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Dynamic Characteristics of Monthly Rainfall in Tabriz under Climate Change

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ORIGINAL ARTICLE

ABSTRACT: Among the factors creating the changes in climate include ever-increasing population, changes in land usage and the development of industrial activities. Thus, studying the effect of this phenomenon on hydrological processes, in particular rainfall is considered as one of the most important issues concerning water engineering. Chaos theory is a tool that can be implemented besides other methods in modeling nonlinear, complicated hydrological phenomena like rainfall, due to its wonderful capabilities. In this study, monthly rainfall in Tabriz has been studied through this theory under historical and climate change conditions. In so doing, the statistical period of 1971 to the year 2000 was considered as the historical period, and the results obtained from the model LARS-WG were also considered under two scenarios in three future periods. The results indicated that historical period data having the fractal dimension of (5.96) has good chaotic nature. In the case of scenario A2, the data of all three series had good chaotic nature as well. In scenario B1, random investigation in all three periods will be appropriate.

Keywords: Climate Change, Rainfall, Chaotic Theory, Tabriz, Lars-WG Model

INTRODUCTION

Today issues of climate change has led to temperature increase, floods, drought, thermal waves, melting of polar ice, Temporal and spatial changes of rainfall, disorders in hydrological balances and management strategies, however, researchers and managers of water resources didn't ever expected such harsh impact of climate change on hydrological parameters, so in most studies the trend of changes in the data observed was also attributed to future, therefore, the role of climate change was not considered in the future predictions. As a result, it is necessary that the analysis of rainfall process be studied simultaneously with climate change issues, so that the realistic process of prospective changes in hydrological parameters and, in particular rainfall, would be accessed.

In recent decades, chaotic theory, which is the basis and foundation of nonlinear dynamic systems, has caused a great revolution in how to understand and express phenomena. This theory deals with studying the systems appearing irregular at first glance, however, they are in fact, ruled by determined laws. These systems are very sensitive to the initial conditions (Williams, 1997; Sivakumar, 1999), in a way that the input which seems irregular is able to have a great effect on them. The systems like these are called chaotic systems.

Concerning the analysis of the rainfall process, some researchers have carried out some several studies in recent decades. SivaKumar (2001) has studied the rainfall dynamics of Leaf River in Mississippi through chaotic theory in four different time stages. He has concluded that the data having higher Coefficient of Variation possess lower correlation dimension and vice versa. Kar Amuz, et al. (2009) carried out some studies concerning forecasting long-term rainfall through the implementation of statistical downscale and artificial nervous network. The results showed that the statistical sub-scale model (SDSM) was more effective than nervous network. Hashemi (2010) compared the two models SDSM and LARS-WG, in which both models had the same capability. Min Su Yang et al (2010) indicated that rainfall data in Peninsula located in Korea had optimal chaos with a suitable fractal dimension. Yang Mi Min et al (2011) evaluated CLIGEN model for the daily rainfall, and they also used T, F, K-S tests for evaluation. The results imply that model CLIGEN has an error equal to 2.3 percent for the daily average and, therefore, it's not suitable for long-term periods of return.

Considering the importance of studying rainfall and the practicality of chaos theory in the analysis and prediction of this factor, Tabriz metropolis has been chosen as the case study. And the purpose of the present study is being aware of rainfall process in future with regard to climate change.

METHODS AND MATERIALS

LARS-WG model

LARS-WG software or model is a kind of climatic generator which is based on series model that can be used

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in simulating meteorology data in an individual station as well as the present and future climatic conditions (Semenov,1999;racsko et al,1999). This generator generates possible distribution parameters of climatic variables, and the data of climate change by accessing the relationship among them as well, by implementing the climate data observed in a given station. By randomly selecting the variables among suitable distributions, these sets of parameters are used to generate artificial series of time with the desirable length.

LARS model uses a semi-experimental distribution to approximate to approximate probability distributions of dry and wet series, daily rainfall, minimum and maximum temperatures and solar radiation. The semi-experimental distribution is defined as a distribution function of collective probability. For any climate variable v, the climate variable v_i Vs the probability p_i is calculated through the following equation:

$$V_i = \min\{V : P(V_{obs} \le V) \ge P_i\} \qquad i = 0,...,n \qquad (1)$$

where P( ) is indicative of the probability gained through the data observed or $\{V_{obs}\}$. For any climate variables, the two P_o and P_n are equal to 0 and 1 respectively, they are constant with the relevant $V_n=\max\{V_{obs}\}$ and $V_o=\min\{V_{obs}\}$ (semonov and stratonovitch,2010) .

Description of selected chaos models

Chaotic behaviors reflect their internal processes in the time history of one of their single variables, normally referred to as time series, which may therefore bear external signals. A range of nonlinear dynamic methods have specifically been developed to identify chaotic behaviors mainly from time series and this study employs a number of them described below, including stochastic techniques.

Phase space reconstruction

Identification of the nature of dynamics of a real-world system can be done by using the concept of phase-space to characterize if a time series is stochastic, deterministic or in between. This is carried out by transforming a time series into the geometry of a single moving point, as if the time series is generated by a nonlinear dynamic system with m degrees of freedom. A popular method for identification of phase space of a time series was presented by Takens(1981).The method, commonly termed as delay-embedding, involves the construction of an appropriate series of state vectors, Y_t, correlated to observed values, which are discrete scalar time series, $X_t = \{x_1, x_2, ..., x_N\}$ with N-observed values, with delay coordinates in the m-dimensional phase space:

$$Y_t = \{X_t, X_{t-\tau}, X_{t-2\tau}, ..., X_{t-(m-1)\tau}\} \qquad (2)$$

where τ is referred to as the delay time and, for a digitized time series, it is a multiple of the sampling interval used, and m is termed the embedding dimension. The values of delay times are obtained as zero intercepts of ACF and values of the ACF evaluated by the TISEAN package (hegger et al,1999).Those systems whose dynamics can be reduced to a set of inherently deterministic behaviours, their trajectories converge towards the subset of the phase space, called the attractor. The reconstruction of phase-space by plotting X_t against $X_{t-(m-1)\tau}$ can show the presence of an attractor as a visual evidence for deterministic chaos in a given time series.

Mathematical approaches for the reconstruction of the phase space diagram of chaotic behaviors may be carried out by one of the following methods: (i) Auto-Correlation Function, ACF, (ii) Average Mutual Information, AMI or Correlation Integral, CI (Fraser and Swinney, 1986). This study uses the ACF, defined as:

$$\rho_t = \frac{E[(x_t - \mu)(x_{t+k} - \mu)]}{\sqrt{E[(x_t - \mu)^2]E[(x_{t+k} - \mu)^2]}} \qquad (3)$$

Where ρ_k is autocorrelation function; E is a functional expression of expectation, x is the observed data. For each value of m there is a value of, ρ_k . Holzfuss and Mayer-Kress (1986) recommend the ascertainment of the value of delay time by displaying ρ_k against m, and obtaining its value at its first zero crossing of the autocorrelation function. This method is selected in this study but Schuster(1988) recommends the value when ACF is 0.5 or when its value is 0.1(Tsonis and Elsner,1988). Behavior of the autocorrelation function ρ_k as a function of m is indicative of the dynamics of the process controlling the time series.

After determining the values of m the phase-space diagram may be reconstructed. The attractor is the geometric description of a single moving point by displaying X_t against $X_{t-(m-1)\tau}$, for which the following outcomes are possible: (i) for a rather periodically regular behaviour, the attractor will be a well-defined closed shape; (ii) for stochastic processes, the attractor would look like a cloud of points; and (ii) for a deterministic chaotic behaviour, the attractor revolve around a recognisable closed curve but every now and then it would tend to get out of track.

Correlation dimension method

The correlation dimension method is one of the most widely used methods to determine the presence of chaos, and more specifically to distinguish between low-dimensional and high-dimensional systems. For chaotic systems, the dimension is non-integer and low. The method uses the correlation function to determine the dimension of the attractor in the phase space. For an mdimensional phase space the correlation function C(r) is given by (Grassberger and Procaccia,1983):

$$C(r) = \lim_{N\to\infty} \frac{2}{N(N-1)} \sum_{i,j=1}^{N} H(r - |Y_i - Y_j|) \quad (4)$$

where H is the Heaviside step function, for $u = r - |Y_i - Y_j|$ and $u \geq 0$, $H(u) = 1$ and $u \leq 0$, $H(u) = 0$, N is the number of points on the reconstructed attractor, r is the radius of the sphere centred on Y_i or Y_j. An attractor is represented by radius, r , and a non-integer fractal dimension, as follows:

$$C(r) \propto \alpha r^{D_2} \quad (5)$$

where α is a constant; and D2 is the correlation exponent or the slope of $\ln C(r)$ versus $\ln(r)$ given by:

$$D_2 = \lim_{r\to 0} \frac{\ln C(r)}{\ln r} \quad (6)$$

The behavior of D_2 provides one technique for determining the presence of chaos in a time series, such that (i) for stochastic processes, D_2 , varies linearly with increasing m, without reaching a saturation value; (ii) for deterministic processes the value of D_2 saturates after a certain value of m.

In this research, the paired model "atmospheric-oceanic HadCM3" is used, whose data had existed since 1961 to 2010, and all data had become normal according to the average (mean) and standard deviation of the data between 1961 to 1990. After data regeneration through the output of climatic model HadCM3, the predictions have been carried out in three time stages (2011-2039, 2046-2065 and 2080-2099) based on the two scenarios of distribution "B1 and A2". Scenario A2 predicts a world with a very fast economical growth, in which the world population reaches the highest level in the mid 21st century, and also in that world more effective and new technologies would emerge very rapidly. Scenario B1 is also showing a parallel and convergent world, the population situation of which is similar to scenario A2, however, there is a difference between them, i.e. the emphasis in scenario B1 would be more on using clean energy, and a sustainable environment and economics in the world.

Area and the data used

Tabriz is located in east Azerbaijan Province in Iran, at latitude 36° to 38° and 6 minute north, and also at longitude 48° and 10 minute east, having the average height of 1350 meters from sea level. The major reasons for the rainfalls in the area studied could be attributed to the systems generating rain, affecting the area alternatively which starts early in fall to mid-spring, causing rainfall there. The type of rainfall in Tabriz is almost Mediterranean. According to the statistics provided by a synoptic station, the maximum rate of annual rainfall is 412.8 mm, with an average of 213.2mm. The data concerning rainfall, solar radiation and daily temperature between the years 1971 to 2000, located in the synoptic station in Tabriz, have been selected as the basic data. The statistical features of daily and monthly data- concerning rainfall- used have been shown in Table 1.

Table 1. statistical feature of data series in monthly and daily rainfall in the primary period (1971-2000)

Statistical features	Daily	Monthly
data number	10958	365
Average (mm)	0.748	22.42
standard deviation	2.56	21.51
Coefficient of Variation	3.42	0.96
Max (mm)	63	134.6
Min (mm)	0.0	0.0
SKEW	6.58	1.628

RESULTS AND DISCUSSIONS

Regenerating the climatic data based on the two scenarios B1 and A2

Different levels of performing the task with LARS-WG model can be divided to two separate groups. The first step (analysis) is known as "calibration level". In this level the statistical tests are implemented to evaluate capability of the model. Statistical test include: Kolmogrov-Smirnov test (KS) is used to compare probabilities distributions, test t to compare averages and test F to compare standard deviation. Tables 2, 3 and 4 show the quantity of these statistics and the relevant probabilities respectively.

Each test calculates one statistic and its relevant probability, indicating that two data distributions observed and produced may be the same. If the quantity of this probability is less very low and less than the significant level, (which is considered 0.01 or 0.05 in general), the equality of the climate simulated and produced, and the real climate will be improbable. Therefore as it appears from the probability quantities in the tables mentioned above, LARS-WG model has significant ability in producing daily rainfall distribution in different months and average quantities of monthly data as well. Furthermore, the generation of standard deviation quantities (i.e. the way data are distributed upon average quantities) having 5 percent probability are acceptable except for August and December. The lowest rainfall in Tabriz occurs in August in summer, and as a result, it's not of high significant. Figure 1 confirms the truth about what was mentioned above. The chart concerning rainfall amount observed and produced by the model match well in all months of the year, and also this matching is better in months having more rainfall than those having less.

After the ability of LARS model was known due to the results in the previous part, the second step (production) starts, and then future climatic scenarios are produced through generating daily data in future periods.

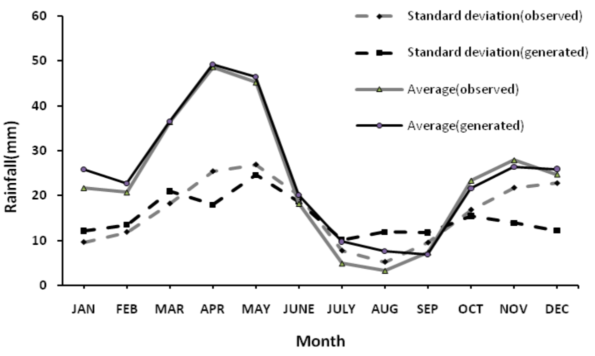

Figure 1. Diagram of average amount observed and generated rainfall in Tabriz station in period 1971-2000

Chaos acceptance (delay time, embedding dimension and correlation dimension)

Figure 2 the delay time opposed to autocorrelation function of the data generated and observed shows Scenario A2. The delay time for the data observed is 2 months. Delay time indicates a real physical mechanism in rainfall dynamics, which is literally not known yet. By so doing, they reflect a physical correlation. Significant and logical delays in correlation functions determine the continuity of time, which may, in turn, be related to the scale or fractal behavior in rainfall process. Autocorrelation function has oscillation randomly, and the potential of this fluctuation decreases with an increase in time delay, until it trend to zero. Exponential descending of autocorrelation function, and in fact the delay time's being large may be a sign of chaotic behavior (Sivakumar and Bemadtsson, 2000).

In these series the first stage of scenario A2 may have a better chaotic nature compared to the others. Autocorrelation function shows the time cycle in all series, however, it's unable to distinguish chaotic behavior from random behavior.

Once the above-mentioned levels were performed for scenario B1, the delay time and embedding dimension for the two scenarios B1, A2 are summarized in table 5. The embedding dimension calculated for the data observed is 11 months.

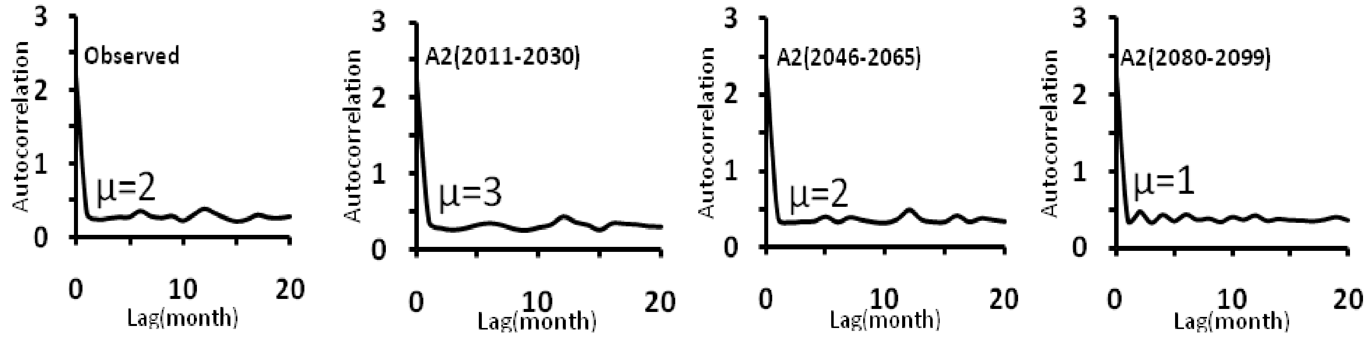

Figure 2. Delay time for autocorrelation dimension of data observed and climate change under scenario A2

Table 2. results of the test of Klomogrov Smirnov (KS) for daily rainfall distribution observed and generated by LARS-WG

MONTH	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
KS	0.049	0.03	0.05	0.025	0.046	0.135	0.137	0.124	0.296	0.056	0.075	0.04
Probable	1	1	1	1	1	0.976	0.973	0.99	0.221	1	1	1

Table 3. comparison of the average data in the monthly rainfall observed and generated by LARS-WG

MONTH	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
Average (observed)	21.73	20.77	36.42	48.68	45.23	18.23	4.93	3.30	7.41	23.38	27.93	24.77
Average (generated)	25.88	22.78	36.60	49.20	46.43	20.16	9.78	7.70	6.92	21.70	26.38	25.97
t	-1.09	-0.60	0.01	-0.35	-0.15	-0.44	-1.69	-1.70	0.20	0.28	0.40	-0.24
Probable	0.28	0.55	0.99	0.73	0.88	0.67	0.10	0.10	0.84	0.78	0.69	0.81

Table 4. Comparison of standard deviation in monthly rainfall data observed and generated by LARS-WG

MONTH	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
Standard deviation (observed)	9.64	11.89	18.23	25.41	26.89	20.09	7.74	5.23	9.54	16.85	21.73	22.76
Standard deviation (generated)	12.15	13.49	21.02	17.99	24.65	18.7	10.2	11.96	11.8	15.47	13.94	12.23
F	1.12	1.21	1.07	2.017	1.049	1.305	1.847	4.417	1.532	1.732	1.853	3.988
Probable	0.76	0.61	0.85	0.064	0.897	0.478	0.104	0	0.256	0.145	0.102	0

Table 5. Delay time and embedding dimension for three future periods under scenario A2, B1

Period	**2011-2030**		**2046-2065**		**2080-2099**	
Scenarios	**A2**	**B1**	**A2**	**B1**	**A2**	**B1**
Delay Time (Month)	3	2	2	1	1	2
Embedding Dimension (month)	4	9	5	8	7	7

Finally, following finding delay time and embedding dimension, it's time to draw a diagram of phase space construction. A real phase space is one in which two different variables are brought about opposed to each other. But in chaotic theory, only a pseudo phase space is used, in a way that one physical feature opposing itself is drawn with the time delay. Figure 3 illustrates the phase space of historical data and the first period of the two scenarios B1 and A2, having a delay time. The phase space diagram tries to show the presence of attraction in each series of data. However, it is possible that the presence of one or some extreme phenomena, distorts the presence of this attraction in phase space construction, and also the intensity of these extreme phenomena is distinguishable in phase space diagram. The existence of attraction is a sign that dynamic chaos exists in the series of data, and as it is obvious in Fig.3, scenario B1 has a lot of extreme phenomena; that is why less attraction is felt here. And naturally its chaotic behavior exists. In general, the correlation dimension is the most effective method for distinguishing chaotic dynamics behavior from random dynamics.

Figure 4a shows the diagram of changes in log C(r) Vs log (r) in the data observed. Due to the presence of noise in data, for any small amount of log(r), some oscillations are seen in the diagram(Ng et al,2007). But a flat section in log(r) limited part observed in data being between 1.25 to 1.60, in which the quantity of logC(r)/log(r) reaches a constant level; the scaling could be selected here. In order to determine the correlation dimension, and studying acceptability of chaos in data, the slope of the curves is calculated using the method of minimum squares which are in the distance 1.25 to 1.60 from log(r); and also for each quantity r in the distance 0 to -1, logC(r) is calculated, and the results are depicted in Figure 4b.

In this Figure, the quantities of the slope or correlation dimension, in other words, are shown for different quantities of the embedding dimension in the two distances mentioned. Correlation dimension starts to saturate opposed to embedding dimension. Saturation size indicates the fixed quantity of correlation dimension, which is 5.96 for the data observed, and this is a sign that nonlinear chaotic dynamics exists.

But the issue which is of great importance includes selecting the venue considered, in which the area shows its complete chaos. If this area is not selected correctly, the chaos dynamics may not be seen in these series. A series of data is noted to clarify the issue, where different conditions appeared through the selection of cross-section (Figure 5a). The diagram of correlation function and radius r shows the first level of scenario A2. Five cross-sections have been selected to find correlation dimension in this figure. The cross-section starts from number 1 close to convergent point and continue toward number 5 to become concave. The correlation dimension gained in this cross-section is shown in correlation power diagram in Figure 5b. As it seems in this figure, all three states of deterministic dynamics, chaos and random can be seen. But it is hard to determine which of these states would be established for the series of data of the scenario under discussion. However, what is definite, is that first of all cross-section selected must not be in the threshold trend to zero (logC(r)). So with these conditions the deterministic dynamics state and semi-deterministic one wouldn't be correct. Secondly the cross-section selected should not be so far that might, otherwise, be placed in intense oscillation limit. And as it is seen is diagram No.5

the slope has intense changes once saturated, and this is not right. And also the farther it goes from convergent point {logC(r)=0}, oscillations become intense; consequently various slopes would appear in the diagram of this cross-section. The correlation dimension lines 4 and 5 are very close to one another, and so in this portion, data series have completely reflected their chaotic nature. But the cross-section 4 matches better with the conditions of the selected area of cross-section.

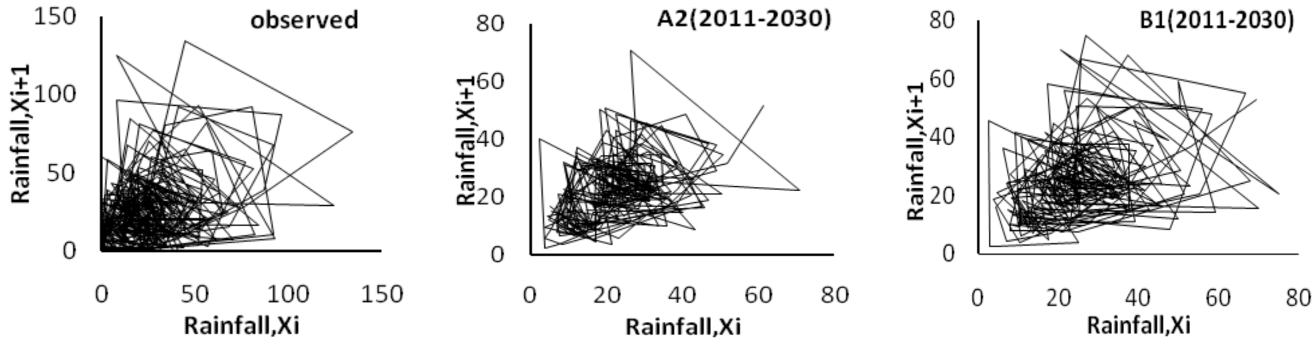

Figure 3. Behavior state in monthly rainfall of Tabriz with a delay of one month for data observed and the first period of scenarios

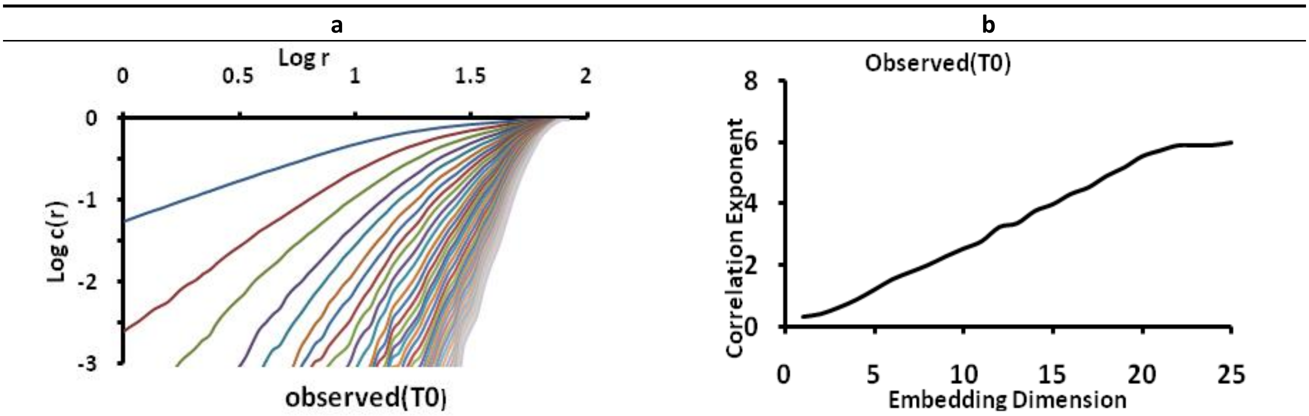

Figure 4. a) The diagram concerning the relationship between correlation function C(r): a radios are with an increase in m. **b)** Diagram of correlation dimension changes with an increase of embedding dimension for the data observed in monthly rainfall of Tabriz

In general, in a portion where the series have chaotic behavior, the quantity of correlation dimension in various cross-sections wouldn't so different from the others. Finally, the two cross-sections 3 and 4 are supposed to be the best cross-section, in which they suggest two completely opposite behavior in the portion (1.19‹log(r) ‹1.44). For better understanding the conditions governing the series of data, it's necessary that the number of embedding dimensions increase so that the changes trend of cross-section 3 would be restudied. In such cases where the adjacent venue clearly shows chaos, often the slope of cross-section 3 makes an effort to make itself closer to saturation behavior through increasing the embedding dimension, and thus it's natural that the quantity of correlation dimension would increase too. In such a state, it can be said that in the cross-section mentioned, there is a dynamic chaos. However, the complexity of these series of data is more than normal, and it has a little tendency to be random; in other words random chaos exists.

In Fig.5c the embedding dimension has increased to 35. Once the embedding dimension is increased, the rate of slope in cross-section 3 moves very slowly toward saturation and almost gains saturation in correlation dimension 8.40, but it is not a full saturation. These conditions are known as random chaos. On the other hand, since the adjacent venue has fully reached saturation and shown a completely chaotic behavior, so in the whole system, chaotic nature is dominant over random nature. As a result, the entire diagram with a correlation dimension of 4.82 is considered chaotic. Cross sections 1 and 2 move like previous trend, in parallel with the embedding dimension axis. State No. 4 keeps going showing the saturation limit, some changes are just at times seem in the slope which are the result of the oscillations available at the end of the diagram of Figure

5a. In state No.5, if the embedding dimension is more than 20, log (r) will be negative; otherwise, like the state No.4, after gaining a little slope, the saturation quality is shown by oscillations. Before drawing the diagram of correlation exponent, the chaos of date series is somewhat determined through the embedding dimension lines on the diagram logc (r)/log (r). Therefore, once the changes of line distances are significantly decreased, they are symptomatic of being chaos, and if the distance changes are little, the stochastic conditions in the data series will exist.

But in the case of deterministic dynamics it is believed that if the close cross-sections are selected as the convergent point, then the diagram of correlation exponent often shows deterministic dynamic state. To show deterministic state, the assertion is made only if the deterministic state reaches in some cross-sections. In the cases where the deterministic dynamics occur, the size of the dimension is usually between zero and one. Once the selected cross-sections change, the maximum correlation dimension reaches, which is equal to two, and this shows that at most two principal variables would be necessary to solve data series under deterministic dynamic conditions.

Number section	1	2	3	4	5
Embedding Dimension=20	**Deterministic**	**Semi deterministic Semi stochastic**	**stochastic**	**chaotic**	**chaotic**
Correlation Dimension	0.54	#2.4	non	4.82	#4

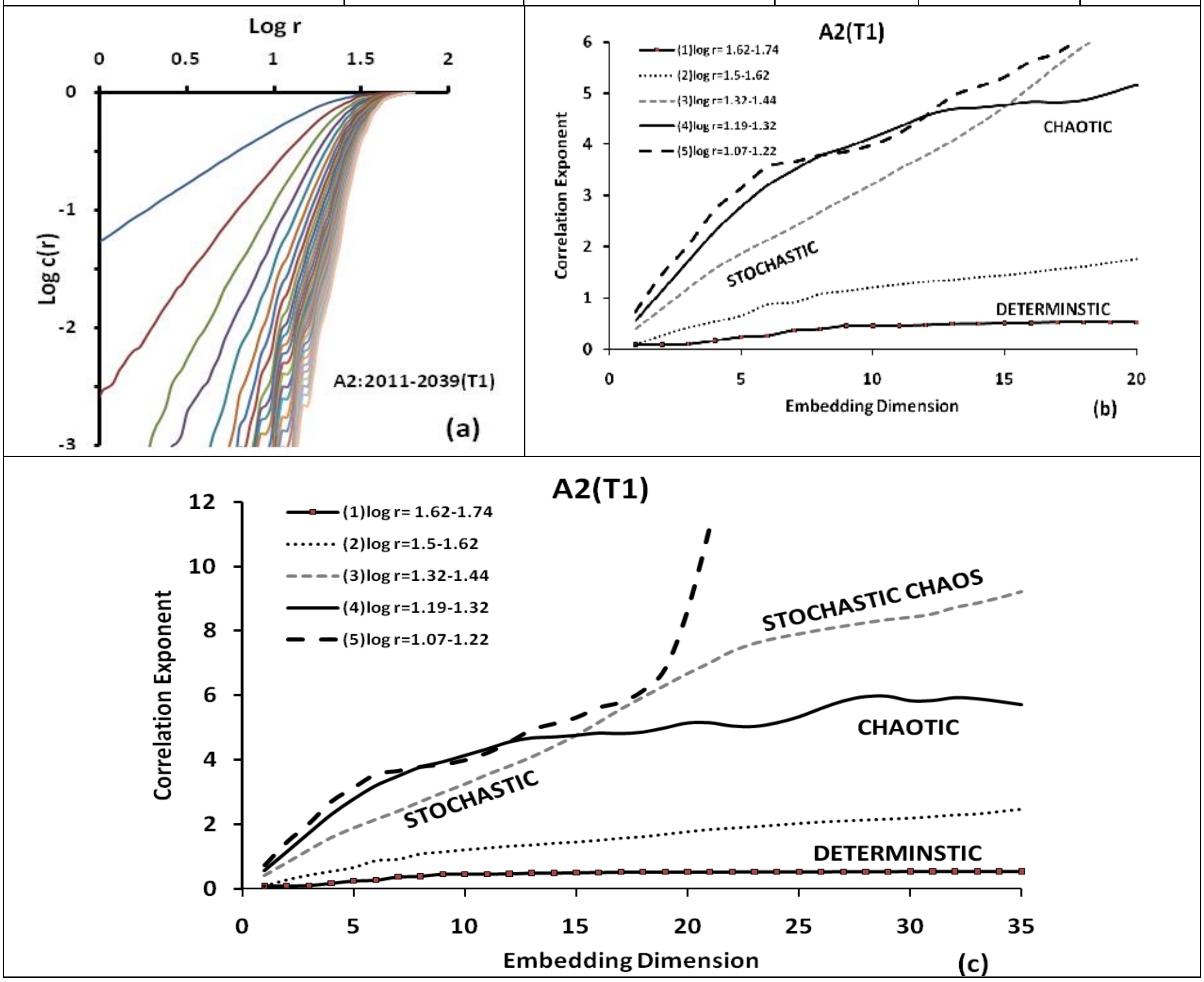

Figure 5. a) Diagram concerning relationship between correction function C(r) with an increase in m. **b)** Diagram of changes in correlation dimension with an increase in embedding dimension for the data series from first period in scenario A2 to embedding dimension m=20 in 5 cross-sections . **c)** Diagram of changes in correlation dimension for the data series from scenario A2 to embedding dimension m=35 in 5 cross-sections

In order to determine the present conditions as well as correlation dimension, the above-mentioned stages would be carried out for the other data series concerning climate change, as shown in fig.6, and the variables of their correlation dimension are listed in table 6.

Casting another glance at figure 6 and table 6, you find that almost all three periods reach saturation in scenario A2, and this shows a chaotic condition. The quantity of correlation dimension of all three periods is nearly around 5, which means the number of variable dominant in this scenario would be 5 or 6, and here number 5 is more concentrated. In scenario B1, all three periods show stochastic behavior until m=20 and if embedding dimension increase until m=30, the first period does not reach saturation and the stochastic behavior is completely clear. But the second and third period reach saturation, however, the rate of correlation dimension is very high, showing a very complicated chaotic behavior. Prediction with a high correlation dimension would be very weak. The quantity of correlation dimension is around number 10, and then, at the very least, 10 variables will be necessary to solve nonlinear dynamics. The complexity of issue is more than normal limit, in a way that the analysis of this issue will be realistic with a stochastic behavior. So, in general, the behavior of scenario B1 can be discussed stochastically.

In this research two scenarios have been discussed, and in both cases, they predict a rapid economical growth. But scenario B1 considers a clean energy and a safe environment. Using clean energy in the coming years may sound wise for the developed countries, while this issue is completely different for the developing and third world countries. If this issue needs to be discussed with certainty, the closest future period may be analyzed, that is, it could be stated with certainty that the bio-environmental condition in the first twenty years (T1) won't be *that* different with the present condition. In this period cleaning the environment seems very remote, because Iran is a developing country having enormous oil resources and with a support of its oil resources Iran tries to increase the domestic production by growing its industry, which is still fed with fossil fuel. And also scientific progress is not in a level to replace fossil fuels so that the clean fuels could be used, the effect of fossil fuel is still seen in industries. Therefore, it can certainly be claimed that replacing clean fuels is not possible at least for the first period, while Tabriz is supposed a powerful industrial city in Iran. So considering scenario B1, at least for the first period loses its points, and therefore, scenario A2 is more probable. And finally Tabriz will face chaotic data series in the first period.

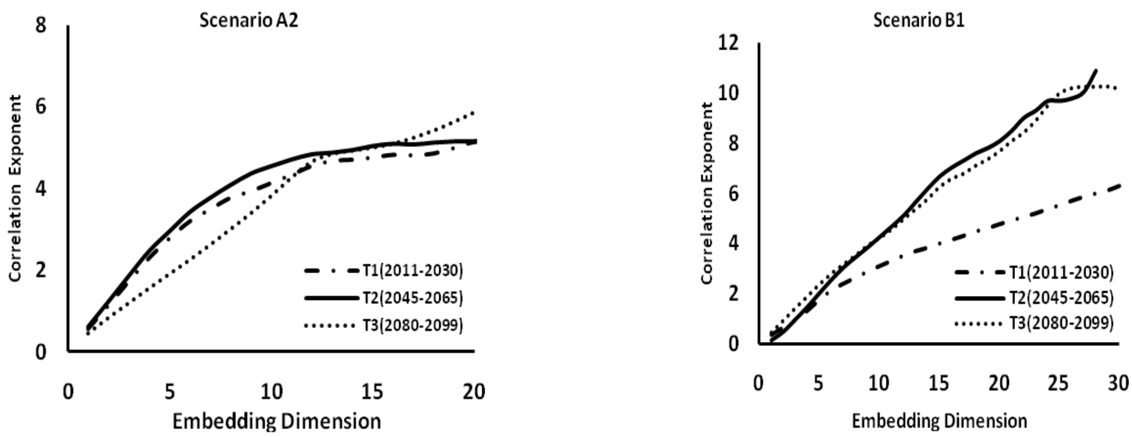

Figure 6. Diagram of changes in correlation dimension with an increase of embedding dimension for generated data of two scenarios B1, A2, monthly rainfall in Tabriz

Table 6. The level of correlation dimension of the two scenarios for three periods of future climatic changes

Correlation Dimension	2011-2030	2046-2065	2080-2099
A2	4.80	5.15	5.09
B1	non	9.80	10.17

CONCLUSION

Rainfall has long been regarded by researchers as one the most important hydrological parameters and the results obtained from analyzing the process of this parameter has a fundamental role in the management of water resources. On the other hand, lack of consideration in the effects of climate change and in the issues, leads to an incorrect understanding in the decision concerning water resources and environment. Thus, in this study the focus was on the monthly rainfall process in Tabriz as well as the effect of climate change, and some steps have

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been taken to compare rainfall process observed (1971–2000) with future rainfalls under climatic change conditions. The future rainfall has been categorized into the three periods (2011-2030) (2046-2065) and (2080-2099) under the two scenarios B1 and A2. LARS-WG model has been used for generating climate data in climatic changes and the chaos theory has also been used to analyze this rainfall process. Some methods used in the chaotic theory include: Phase space construction, autocorrelation and correlation dimension. The phase space construction tries to show the presence of one attraction in each series of data. But the existence of one or some extreme phenomena can distort the presence of this attraction in the phase space construction, and the severity of these natural phenomena like flood and draughts are determined in the diagram of phase space. More powerful attraction in the diagram means more chaotic behavior in those series. The autocorrelation function shows time cycle in each series. The exponential descending order of autocorrelation function implies, to some extent, the chaotic nature. But it is unable to distinguish chaotic behavior from random one.

The correlation dimension is the most effective method for distinguishing chaotic dynamics behavior from random dynamics. The selection of cross-sections for identifying the present conditions is supposed to be one of the major stages in correlation dimension method. An incorrect selection of cross-sections may predict completely different conditions for the system. The best cross-section is chosen in a distance from convergent point {logC(r)=0} which won't encounter oscillations of correlation function diagram and the radius of embedding area, and at this distance the slope in diagram lines should be straight. Results obtained from performing correlation dimension method show a good chaotic exiting for all series of scenario A2 with fractal dimension of around 5. And the data about the first period of scenario B1 is completely stochastic, and also the data of the second and the third one have complicated chaotic nature with a fractal dimension around 10. So, in general, the behavior of scenario B1 can be discussed stochastically.

Therefore regarding the present conditions of Tabriz for the first period, scenario A2 is predicted to have good chaotic nature.

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