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Forecasting Models for the Three Highest Daily Precipitation Monthly Values at Sulaimania Governorate in Iraq

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Abstract
Four forecasting models were developed for the monthly series of the first three highest maximum values of daily precipitations in Sulaimania governorate, Iraq. Three of them are a first order single variable autoregressive models one for each series. The fourth one is a multi-variable Matalas(1967) model that incorporate the three series simultaneously in order to investigate the effect of the dependence of the first three daily maximums on the forecasting capability compared to the single variable models. The models were developed using the series of the three highest daily precipitations in Sulaimania governorate using the data on monthly basis for the years (1992-2006). Verification of the models was conducted by comparing the statistical properties of three generated series for each model for the period (2007-2013), with the observed properties for the same period. Results indicate the capability of the two types of the model to preserve these statistical properties very well. However, the AKIKE test indicates that the single variable model can perform better than the multi-variables one, the ranges of these test for three generated series are (22.63-29.68) and (27.81-34.91), for the single and multi-variable models ,respectively. The maximum absolute differences in the statistical properties are all higher for the multi-variables model than those for the single variable one. The t-test and F-test for the monthly means and standard deviations support this conclusion. These results may be attributed to the high randomness in the successive extreme daily precipitations values.
Key words: Maximum daily precipitation, Data generation, Multi-variables data generation models, Single variable data generation model. Sulaimania governorate. AKIAKE test.

I. Introduction

Hydrologic Forecasting models are frequently used in the design and operation of water resources systems. Many researches had been conducted to develop such models for annual, monthly and daily hydrological data series. The long term forecasting's are needed to provide future view of the variations of hydrologic variables such as precipitation and evaporation. Weather generation models have been used successfully for a wide array of applications. They became increasingly used in various research topics, including climate change studies. They can be used to generate series of climatic data that preserve the same statistical properties of the observed historical time series. Furthermore, weather generators are able to produce series for any length of time, which allows developing various applications linked to extreme events, such as flood analyses, and draught analysis.

Wilks (1998, 1999) had described stochastic generation of daily precipitation, maximum temperature, minimum temperature and solar radiation, simultaneously at a collection of stations in a way that preserves realistic spatial correlations. The procedure is a generalization of the familiar Richardson (1984) weather generator (WGEN) approach using the same basic model structure and local parameter sets, and to extend the multi-site approach to the generation of daily maximum temperature, minimum temperature and solar radiation data. Makhnin and Mcallister (2009) proposed a new precipitation generator based on truncated and power transformed normal distribution, with the spatial-temporal dependence represented by multivariate auto-regression. Kisi and Cimen (2012) had developed a daily precipitation forecasting model using discrete wavelet transform and support vector machine methods for two stations in Turkey, Izmir and Afyon. Tesini et al. (2010) had used representative value approach method and full distribution function approach methods to evaluate the forecasting of mean and maximum precipitation in Italy. They found that the frequency of precipitation exceeding a threshold value could be found using these approaches. Sloughter et al. (2007) had used Bayesian model averaging (BMA) method for post processing forecast ensembles to create precipitation. They concluded that this method dose not applied in its original form to precipitation because it is non-normal in two major ways, it has positive probability for being equal to zero, and it is skewed. Furrer and Katz (2008) had stated that parametric weather generators do not produce heavy enough upper tail for the distribution of daily precipitation amount. Sommler and Jacob (2004) had used the regional climate model REMO1.5 to find the changes of the frequency and intensity of extreme precipitation events for different regions in Europe. Al-Suhaili and Mustafa (2012) had developed a daily forecasting model for daily precipitation at Sulaimania governorate, Iraq, at three metrological stations, Sulaimania, Dokan and Derbendikhan. They used a forecasted code of occurrence non-occurrence of the precipitation and gamma distribution for forecasting non-zero daily precipitation. Even though the model performance is good, extreme values need to be modeled much more precisely. Most of the forecasting models had used the time series of the hydrological variable itself and extract the extremes (maximum and minimum values) from the generated series using these models.

In this research an attempt was made to model the series of the first three highest daily maximum precipitations in Sulaimania governorate, Iraq, based on monthly values. It is believed that this direct modeling of these maximums precipitation daily values will provide more reliable estimates of the extremes from those extracted from the normal trend of forecasting the original time series and then extract the maximums. This was concluded from the fact that the extreme values time series are usually exhibits different averages and variances than those of the original normal values and hence their direct modeling will preserve these averages and variances in the modeling process. Moreover these extremes are usually exhibits more randomness than the original data and hence reflects different model parameters related in their estimations to the serial and cross correlations.

II. Methodology of the developed models

Four models were developed herein, a single variable first order autoregressive model for each of the first three maximums of the daily precipitation in Sulaimania governorate. The fourth model is a multi-variable first order model (Matalas(1967)) that includes the three maximums simultaneously to investigate whether there is an effect of the interdependence if any between the three successive highest daily precipitation values. This will be observed upon the comparison between the single variable models and the multivariable one, results.

The modeling process was conducted according to the following steps:

1- Extracting the daily three highest values of the daily precipitation for each month from the available daily precipitation data.

2- Perform the test of homogeneity for the historical data using the Split-Sample Test suggested by Yevjevich (1972), and remove non-homogeneity if any. This was done by dividing the sample into two sub-samples based on the observed annual averages and annual standard deviations and applying the following equations.

$$t\ mean = \frac{\bar{x}_1 - \bar{x}_2}{s\sqrt{\frac{n_1 + n_2}{n_1 * n_2}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (1)$$

$$s = \sqrt{\frac{\sum_{i=1}^{n_1}(x_i - \bar{x}_1)^2 + \sum_{j=1}^{n_2}(x_j - \bar{x}_2)^2}{n_1 + n_2 - 2}} \quad \ldots\ldots (2)$$

$$t\ st.dev. = \frac{\bar{S}_{d1} - \bar{S}_{d2}}{S_d.\sqrt{\frac{n_1 + n_2}{n_1.n_2}}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$S_d = \sqrt{\frac{\sum_{i=1}^{n_1}(S_{di} - \bar{S}_{d1})^2 + \sum_{j=1}^{n_2}(S_{dj} - \bar{S}_{d2})^2}{n_1 + n_2 - 2}} \quad .. (4)$$

where:

n_1,n_2 :are the subsample sizes,

x_i,x_j :are the annual means of the n_1 and n_2 subsamples respectively.

S_{di}, S_{dj} : are the annual standard deviations of the n_1 and n_2 subsamples respectively.

$\bar{x}_1, \bar{x}_2$: are the means of the annual means of the first and

Second sub-samples respectively.

$\bar{S}_{d1}, \bar{S}_{d2}$: *are the means of the annual standard deviations*

of the first and second sub-samples, respectively.

$t\ mean, t\ st.dev$: *are the te*st values for the non-homogeneity in means and standard deviations , respectively. . The variable (t) follows the Student t-distribution with (n_1+ n_2-2) degree of freedom .The critical value (t_c) for the (95%) percent significant probability level is taken from the Student distribution t-table. If the computed t value is greater than the critical t-value then the data is non-homogeneous and should be homogenized

3. The third step in the modeling process is to check and remove the trend component in the data if it is exist. This was done by finding the linear correlation coefficient (r) of the annual means of the homogenized series, and the T-value related to it . If the t-value estimated is larger than the critical t-value then trend exists otherwise it is not. The following equation was used to estimate the t-values.

.

$$T = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \qquad (5)$$

Where

n: is the total size of the sample

4- The fourth step of the modeling process is the data normalization of the data to reduce the skewness coefficient to zero. The well known Box-Cox transformation Box and Jenkin (1976), was used for this purpose as presented in the following equation:

$$XN_{i,j} = \frac{(X_{i,j}+\alpha)^{\mu}-1}{\mu} \qquad (6)$$

Where:

μ : is the power of the transformation.

α : is the shifting parameter.

$XN_{i,j}$: is the normalized series $of\ year\ i, month\ j$

.$X_{i,j}$: $is\ the\ homogeneous\ series\ of\ year\ i, month\ j$

5- The fifth step in the modeling process is to remove the periodic component to obtain the stochastic dependent component of the series, which is done by using eq.(7), as follows:

$$\epsilon_{i,j} = \frac{XN_{i,j}-Xb_j}{Sd_j} \qquad (7)$$

Where:

$\epsilon_{i,j}$: is the obtained dependent stochastic component for year i, month j.

Xb_j : is the monthly mean of month j of the normalized series XN.

Sd_j : is the monthly standard deviation of month j of the normalized series XN.

The existence of the periodic components is detected by drawing the corrlogram up to at least 24 lags, if the curve exhibits periodicity then the periodic components are exist, otherwise it is not. Equation (8) can be used with k=1,2, …24 to find the correlogram.

6- The sixth step in the modeling process is to estimate the parameters of the models. The $\epsilon_{i,j}$ obtained series are used to estimate the Lag-1 serial correlation coefficients r , and σ for the single variables models using the following equations:

$$r_k = \frac{\sum_{i=1}^{n-k}(x_i-\bar{x})(x_{i+k}-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad for\ k = 1,2,\dots k. \ (8)$$

r_k: lag (k) sample autocorrelation coefficient for the time series,

n:sample size, and

$\bar{x}$:sample mean.

$$\sigma = (1-r_1^2)^{0.5} \qquad (9)$$

Where r_1 is the lag-1 serial correlation coefficient obtained using equation (7) with k=1. At the end of these calculations the single variable model parameters are now estimated and can be used for data generation as will be shown later.

For the multi- variable model (Matalas(1967)) the following equation should be used to find the lag-0 and Lag-1 cross variables correlation coefficient ,matrices M_o, and M_1, respectively and then find the model parameters matrices A1 and B1 as follows:

The dependence structure among time series can be determined by computing the lag-k cross-correlation between the series. For instance, considering the series xt[(i)] and xt[(j)] , the lag-k cross-correlation coefficient rk[ij] is given by:

$$r_k{}^{ij} = \frac{\sum_{t=1}^{N-k}\left(x_t{}^i - \bar{x}_t{}^i\right)\left(x_{t+k}{}^j - \bar{x}_{t+k}{}^j\right)}{\sqrt{\sum_{t=1}^{N-k}\left(x_t{}^i - \bar{x}_t{}^i\right)^2 \sum_{t=1}^{N-k}\left(x_{t+1}{}^j - \bar{x}_{t+1}{}^j\right)^2}}. \ (10)$$

where:

$\bar{x}_t{}^i$: is the mean of the first (n-k) values of series (i), and

$\bar{x}_{t+k}{}^j$: is the mean of the last (n-k) values of series j.

And then ;

$$M_o = \begin{matrix} ro_{1,1} & ro_{1,2} & ro_{1,3} \\ ro_{2,1} & ro_{2,2} & ro_{2,3} \\ ro_{3,1} & ro_{3,2} & ro_{3,3} \end{matrix} \qquad (11)$$

$$M_1 = \begin{matrix} r1_{1,1} & r1_{1,2} & r1_{1,3} \\ r1_{2,1} & r1_{2,2} & r1_{2,3} \\ r1_{3,1} & r1_{3,2} & r1_{3,3} \end{matrix} \qquad (12)$$

Where

$ro_{1,2}$: is the Lag-0 cross correlation coefficient between the first maximum and the second maximum daily precipitation variables, while $r1_{2,3}$ is the Lag-1 cross correlation coefficient between the second and the third maximums of the daily precipitations. Then the model matrices can be estimated as follows:

$$A_1 = M_1 M_0{}^{-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(13)$$

And,

$$B_1 B_1{}^T = M_0 - A_1 M_1{}^T \dots\dots\dots\dots\dots\dots\dots\dots.(14)$$

The forecasting process was conducted according to the following steps:

The developed models mentioned above are used for data forecasting, recalling that the estimated parameters above are obtained using the 15 years data series (1992-2006). The forecasted data are for the next 7- years (2007-2013), that could be compared with the observed series available for these years, for the purpose of model validation. The forecasting process was conducted using the following steps:

1. Generation of an independent stochastic component (ξ) using normally distributed generator, for 7 years, i.e., (3*7) values.

2. Calculating the dependent stochastic component ($\epsilon_{i,j}$) using equation (15) for the single variable models and equation (16) for the multi-variables model as follows:

$$\in_{i,j} = \boldsymbol{r1} \in_{i,j-1} + \boldsymbol{\sigma\xi_{i,j}} \qquad (\mathbf{15})$$

And

$$\begin{bmatrix} \in^{(1)} \\ \in^{(2)} \\ . \\ . \\ . \\ \in^{(n)} \end{bmatrix}_{i,j} = \begin{bmatrix} a^{(11)} a^{(12)} a^{(1v)} \\ a^{(21)} a^{(22)} a^{(2v)} \\ . \quad . \quad . \\ . \quad . \quad . \\ . \quad . \quad . \\ a^{(v1)} a^{(v2)} a^{(v,v)} \end{bmatrix} \begin{bmatrix} \in^{(1)} \\ \in^{(2)} \\ . \\ . \\ . \\ \in^{(n)} \end{bmatrix}_{t-1 i,j-1} + \begin{bmatrix} b^{(11)} b^{(12)} b^{(1v)} \\ b^{(21)} b^{(22)} b^{(2v)} \\ . \quad . \quad . \\ . \quad . \quad . \\ . \quad . \quad . \\ b^{(v1)} b^{(v2)} b^{(v,v)} \end{bmatrix} \begin{bmatrix} \xi^{(1)} \\ \xi^{(2)} \\ . \\ . \\ . \\ \xi^{(v)} \end{bmatrix}_{i,j} \ldots\ldots\ldots..(16)$$

Where n=3, for the present application since three variables are used as mentioned before.

3. Reversing the standardization process by using the same monthly means and monthly standard deviations which were used for each variable to remove periodicity using eq. (7) after rearranging.
4. Applying the inverse power normalization transformation (Box and Cox) for calculating un-normalized variables using normalization parameters for each variable and eq.(6).

The Case Study

Sulaimania governorate is selected as a case study. This governorate is located north of Iraq as shown in figure (1) with a total area of (17,023 km2) and a population of 1,350,000 according to(2009) records. The city of Sulaimania is located (198) km from Kurdistan Regional capital (Erbil) and (385) km from the federal Iraqi capital (Baghdad).

Sulaimania city is surrounded by the Azmar Range, Goizja Range and the Qaiwan Range in the north east, Baranan Mountain in the south and the Tasluje Hills in the west. The area has a semi-arid climate with very hot and dry summers and very cold winters.The site coordinates are (350 33' 18" N) and (450 27' 06" E), Barzinji,(2003). The Satellite image of the location of the station is shown in figure (1)

The application of the Developed Model to the case study

The developed maximums daily precipitation models were applied to the first three maximums daily precipitation series for the case study mentioned before (Sulaimani,) data. The model parameters estimation and its verification was done using the daily precipitation records for the metrological station for the period (1992-2013).The first (15) years (1992-2006) were used for estimating the model parameters, while the other (7) years (2007-2013) were left for models validation. The model was applied for the three daily precipitation maximums of seven months per year, November to May.

The available date are from (1972-2013), however there are three years of missing data of (1989, 1990, and 1991). Figures (2 to 4) shows the annuals means and annual standard deviations of the first highest ,second highest and the third highest daily maximum values, respectively. The missing values were set to zeros. In order to avoid the problem of missing data the data from (1972 to 1988), were ignored and the further analysis was conducted for the data from (1992 to 2013). Figures (5,6 and 7) shows the monthly means and monthly standard deviations for the period (1992-2006) which was selected for estimating the models parameters. These figures indicate considerable monthly variations of those means and standard deviations. The maximum monthly values for the three variables are located in the mid region from month (3, January) to month (5, March).

The analysis was done according to the steps mentioned above. Table (1) shows the test of homogeneity for annual means and annual standard deviations. Results indicate that the data of the three variables are homogeneous in both statistics since the estimated t-test values are all less than the critical t-value(1.69) at the 95% significance level of confidence. Table (2) shows the analysis of trend detection which indicates the absence of the trends in the three variables. These results indicate that there is no need for removing non-homogeneity and trend and the data series could be considered as homogeneous.

Table (3) shows the general statistical properties of the homogenized series for the data period selected for obtaining the models parameters (1992-2006).

The Box-Cox normalization transformation was used for different transformation power as given by equation (6). Table (4) shows the selected power of the transformation that minimized the skewness coefficients of the three variables and the corresponding skewness values which are all nearly zeros, which indicates normality.

Figures (8,9 and 10) shows the correlograms of the of the three variables of the normalized series, which was obtained using equation (8). These figures indicates low periodicity, however equation (7) was used to obtain the dependent stochastic components of the three series to remove any even small periodicity. Figures (11,12, and 13) shows the correlograms of the dependent stochastic components of the three series ,which indicates relatively low values which reflect in turn the high randomness of the obtained series.

Table (5) shows the single variable models parameters r1 and σ estimated using equations (8) and (9), respectively. The r values were found relatively small with a maximum value of 0.105357 obtained for the third maximum daily precipitation series. This observation indicates that as the variable become more extreme the randomness increases.

Table (6) shows the multi-variables model parameters estimated as mentioned above. The matrix of Lag-0 cross correlation indicates cross variable correlation coefficients with considerable higher values than those of the serial correlation time Lags. These results indicates that even if each variable indicates randomness time wise , considerable cross correlation could be exists between the successive maximum daily precipitation values. However, the Lag-1 cross correlation matrix indicate lower cross variable correlations which reflects again the high randomness time wise.

III. Models Validation

The models validations were conducted using both graphical and statistical tests comparisons between the observed series of the three variables for the period (2007-2013), with three generated series for the same period for each of the single variable models and the multi-variables model. Figure (14 to 16) show the comparisons between the generated and observed monthly seven years series, their monthly means and monthly standard deviations, using the single site models for the first three maximums daily precipitation at Sulaimania. Figures (17 to 19) show the same comparisons but with using the multi-variables model. These figures indicate that the monthly means are preserved well for both single variable model and multi-variables model. The monthly standard deviations are preserved better by the single variable models than that for the multi-variables model, especially for the first and second variables. However graphical comparisons are not enough and should be supported by numerical measures of statistical tests. Tables (7 and 9) shows the comparisons of the general properties of the observed and three generated series of the three variables, using single variable and multi variable models, respectively. These properties are the overall means and standard deviations, the maximum and minimum values and the AKIKE test values. The maximum absolute deviations of these properties from the observed series are higher for the multi-variables model then those for the single variable model. Table (11) shows these results, which indicates that the single variable model produce better results. Moreover this model gave lower values for the AKIKE test which indicate better performance. Tables(8 and 10) shows the number of succeeded values of the t-test and F-test for the monthly means and monthly standard deviations , respectively, which again indicate that the single variables models provide better performance.

IV. Conclusions

From the above analysis the following conclusions could be deduced**:**

1- The test of homogeneity and trend test indicate that the data of the three highest daily precipitation monthly series at Sulaimania for the period (1992-2013) are all homogeneous and trend free series.
2- The serial correlation analysis indicates low time lags correlations for each individual series which indicates the high randomness in the daily precipitation maximum values.
3- The Lag-0 cross correlation matrix indicates relatively high cross correlations between the three variables, which reflect a correlated monthly persistency in the high values of the daily precipitation.
4- The Lag-1 cross correlation matrix indicates relatively low values which reflect the high randomness time wise between the successive monthly maximum daily precipitation values.
5- The AKIAKE test indicates that the single variable model can perform better that the multi-variables one.
6- The maximum absolute deviations in the statistical properties had indicated that the single variable model performance is better than that of the multi-variables one. The t-test and F-test value support this conclusion.

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Figure (1) Sulaimania governorate location in Iraq and satellite image shows the location of the selected meteorological station. (Google Earth)

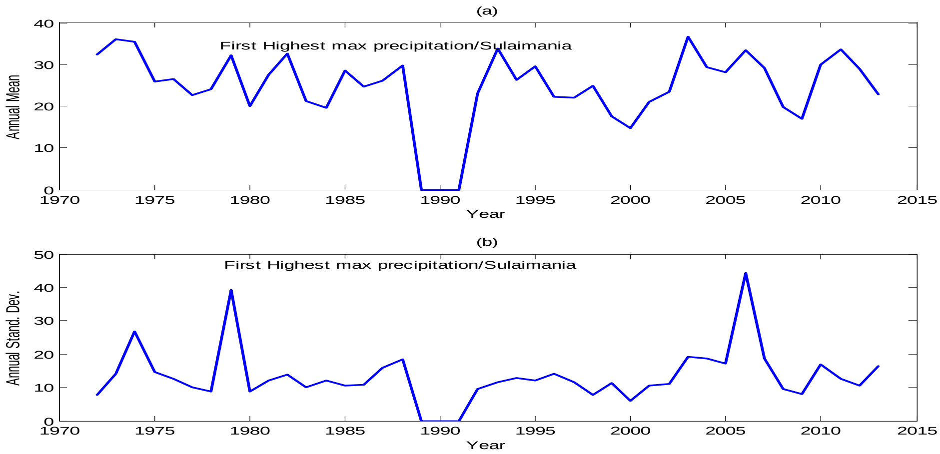

Fig.(2) Annual Means and Standard Deviations of the Original Data of the first Maximum Precipitation at Sulaimania Governorate, Iraq, (1970-2015).

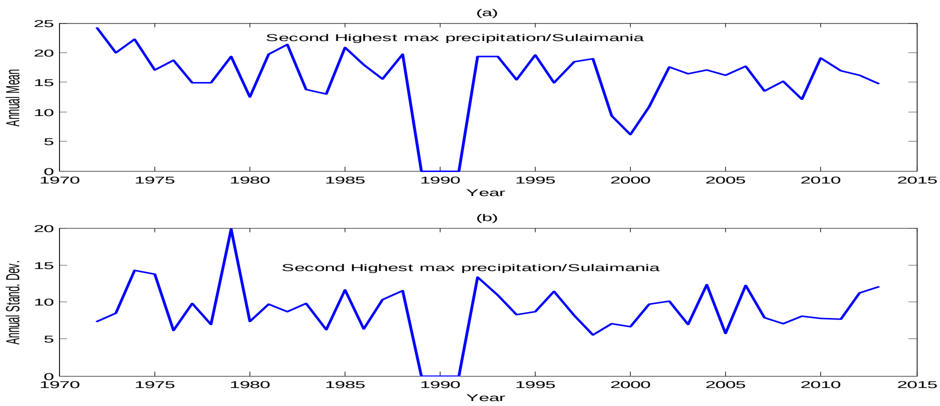

Fig.(3) Annual Means and Standard Deviations of the Original Data of the Second Maximum Precipitation at Sulaimania Governorate, Iraq , (1970-2015).

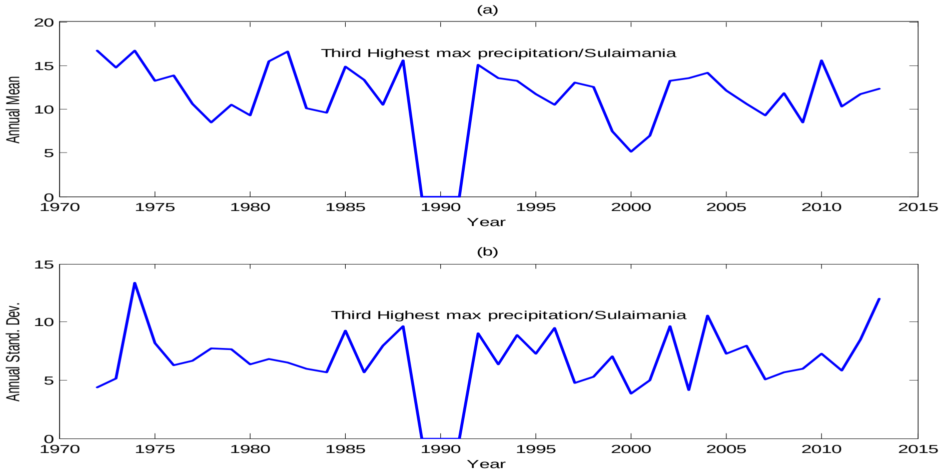

Fig.(4) Annual Means and Standard Deviations of the Original Data of the Third Maximum Precipitation at Sulaimania Governorate, Iraq, (1970-2015).

Table 1 Test of Homogeneity of the Original Data in Mean and Standard Deviation of the First three Maximums of Daily Precipitation in Sulaimania Governorate , Iraq with n1=17 (1992-2006),n2=7 (2007-2013), t-critical=1.69.

	tmean	Mean1	Mean2	sd1	sd2	s	Case
First Max.	-0.05456	25.743	25.9	6.143	6.1	6.13	Hom
Second Max.	0.271259	15.831	15.39	4.02	2.29	3.59	Hom
Third Max	-0.57539	11.534	12.22	2.89	1.8	2.61	Hom
	tsd	Mean1	Mean2	sd1	sd2	s	Case
First Max.	0.351764	14.49	13.22	9.014	4.06	7.86	Hom
Second Max.	-0.04681	9.1353	9.185	2.513	1.85	2.33	Hom
Third Max	-1.41309	7.1016	8.462	2.149	1.99	2.1	Hom

Table 2 Trend Test Analysis Results of the First Three Maximum Daily Precipitations at Sulaimania Governorate, Iraq, (1992-2013).

Variable	r	t
First Max.	0.1208	0.544
Second Max.	0.1401	0.633
Third Max.	-0.103	-.463

Table 3 General Statistical Properties of the Homogeneous Data of the First Three Maximum Daily Precipitations at Sulaimania Governorate, Iraq, (1992-2006).

	mean	St. Dev.	Skew.	Kurt.
First Max.	25.74	16.819	2.669	16.63
Second Max.	15.83	9.62	0.595	3.053
Third Max.	11.53	7.4327	0.736	3.194

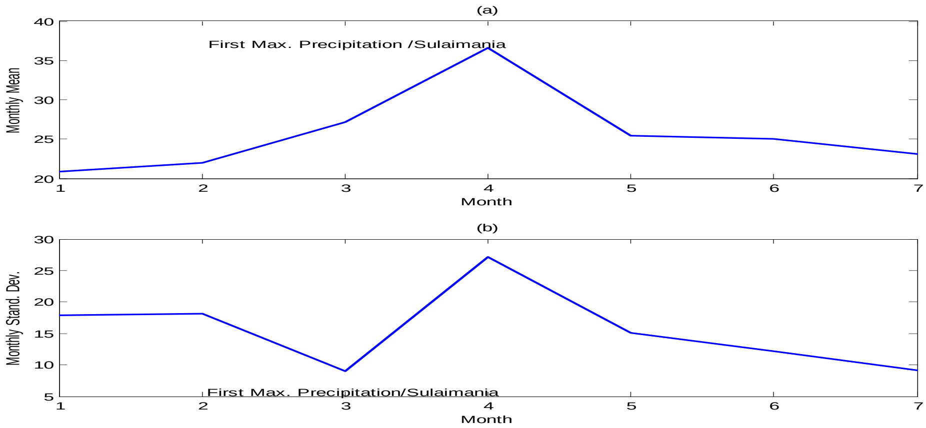

Fig.(5) Monthly Means and standard Deviations of Homogeneous Data of First Maximum Precipitation at Sulaimania Governorate, Iraq ,(1992-2006).

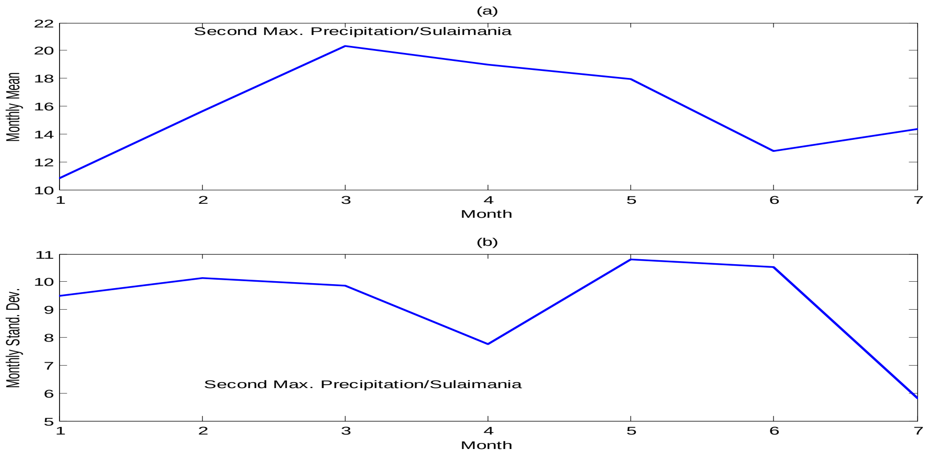

Fig.(6) Monthly Means and standard Deviations of Homogeneous Data of Second Maximum Precipitation at Sulaimania Governorate, Iraq,(1992-2006).

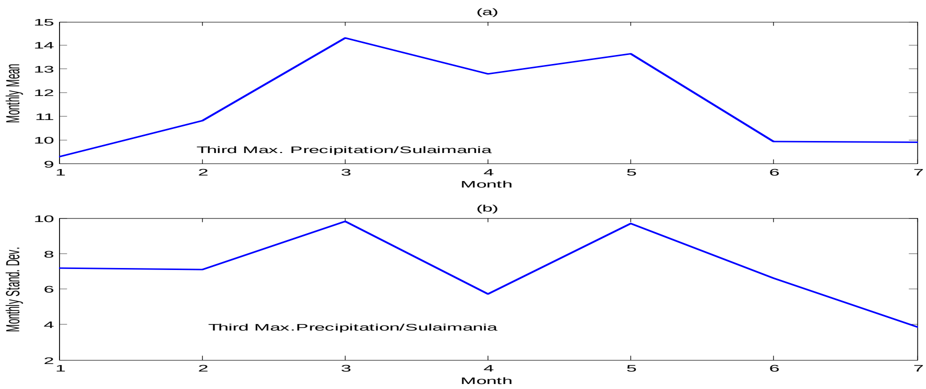

Fig.(7) Monthly Means and standard Deviations of Homogeneous Data of Third Maximum Precipitation at Sulaimania Governorate, Iraq,(1992-2006).

Table 4 Normalization Transformation Coefficients and Corresponding skewness of the First Three Maximum Daily Precipitations at Sulaimania Governorate, Iraq, (1992-2013).

	First Max.	Secon Max.	Third max.
Transformation Coefficient	0.4	0.665	0.565
Skewness Original Data	2.67	0.600	0.74
Skewness Transformed Data	0.012	0.0017	0.0039

Table 5 Parameters of the Single Site Models of the First Three Maximum Daily Precipitations at Sulaimania Governorate, Iraq, (1992-2013).

Variable	r1	Sigma
First Max.	0.08962	0.995976
Second Max.	0.045534	0.9989628
Third Max.	0.105357	0.9944345

Table 6 Parameters of the Multi-Variables Models of the First Three Maximum Daily Precipitations at Sulaimania Governorate, Iraq, (1992-2013).

m1	0.089619877	0.101402	0.1139305
	0.122046989	0.045534	0.0721122
	0.176447594	0.096192	0.1053568
mo	1	0.673142	0.6857727
	0.673142157	1	0.8375483
	0.685772733	0.837548	1
A	0.019135524	0.013699	0.0893344
	0.155950406	-0.101393	0.0500868
	0.204344614	-0.04098	-4.54E-04
B	0.887642064	0.286073	0.3333226
	0.286073337	0.454868	0.8338118
	0.333322587	0.833812	0.4163843

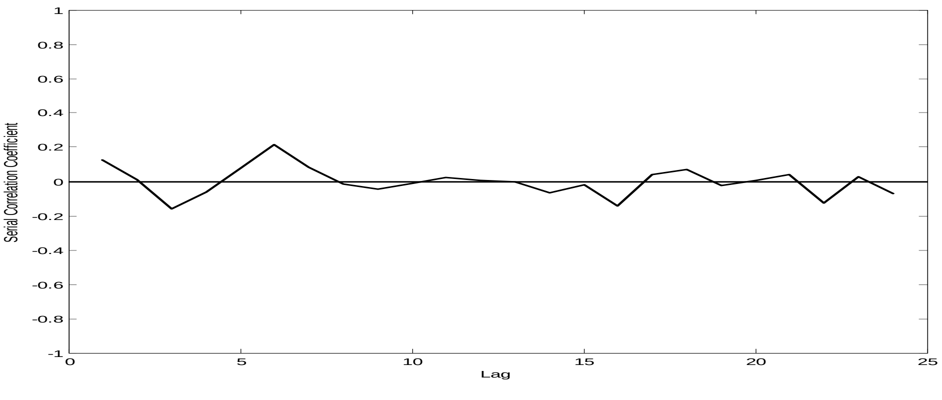

Fig.(8) Correlogram of the Normalized Data of The First Maximum Precipitation at Sulaimania Governorate, Iraq (1992-2006).

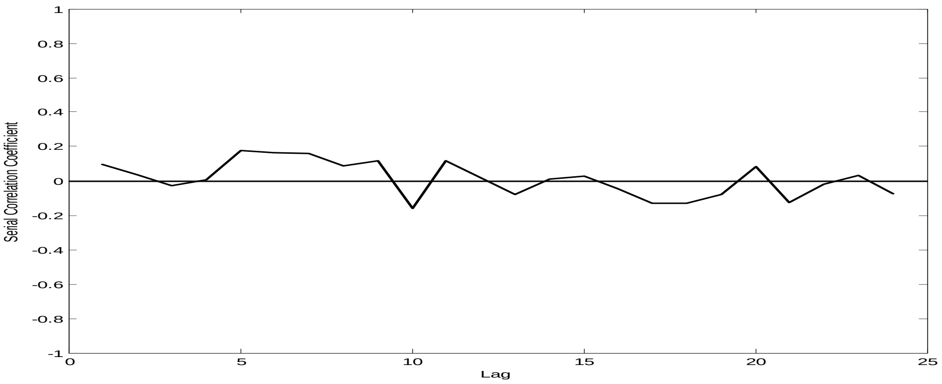

Fig.(9) Correlogram of the Normalized Data of The Second Maximum Precipitation at Sulaimania Governorate, Iraq (1992-2006).

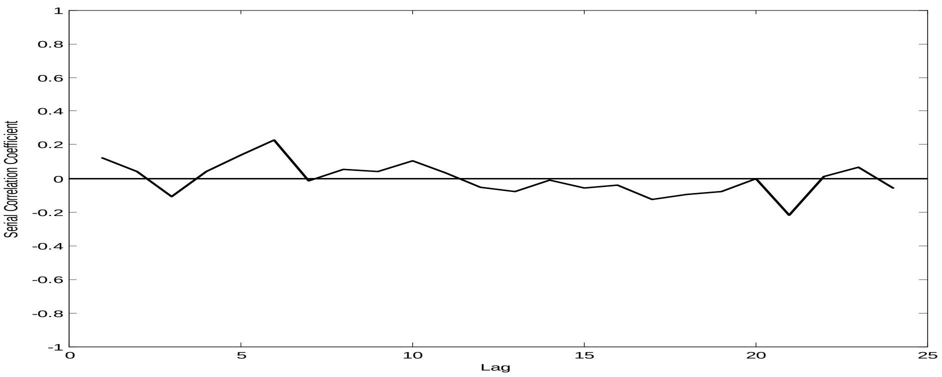

Fig.(10) Correlogram of the Normalized Data of The Third Maximum Precipitation at Sulaimania Governorate, Iraq (1992-2006).

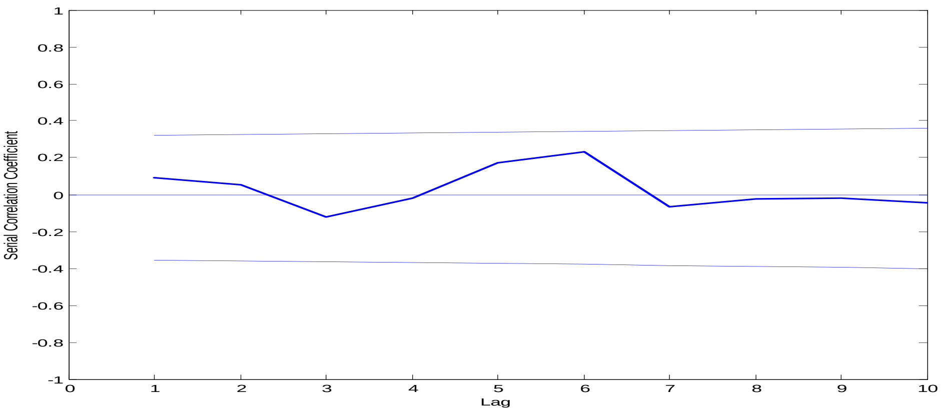

Fig.(11) Correlogram of the Independent Stochastic Component of The First Maximum Precipitation at Sulaimania Governorate, Iraq (1992-2006).

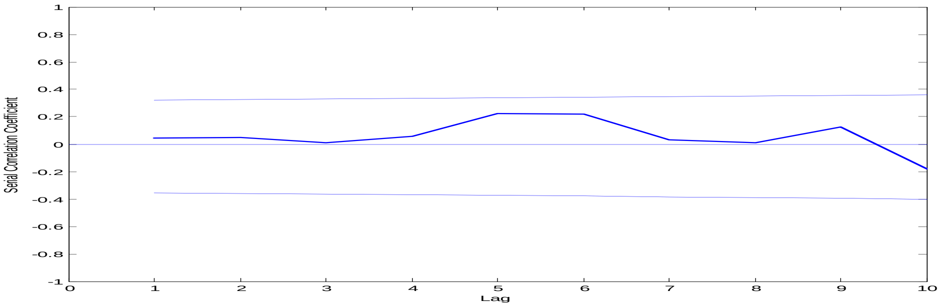

Fig.(12) Correlogram of the Independent Stochastic Component of The Second Maximum Precipitation at Sulaimania Governorate, Iraq (1992-2006).

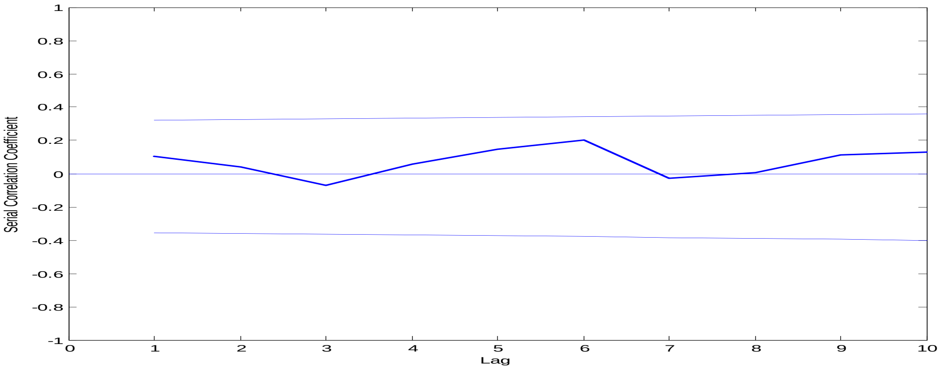

Fig.(13) Correlogram of the Independent Stochastic Component of The Third Maximum Precipitation at Sulaimania Governorate, Iraq (1992-2006).

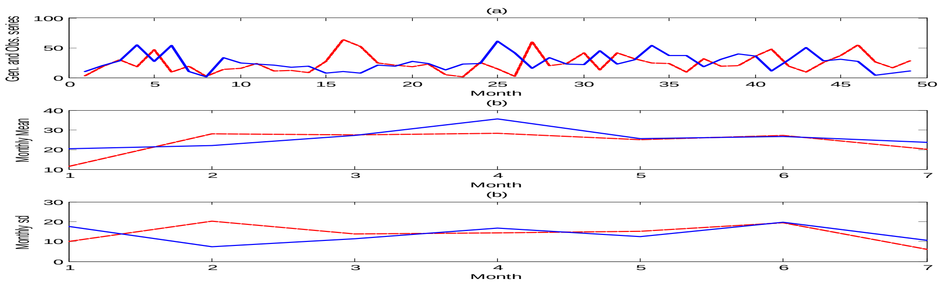

Fig.(14) Comparison Between Observed and Generated Series, Monthly Means, and Monthly Standard Deviations of the First Maximum Daily Precipitation at Sulaimania Governorate, Iraq, (2007-2013), Using Single Variable First order Auto-Regressive model.

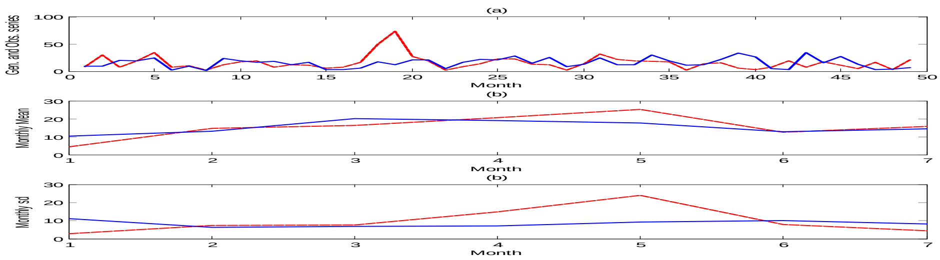

Fig.(15) Comparison Between Observed and Generated Series, Monthly Means, and Monthly Standard Deviations of the Second Maximum Daily Precipitation at Sulaimania Governorate, Iraq, (2007-2013), Using Single Variable First order Auto-Regressive model.

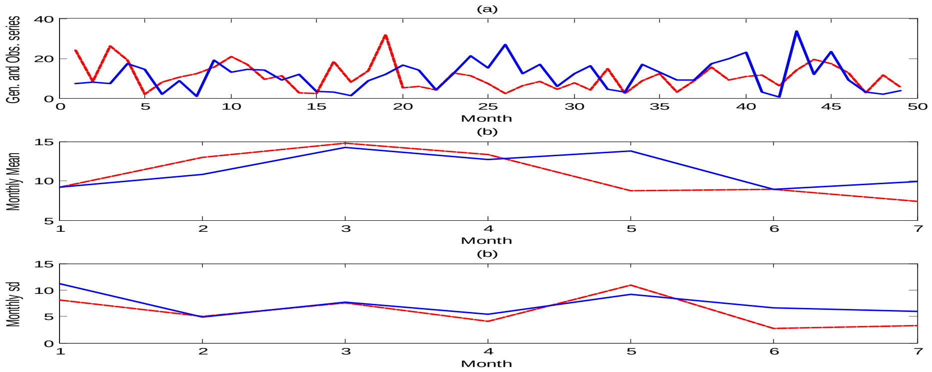

Fig.(16) Comparison Between Observed and Generated Series, Monthly Means, and Monthly Standard Deviations of the Third Maximum Daily Precipitation at Sulaimania Governorate, Iraq, (2007-2013), Using Single Variable First order Auto-Regressive model.

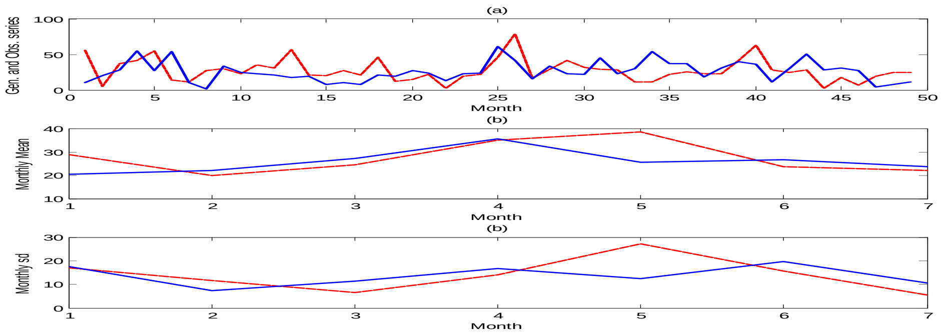

Fig.(17) Comparison Between Observed and Generated Series, Monthly Means, and Monthly Standard Deviations of the First Maximum Daily Precipitation at Sulaimania Governorate, Iraq, (2007-2013), Using Multi Variables First order Auto-Regressive model, (MATALS).

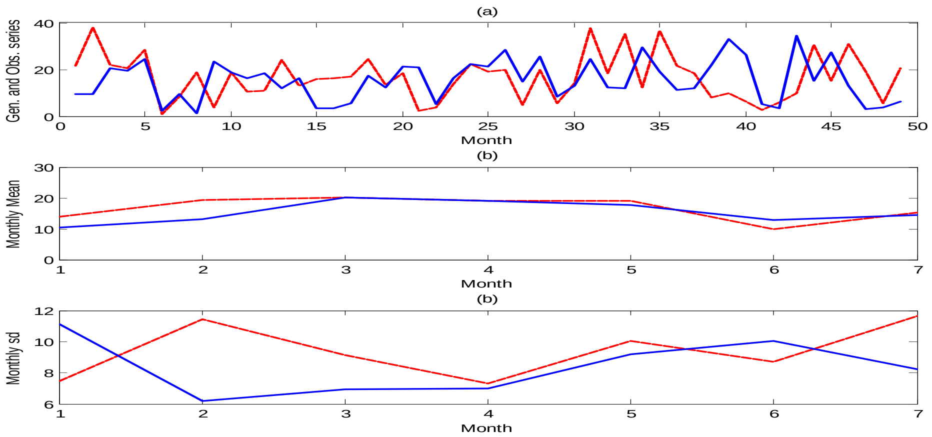

Fig.(18) Comparison Between Observed and Generated Series, Monthly Means, and Monthly Standard Deviations of the Second Maximum Daily Precipitation at Sulaimania Governorate, Iraq, (2007-2013), Using Multi Variables First order Auto-Regressive model, (MATALS).

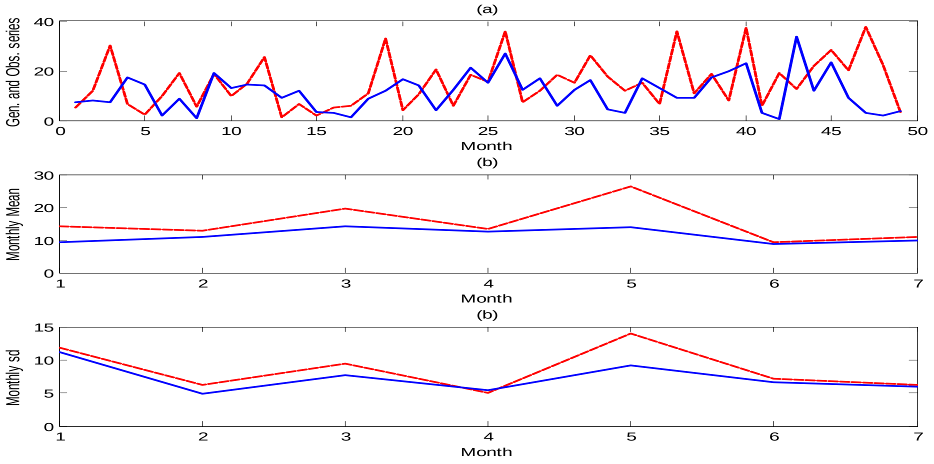

Fig.(19) Comparison Between Observed and Generated Series, Monthly Means, and Monthly Standard Deviations of the Third Maximum Daily Precipitation at Sulaimania Governorate, Iraq, (2007-2013), Using Multi Variables First order Auto-Regressive model, (MATALS).

Table 7 Comparison between the Observed and Three Generated Series of the First Three Maximums Daily Precipitation at Sulaimania Govenorate, Iraq (2007-2013) Using Single Variable Auto-Regressive First Order Model ,.

		First Max.	Second Max	Third Max
Mean	Observed	25.89	15.38	11.37
	Gen. 1	23.44	16.79	11.11
	Gen. 2	24.09	16.30	11.44
	Gen. 3	28.61	14.49	10.77
St. Dev.	Observed	14.06	8.67	7.37
	Gen. 1	15.24	9.21	7.12
	Gen. 2	13.62	10.10	7.12
	Gen. 3	14.25	9.12	6.98
Maximum	Observed	61.2	34.30	33.70
	Gen. 1	77.31	38.11	31.42
	Gen. 2	58.18	32.28	37.26
	Gen. 3	68.69	36.73	29.63
Minimum	Observed	1.7	1.2	0.6
	Gen. 1	2.15	1.27	1.01
	Gen. 2	1.88	1.41	0.91
	Gen. 3	1.97	1.36	1.01
AKIKE	Gen. 1	28.28	23.54	24.3
	Gen. 2	28.2	25	23.4
	Gen. 3	29.68	24.98	22.63

Table 8 T-test for Monthly Means, F-test for Monthly Standard Deviations, for the three Generated series using sing variable model.

Variable	No. Succ. In t-test	No. Succ. In F-test
First Max.		
Generated Series 1	6	7
Generated Series 2	7	6
Generated Series 3	7	6
Second Max.		
Generated Series 1	7	6
Generated Series 2	7	7
Generated Series 3	7	6
Third Max		
Generated Series 1	7	7
Generated Series 2	7	6
Generated Series 3	7	7

Table 9 Comparison between the Observed and Three Generated Series of the First Three Maximums Daily Precipitation at Sulaimania Govenorate, Iraq (2007-2013) Using Multi Variables Auto-Regressive First Order Model (MATALAS)

		First Max.	Second Max	Third Max
Mean	Observed	25.89	15.38	11.37
	Gen. 1	31.11	14.97	10.4
	Gen. 2	27.46	16.63	12.27
	Gen. 3	26.35	17.62	11.15
St. Dev.	Observed	14.06	8.67	7.37
	Gen. 1	18.5	8.74	8.75
	Gen. 2	15.89	10.6	9.09
	Gen. 3	14.46	8.49	7.24
Maximum	Observed	61.2	34.3	33.7
	Gen. 1	74.3	38.69	41.45
	Gen. 2	79.14	39.16	37.76
	Gen. 3	76.51	37.41	32.81
Minimum	Observed	1.7	1.2	0.6
	Gen. 1	2.21	1.38	1.03
	Gen. 2	1.86	1.33	1.01
	Gen. 3	2.02	1.41	1.11
AKIKE	Gen. 1	32.29	28.07	29.48
	Gen. 2	33.21	29.00	28.46
	Gen. 3	34.91	28.06	27.81

Table 10 T-test for Monthly Means, F-test for Monthly Standard Deviations, for the three Generated series using Multi-variable model.

Variable	% Succ. In t-test	% Succ. In F-test
First Max.		
Generated Series 1	6	6
Generated Series 2	7	7
Generated Series 3	6	6
Second Max.		
Generated Series 1	7	6
Generated Series 2	7	7
Generated Series 3	6	7
Third Max		
Generated Series 1	7	6
Generated Series 2	7	7
Generated Series 3	7	6

Table 11 Comparison between the Maximum Absolute Differences in Statistical Properties of the Observed series and the Generated Series by the Single Variable Model and the Multi-Variables Model for a three Generated Series for Each of the Three Variables

	First Max.	Second Max	Third Max
Max. Absolute Difference in Means			
Single Variable Model	2.72	1.41	0.6
Multi-variable Model	5.22	2.25	0.97
Max. Absolute Difference in Standard Deviations			
Single Variable Model	1.18	1.43	0.72
Multi-variable Model	4.44	1.93	1.72
Max. Absolute Difference in Maximum Value			
Single Variable Model	16.11	3.86	4.07
Multi-variable Model	17.94	4.86	7.75
Max. Absolute Difference in Minimum Value			
Single Variable Model	0.45	0.21	0.41
Multi-variable Model	0.51	0.21	0.51