or Z, which has a standard normal distribution with a mean of zero and a variance of 1, is obtained as follows:

$$Z_{gk} = \frac{S'_{gk}}{(\sigma_{gg})^{1/2}} \quad (5)$$

If the value of Z is greater than ±1.96, the data has a trend and the null hypothesis is rejected, otherwise it has no trend. Z: is a standard normal distribution statistic and can take different values in a two-domain test depending on the confidence levels tested. The value of Z statistic for 95% and 99% confidence levels is considered equal to 1.96 and 2.58, respectively.

2.2. Time series modelling

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 instant 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 this case, a combination of autoregressive and moving average models and cumulative moving average autoregressive models are used, (Soltani Gordfaramarzi et al., 2017).

3.2. ARIMA integrated correlation-moving average model ARIMA (p, d, q)

In this type of model, the best time series model for fitting the data is determined through two functions, ACF autocorrelation and PACF autocorrelation, and according to these two functions, the seasonal properties and static nature of the data are investigated. One of the most widely used of these models is the Arima model, Box et al., (2015) Two general forms of the Arima model, including 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 autoregressive parameters and the seasonal moving average. The other two parameters, d and D, are differential parameters for static time series. The differential operators used for dynamic time series are: $\Delta = (1-B)$, $\Delta^d = (1-B)^d$ (B is the reverse jump operator). This form of non-seasonal Arima models is in the form of Equation 6:

$$\phi(B)Z_t = \phi(B)(1-B)Z_t = \theta(B)at \quad (6)$$

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

$$\varphi_p(B)\Phi_p(B^s)\Delta^d\Delta_s^D\left(z_t - \overline{Z}\right) = \theta_q(B)\Theta_Q(B^s)a_t \quad (7)$$

Where qΘ: seasonal polynomials Q and pΦ: seasonal polynomials of P. The rank of seasonal-multiplicative Arima models is (p, d, q) * (P, D, Q).

4.2. Parameter determination step

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 autoregressive. The parameters should be tested for significance, which is related to the error values of the estimates and the estimation of the t values (Box et al., 2015). If Θ is a point estimation of the desired parameter and SΘ is the error of this estimation, the value of t is obtained as relation 8:

$$t = \frac{\theta}{S_\theta} \quad (8)$$

If the assumption of error equal to or greater than $\alpha = 0.05$ is assumed to be zero, then the parameter will be significant and will remain in the model.

5.2. Good fit test

Good fit test the accuracy of the 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 QQ Plot, Shapiro-Wilk and Kolmogorov-Smirnov tests. In this section, SPSS and Minitab software were used to check the normality of data and homogeneity, and also T and P-VALUE statistics and Bayesian information criterion (BIC) to check the relationship between observational and predicted data Used (Niromand, 2012).

6.2. Checking the suitability of the model

To check the suitability of the model, two methods that are complementary are used (Ahmadi, 2004) :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 by the Pert-Manto test. 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 the modified Box-Pearson statistic, is used as a more formal method in testing the residual correlation hypothesis. Pert-Manto test is written as Equation 9 (Abdullah Nejad, 2015):

$$Q(LBQ) - n(n+2)\sum_{h=1}^{k}(n-h)^{-1}\rho_h^2 \quad (9)$$

Where: n is the number of observations, Q is the test statistic Which modified is LBQ Lejangbox. Assuming H0 has an almost Kido distribution.

First condition: If the value of Q statistic is more than the corresponding value in the 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.

3. Results and Discussion

In the present study, using the 32-year precipitation information (2018 (1397 Shamsi)-1986 (1365 Shamsi)) of Dezful synoptic station, the trend of precipitation changes over time has been modeled. For this purpose, data were prepared (normalization and process elimination), model recognition, order determination and model parameters. The results of the Mann-Kendall test to investigate the trend of 32-year changes in precipitation show a decreasing trend of this parameter (Z = -1.62). But according to the value of Mann-Kendall statistic, this decrease was not statistically significant at the 95% level. Fig. 2 shows the Man-Kendall diagram related to the annual precipitation of Dezful, which shows the decreasing trend of this parameter.

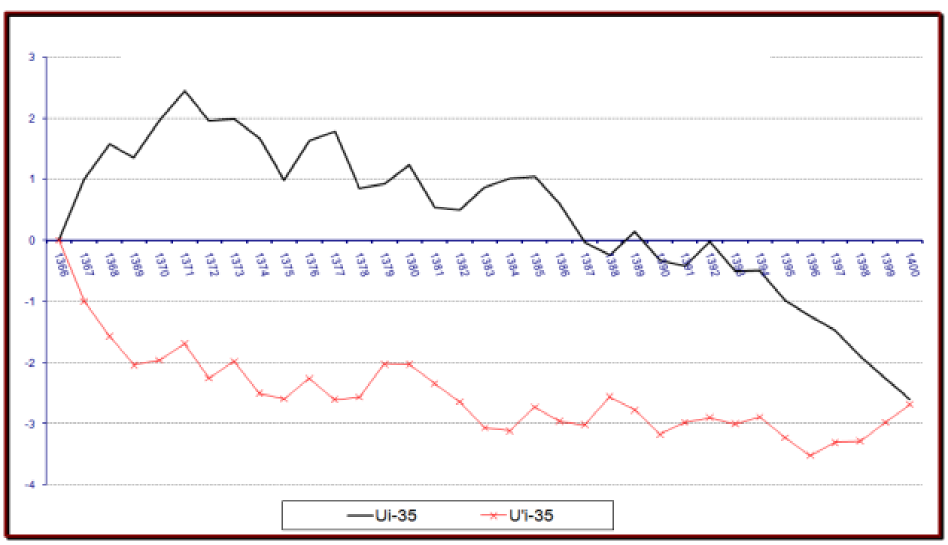

Fig. 2- Mann-Kendall chart of annual precipitation over a 32-year period

1.3. Results of precipitation time series analysis

In the first step, the data were examined for normality (Table 2 and Fig. 3). QQ Plot, Shapiro-Wilk and Kolmogorov-Smirnov tests were used to evaluate the residual normality of autocorrelation.

According to the results of the Kolmogorov-Smirnov and Shapiro-Wilk tests, the significance level (sig) is greater than 0.05, so this null hypothesis based on the normality of the data is confirmed. Also, according to the QQ Plot results, the data have a normal distribution and no skewness around the straight line, which indicates that the data is normal.

Table 2 - Results of Klomogorov-Smirnov and Shapiro-Wilk normality tests for annual precipitation

	Kolomogorov -Smirnov			Shapiro-Wilk		
	parameter	Freedam degree	sig	parameter	Freedam degree	sig
Annual precipitation	0.105	31	0.2	0.956	31	0.223

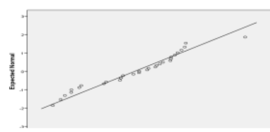

Fig. 3 - QQPlot test result of annual precipitation

After checking the normality, determining the trend of changes to determine the seasonality and identify the outgoing data, a data trend diagram was drawn. Fig. 4 shows the trend of 32-year precipitation changes. According to this chart, the trend of change has decreased with a slope of -3.92.

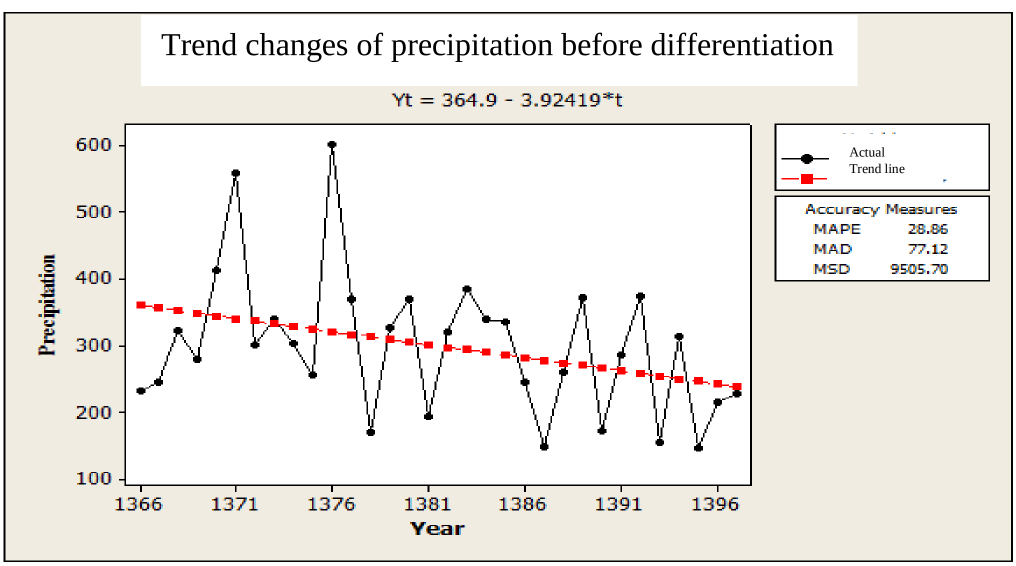

Fig. 4 - Graph of annual precipitation changes before differentiation

To remove the trend from non-seasonal and annual data, the trend is deleted with a first-time differential. To eliminate this decreasing trend, differentiation was performed once and the data were static Fig. 5.

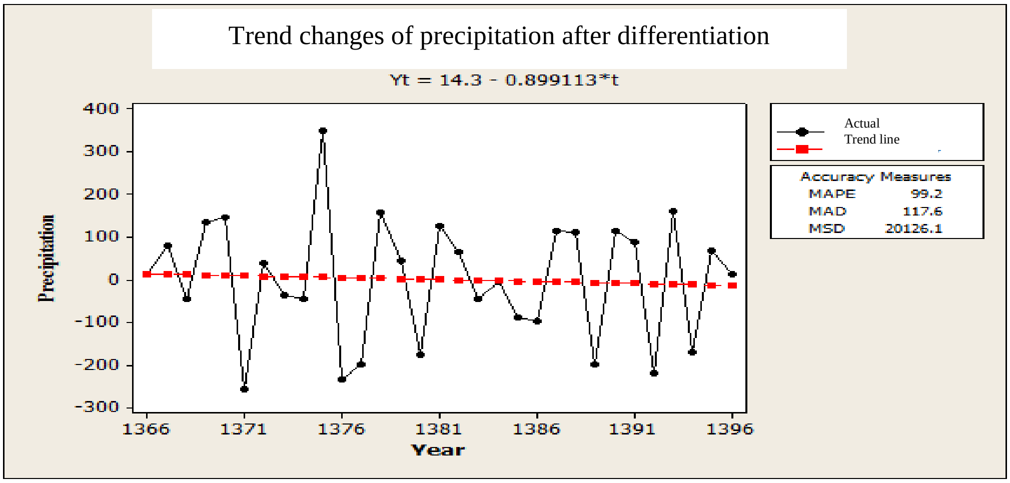

Fig. 5 - Graph of changes in annual precipitation data after one time differentiation

Autocorrelation and partial autocorrelation diagrams for annual precipitation before and after differentiation are presented in Fig. 6 and 7, through which the appropriate coefficients q and p can be derived. As can be seen from the autocorrelation graph in Fig. 6, the autocorrelation value decreases sinusoidally and gently. This way of fluctuation is due to the trend in the relevant series. But the autocorrelation chart after the first-degree differentiation Fig. 7 only tends to alternate. According to Fig. 7, the ACF of the variables, which are attenuated as a combination of exponential and sinusoidal waves, can be suggested as the MA model. On the other hand, PACF is significant in the first-time delays, which is a characteristic of the AR model. Therefore, a combination of MA and AR (ARIMA) models was proposed for modeling.

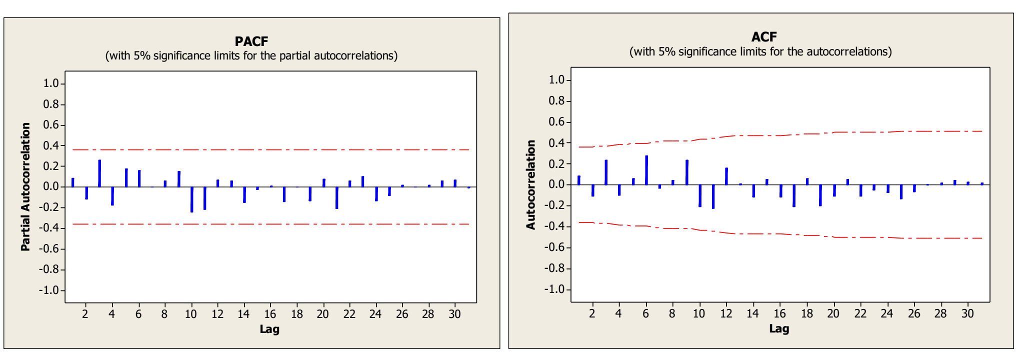

Fig. 6 - Autocorrelation and partial autocorrelation of precipitation data before differentiation

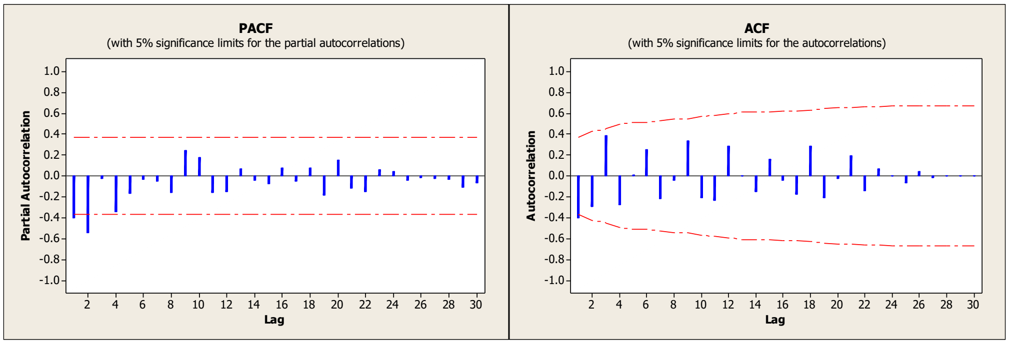

Fig. 7- Autocorrelation and partial autocorrelation of precipitation data after differentiation

According to the studies performed, the results of fitted models for annual precipitation are given in Table 3. This table shows the comparison of different time series models for static annual precipitation data during the statistical period [1986-2018]. In this table there are, MA (moving average), AR (autoregressive) and BIC (Bayesian information criterion). According to this table, the ARIMA model (1,1,3) has the best result due to having the absolute value of T statistic more than 2 and P-value less than 0.05. Although the Bayesian criterion (BIC) is the same or less seen in other models, but due to the unsuitability of other conditions (high P-Value and low T-value) is not considered in selecting the appropriate model.

Table 3 - Fitting random models to static data series

BIC	t	P_value	parameter	model
10.92	-3.42	0.002	AR1	Arima(1.1.0)
	-0.00	0.997	Constant	
10.32	-2.18	0.038	AR1	Arima(1.1.1)
	4.84	0.000	MA1	
	-0.31	0.756	Constant	
9.74	-0.31	0.761	AR1	Arima(1.0.1)
	8.31	0.000	MA1	
	-4.15	0.000	Constant	
10.34	3.82	0.001	MA1	Arima(0.1.1)
	-0.07	0.942	Constant	
10.17	7.64	0.000	MA1	Arima(0.1.3)
	0.93	0.359	MA2	
	-2.09	0.046	MA3	
	-0.07	0.944	Constant	
10.19	-2.57	0.016	AR1	Arima(1.1.3)
	8.84	0.000	MA1	
	2.15	0.041	MA2	
	-2.99	0.006	MA3	
10.13	-3.90	0.001	AR1	Arima(2.1.1)
	-3.45	0.002	AR2	
	4.95	0.000	MA1	
	-1.62	0.118	Constant	
11.26	-3.10	0.005	AR1	Arima(1.2.1)
	3.66	0.001	MA1	
	0.25	0.801	Constant	

*2.3. **Check the fit of the model***

The results related to the residual autocorrelation according to Pert-Manto statistics are shown in Table 4 for the selected model ARIMA (1,1,3). According to the P-VALUE value of this table in all delays, the Kido test is greater than 0.05, these results indicate the autocorrelation of the residuals. In this test, the purpose of the delays is to investigate the partial correlation between different delays and confirm the H0 hypothesis in the selected model.

Table 4 - Perth Manto test results for the appropriate model on static data

lag	12	24	36	48
kido	**15.1**	**26.1**	**-**	**-**
Freedom defree	**7**	**19**	**-**	**-**
P-Value	**0.064**	**0.128**	**-**	**-**

3.3. Model validation

To validate the selected model, forecasts were made for years with available data, and the values predicted by the model were compared with actual values to determine the accuracy of the model estimate. For this purpose, the time period [2018 (1397 Shamsi) -2011 (1390 Shamsi)] was predicted using the Arima model (1,1,3). The results showed that according to the available meteorological data, the model has an acceptable forecast of precipitation data for this period. The diagram in Fig. 8 shows the predicted and real values for the period [2011-2018].

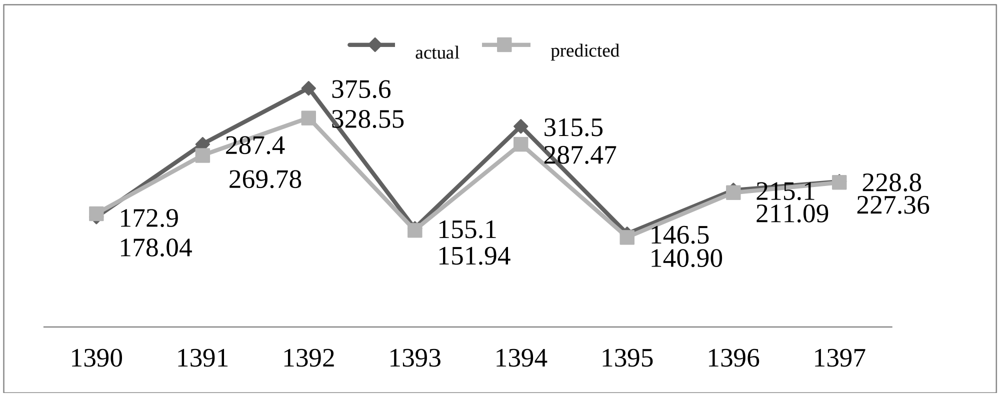

Fig. 8- Diagram of predicted and actual values of precipitation for the period [2018 (1397 Shamsi)-2011 (1390 Shamsi)]

After the validation stage of the selected model, the amount of precipitation for 10 statistical years [2019-2028] was predicted, which is shown in Figure 9, the observed values and predicted by the appropriate model. According to this graph, it can be seen that the trend of precipitation changes in all years almost follows a sinusoidal cycle, which in 1996 the most increase and in 1997 the most decrease in the trend of precipitation changes occurred. In the predicted period [2028 (1407 Shamsi)-2019 (1398 Shamsi)], we see a decrease in precipitation compared to the long-term average. It is important to note that predicting means determining the amount of precipitation with the highest probability of occurrence and does not in any way imply an accurate prediction of precipitation.

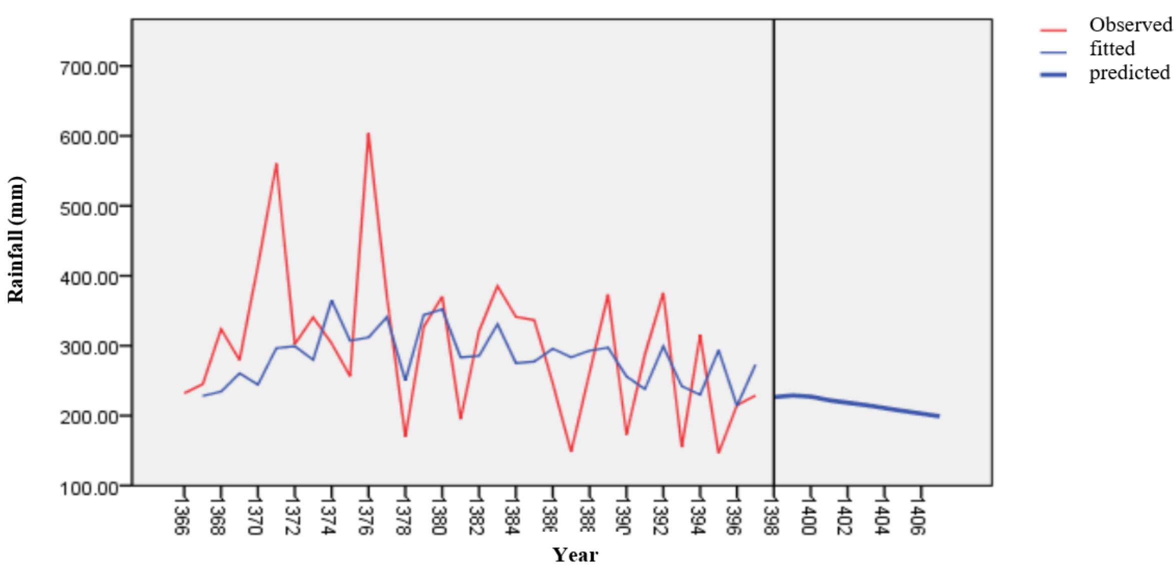

Fig. 9- Diagram of predicted and observed values for static data based on Arima model (1,1,3)

4. Conclusion

Examination of the trend of annual precipitation changes during the last 32 years by the Mann-

Kendall test showed that the amount of precipitation in Dezful plain during this period has had a decreasing trend (Z <0) But considering the value of Z statistic, this trend is not significant. Drawing the time series diagram of the data showed that once differentiation is sufficient to convert an unstable to a static time series. In the model recognition stage, according to the autocorrelation diagrams (ACF), which is attenuated as a combination of exponential and sinusoidal waves, and partial autocorrelation (PACF), which is significant in the first-time steps, a combination of AR and MA models as the Arima model.

A combination for modeling was proposed. Dodangeh et al. (2011), Ghahraman and Gharahkhani (2011), Khazaei and Mirzaei (2014), Soltani Gordfaramarzi et al. (2017), Rhif et al. (2019), Mishra et al. (2021), Ghaderpour et al., (2021), Jamali et al., (2021), Jamali et al., (2022), and Ouma et al. (2022) have reported similar results in this regard. Finally, by selecting the most suitable model, annual precipitation was predicted for the next 10 years which selected model validated by real data and then used for the prediction of rainfall that this step helped to choose better. Many researchers have used the ARIMA time series model in their research.

These include: Bashari and Vafakhah (2010) in predicting the monthly discharge of Karkheh Basin, Dudangeh et al. (2012) in modeling relative humidity, evaporation, air temperature, wind speed (Ghane Ezabadi et al., 2021), and sunny hours and Abdullah Nejad, (2015) to predict the monthly precipitation of Hashemabad station in Gorgan, pointed out. In the end, it is suggested to predict the precipitation of the study station with analyses such as neural networks and compare it with the results of the present study. This can be useful for achieving more accurate methods for predicting.

Declarations

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Conflict of Interest /Competing interests (None)

Availability of Data and Material (Data are available when requested)

Consent to Publish (Authors consent to publishing)

Authors Contributions (All co-authors contributed to the manuscript)

Code availability (Not applicable)

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