Nonlinear Multivariate Rainfall Prediction in Jordan Using NARX-ANN Model with GIS Techniques

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ABSTRACT

This paper aims to simulate and predict the amounts of rainfall in semi-arid regions using Artificial Neural Network (ANN) with nonlinear autoregressive exogenous (NARX) input model. The rainfall precipitation readings of 26 stations for the last 30 years were used as an input for the ANN model. A code, developed in MATLAB at different hidden layers and delay times, was used for this purpose to select the best combination that could simulate the case in Jordan. The results revealed that a reduction of 1.4% in the annual average rainfall amounts in the next 10 years might happen. The simulation criteria depended on changing number of delays and number of neurons (hidden layers), which showed that using 2 delay inputs and 8 neurons gives best training for the ANN as per the computed mean squared error (MSE).

KEYWORDS: Rainfall, NARX, GIS, Time series prediction, Time delay, Neural network.

INTRODUCTION

Jordan is located between 29 and 33 degrees north and between 36 and 19 degrees east, near the southeastern coast of the Mediterranean. The population of Jordan is around 7.839 million. It is surrounded by Syria from the north, Iraq from the east, Saudi Arabia from the south and Palestine from the west. The area of Jordan is around 89200 square kilometers. Land area represents 99.3% of the total area, while 0.7% is water; mainly the Dead Sea as shown in Figure 1.

Water scarcity is one of the most crucial problems in Jordan. Currently, according to Jordan Meteorological Department (JMD), the average annual precipitation ranges from about 30 mm to 570 mm, which is a very low rainfall amount. Less than 10% of the total annual precipitation (ca. 7000 million m^3) is turned into renewable useable water resources; i.e., river discharge and groundwater recharge less than 700 million m^3 (MWI, 2016). Fluctuations in rainfall can affect soil erosion rates and soil moisture, both of which are important for crop yields. The Intergovernmental Panel on Climate Change (IPCC) forecasts that rainfall will increase at high latitudes and decrease in most sub-tropical land regions, while regional rainfall will vary and the number of extreme rainfall events is predicted to increase (IPCC, 2007).

In Jordan, rainfall zones can be grouped into three regions, the highest rainfall (400-600 mm/yr.) occurring in the northwest of the country in upland areas. The second region is far north of the Jordan Valley, with lower mean annual rainfall of 250-350 mm occurring in central Jordan. The third region is southern uplands and

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the lowest rainfall (less than 170 mm/yr.) occurs in the lowland regions of the east and south of the country. This last zone may be separated into steppe (140-170 mm/yr.) and desert (less than 100 mm/yr.), with the lowest rainfall occurring in the most southerly regions (Freiwan and Kadioglu, 2008).

Artificial neural networks have many attractive theoretical properties, specifically the ability to detect non-predefined relations, such as nonlinear effects and/or interactions (Sargent, 2001). Over the last few decades, development and continuous improvement of ANNs resulted in a powerful predictive tool. A major advancement was achieved by Werbos (1974), who expanded the applicability of ANNs to nonlinear systems and this development formed the basis of many ANNs used today (Maanen et al., 2010). Dynamic neural networks which include tapped delay lines are used for nonlinear filtering and prediction (Wang, 2015). Simulation and prediction of nonlinear data such as rainfall are demanding; therefore, considerable attention has been given to the development of sophisticated techniques for exploring this kind of data sets. One such class of techniques is artificial neural networks (ANNs).

The development of nonlinear models for rainfall prediction has recently gained wide attention, represented by noticing considerable research conducted on the rainfall prediction since the first model introduced by Van Lent (1995). The first attempt to model the rain stage process was in the Florida Everglades wetlands based on the original linear autoregressive model with exogenous input (ARX). Van Lent (1995) applied the moving average coefficient matrix to rainfall, taking advantage of the model developed by Box and Jenkins (1970). Here, the current study will not introduce the linear case as developed by Van Lent (1995), but will focus on the nonlinear NARX model and give a brief review in this field.

According to Ganapathy and Hada (2012), NARX is a recurrent dynamic neural network with feedback connections comprising several layers of the network. NARX model is based on linear autoregressive exogenous model (ARX), which is commonly used for the task of prediction. Thus, the model relates the current value of a time series which one would like to predict to both past values of the same series and current and past values of the driving (exogenous) series.

Byakatonda et al. (2016) have conducted a recent study on modeling dryness severity using NARX, to predict the future dryness scenarios and how to facilitate future water management options and assess climate variability. For proper water management, forecasts ranging from a few months to a few years play a vital role (Dastorani and Afkhami, 2011; Mishra and Singh, 2011). Linear parametric autoregressive (AR), moving-average (MA) and autoregressive moving-average (AMA) models introduced by Box and Jenkins (1976) have been widely used in the prediction of time series (Machiwal and Madan Kumar, 2012). Since these models are solely based on a linear model, these models are not able to handle non-stationary signals and signals of nonlinear mathematical models (Diaconescu, 2008). Moreover, in recent years, researchers have noticeably paid attention to use artificial intelligence through Artificial Neural Networks (ANNs) to handle complex systems characterized by nonlinearity.

Illeperuma and Sonnadara (2009), Ardalani-Farsa and Zolfaghari (2010), Menezes and Barreto (2008) and Maier and Dandy (2000) have tested various ANN model formulations.

Gao and Meng Joo (2005), Diaconescu (2008) and Menezes and Barreto (2008) all have demonstrated that Recurrent Neural Networks (RNNs) with sufficient number of neurons are a recognition of Nonlinear Autoregressive Moving Average (NARMA) process. Most artificial neural networks (ANNs) with engineering applications are used for prediction, based on unknown relationships existing between a set of input factors and an output (Shi, 2002). ANNs have become a valuable tool for modeling nonlinear phenomena, such as temperature predictions (Sahin, 2012; Chenard and Caissie, 2008), rainfall predictions (French et al., 1992; Aksoy and Dahamsheh, 2009; Mandal and Jothiprakash, 2012; Farajzadeh et al., 2014) and groundwater level forecasts (Daliakopoulos et al., 2005; Yang et al., 2009).

Research studies conducted on rainfall forecasting using ANNs across the globe are mostly for hydrology applications, like rainfall-runoff modeling, flood warning systems, catchment management, reservoir operation and flooding prevention. Therefore, the use of NARX models is a recent one in the past decade. For example, José Maria et al. (2008) have evaluated the predictive ability of NARX networks to estimate rainfall. They found that best performance of NARX has been obtained in comparison to several ANN models. In addition to that, in a study conducted by Shen and Change (2013) in the hydrological field, they compared different models of NARX and their results came up with a proposed R-NARX model that gives the ability to tolerate imperfect inputs and effectively inhibit error growth and accumulation when applied to multistep-ahead forecasts. They also concluded that NARX model has an outstanding capability for flood inundation depth forecasts for a long period solely based on real-time rainfall information.

Another research to forecast short-term wind speed using NARX was conducted by Senthil and Lopez (2015). The results indicated that NARX with feature selection has come up with a good fitting model in terms of wind direction, temperature and humidity. They also reported that the results obtained have given the knowledge on wind speed and forecast, which was used for scheduling and planning wind power generation.

Matouq (2008) has previously investigated the use of ANN (back propagation network) and GIS for prediction of rainfall and temperature patterns for the period of 1953-2008. He has come up with the conclusion that the country is witnessing dramatically changes in both rainfall and average annual minimum and maximum temperatures. Moreover, Matouq et al. (2013) and Tariq Alwada'n et al. (2015) introduced the techniques of GIS and ANN to investigate the impact of climate change in Jordan on both rainfall and temperature patterns. The previously conducted studies in Jordan have used different models of ANN, but none of them used the NARX model. This study will fit meteorological data for rainfall during the period from 1985 to 2016 using a NARX model and predict the future patterns of rainfall for the coming ten years. Furthermore, a GIS map will be introduced here.

METHODOLOGY

Annual rainfall readings for the last 30 years from 26 stations spread all over Jordan were obtained from the Jordan Meteorological Department (JMD). Average annual rainfall was then computed. GIS tool was used to interpolate this data and present it as a surface to generate contours for the whole area as shown in Figure 1. Sufficient data is needed, so that the ANN model can actually predict rainfall performance after sufficient training. Time delay neural network, which is an artificial neural network architecture whose main purpose is to work on sequential data, was used to generate such kind of data with different delays. Accordingly, the collected and generated data was fed into an ANN model to simulate the average annual rainfall events computed by summation of the annual rainfall for the last 30 years divided by 30. After that, the trained data was used to predict the rainfall events for the next 10 years.

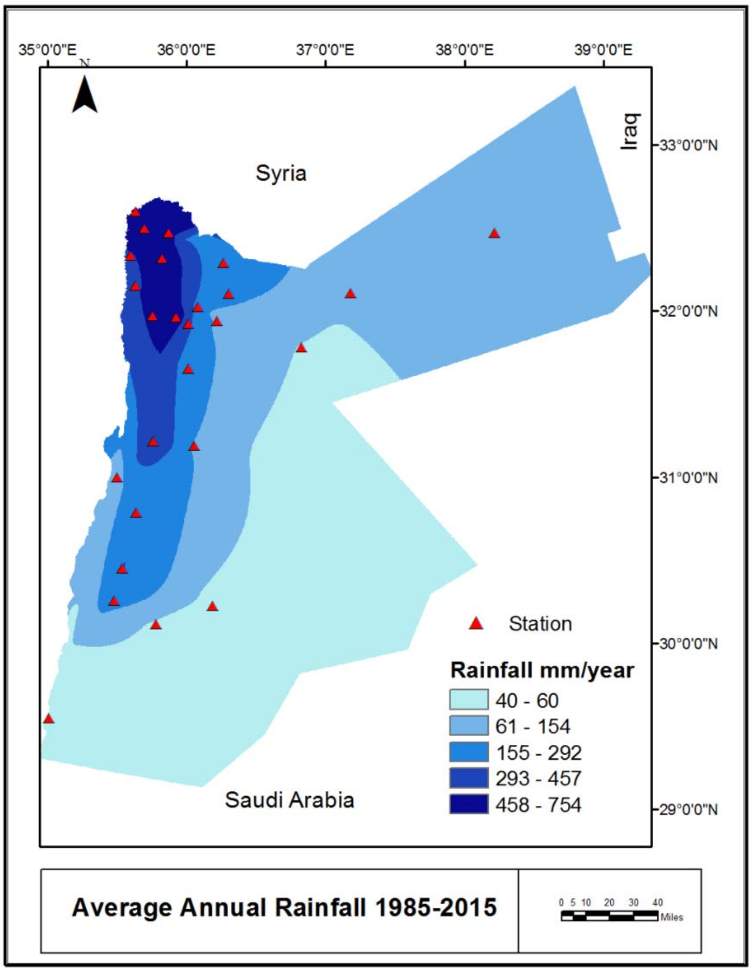

Figure (1): Interpolated average annual rainfall of the study area for the period (1985-2015)

The performance of trained networks depends on their architecture and the number of hidden neurons. The training accuracy is affected by several other parameters, including number of layers, number of training samples, length of learning period, choice of neuron activation functions and training algorithm (Liu et al., 2008). The architecture of the used ANN in the current study is shown in Figure 2, consisting of input layers, 8 hidden layers and one output layer.

ANN is used with a nonlinear autoregressive exogenous (NARX) model, which assumes that the current value of a time series that one would like to explain or predict depends on both past value of the same series, as well as on current and past values of the driving (exogenous) series. A standard approach for representation of nonlinear data in discrete time is to use a nonlinear autoregressive model with exogeneous inputs (NARX), which relates the output y at the discrete time instant t to past outputs and inputs u (Anderson, 2011).

$$y(t) = f(y(t-1), \dots, y(t-n), y(t-d), \dots, u(t-n))$$

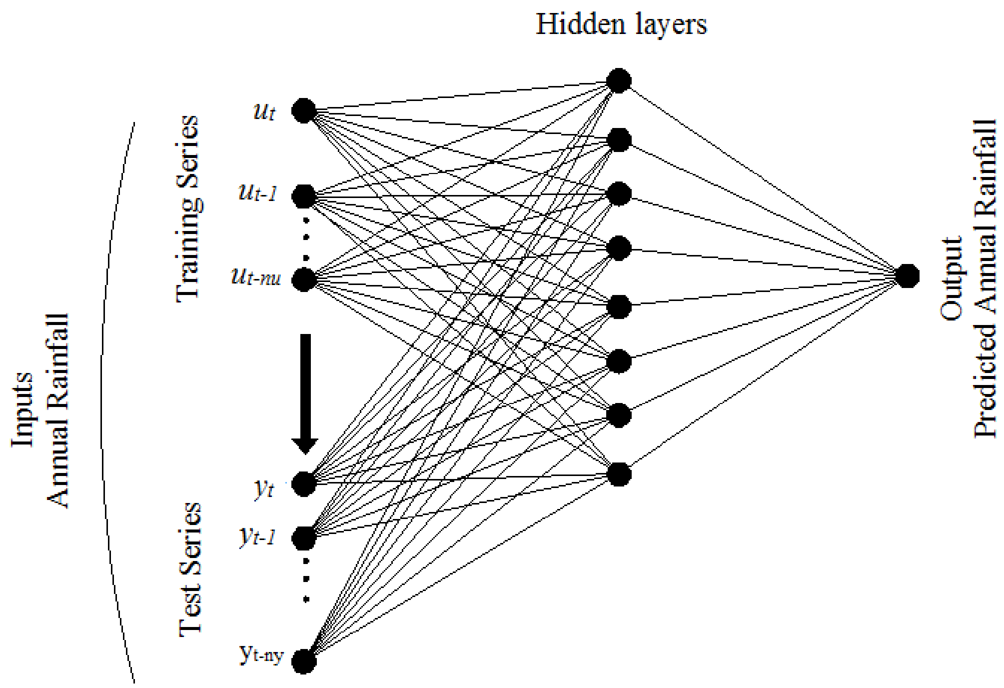

Figure (2): General architecture of the used ANN

For learning purposes, Levenberg-Marquardt training algorithm (TrainLM) is used for training the network. In order to find the best structure of the network in this study, various network structures are evaluated. Setup division of data for training, validation and testing were as follows: Training set consists of 70 percent of data to build the model and determine the parameters, such as weights and biases. Validation data set includes 15 percent of data to measure the performance of the network by holding parameters constant. Finally, 15 percent of data is used to increase the robustness of the model in the test phase. In the same line, network parameters and their evaluated values in the study are given in Table 1 for Amman Airport station as an example, which shows that using 2 delay inputs and 8 neurons will give best training for the ANN with 0.0038 MSE. The used model is shown in Figure 3.

Table 1. Network parameters and their evaluated values

No. of Nodes	No. of Delays		
	2	3	4
2	0.0120	0.0117	0.0083
3	0.0101	0.0120	0.0089
4	0.0115	0.0088	0.0093
5	0.0086	0.0095	0.0220
6	0.1147	0.0073	0.0073
7	0.0095	0.0069	0.0062
8	0.0038	0.0730	0.0106
9	0.0085	0.0431	0.0203
10	0.0415	0.0492	0.0103

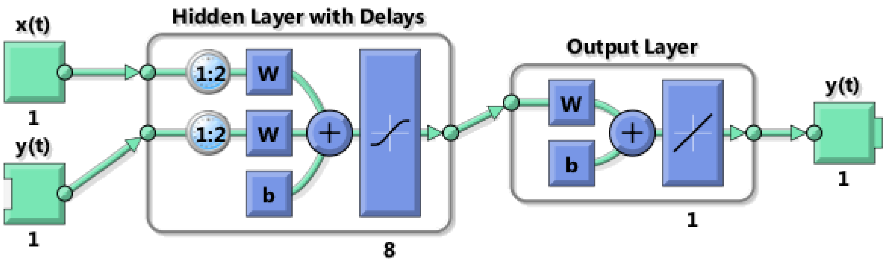

Figure (3): Schematic architecture of the used ANN

RESULTS AND DISCUSSION

One of the common problems of using ANNs is identifying the best stopping point for training (Haykin, 2001), because the training error starts with a maximum value, decreases rapidly and then levels off, indicating that there is no more error to correct (Santos et al., 2016). The results obtained show that satisfactory prediction accuracy has been achieved through NN use, which is a promising approach for rainfall forecasting. Here, the ANN is used to predict the rainfall patterns in Jordan.

The use of GIS tools with the help of ANN will be tested here to predict values of rainfall for the next 10 years. The study included all weather stations located in Jordan. The contours and surfaces for the produced map through GIS tools among located weather stations will give values for rainfall during the period of (2012-2016) as a sort of prediction. Figure 4 shows the located weather stations, contours and surfaces produced by GIS tools and values of predicted rainfall.

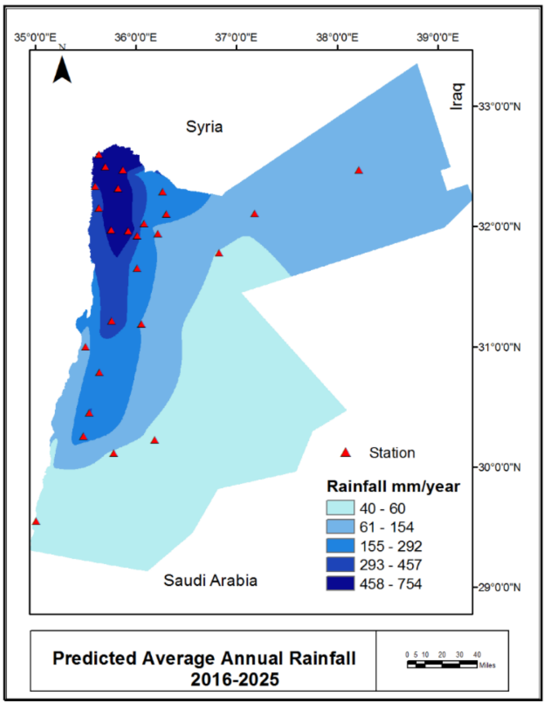

Figure (4): Interpolated predicted average annual rainfall of the study area for the period (2016-2025)

According to Figure 5, the values of rainfall predictions for all weather stations have been introduced; however, in order to give a better understanding to the model prediction accuracy, a linear regression between the network outputs and the corresponding targets of the model will be demonstrated here for Amman Airport weather station as an example. Figure 5 shows the result of linear regression between ANN outputs and the corresponding targets for Amman Airport weather station. A high linear regression is seen in Fig. 5 (R=0.95041). The same procedure is used for other weather stations and good results are obtained, supporting the predicted values according to the model.

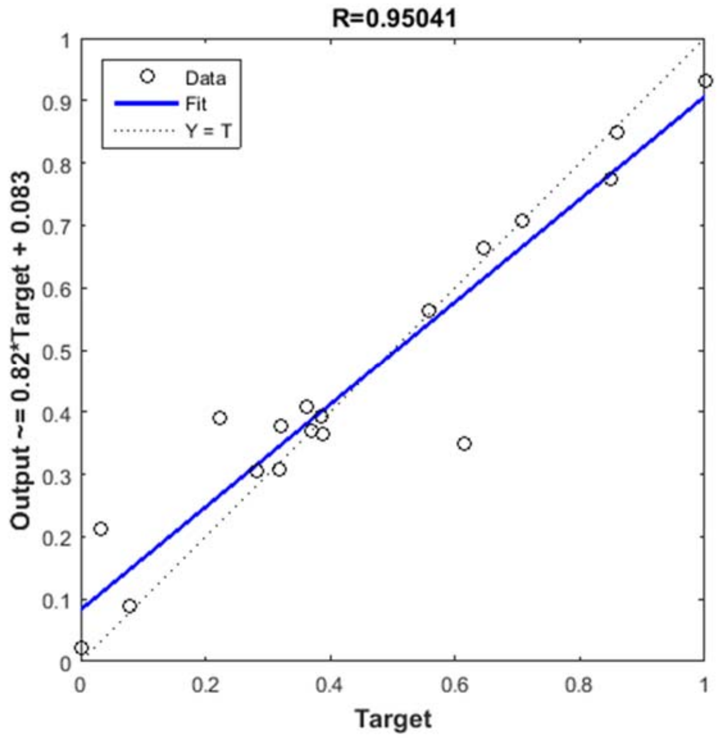

Figure (5): Linear regression between ANN outputs and the corresponding targets for Amman airport station

The predicted values obtained for rainfall in all investigated weather stations during the period of 2016-2025 are compared to the actual values for all weather stations during the period of 1985-2015 as shown in Figure 6. Here, the GIS tools used to compute the change of average annual rainfall in the period of 1985-2015 and the future predicted period of 2016-2025 are ArcGIS and raster calculator. The average annual values for both predicted and actual rainfall revealed a reduction of 1.4% in the forthcoming rainfall in Jordan in areas where rainfall in its actual situation is having higher annual average values, like Amman Airport and Ras Muneef. Results show that the southern part of Jordan is expected to have more rainfall in the next 10 years. Results also show an increase in rainfall intensity in different areas and changes in rainfall patterns. The predicted rainfall values for the 26 stations are shown in Figure 6, where a considerable reduction in some areas is clearly seen and a considerable increase in some areas is also recognized from this prediction. Figure 6 will be of great benefit for those who are thinking about building a better planning strategy to manage water resources in Jordan. Changing rainfall patterns may affect the infrastructure in some certain areas where there is an increase in precipitation values.

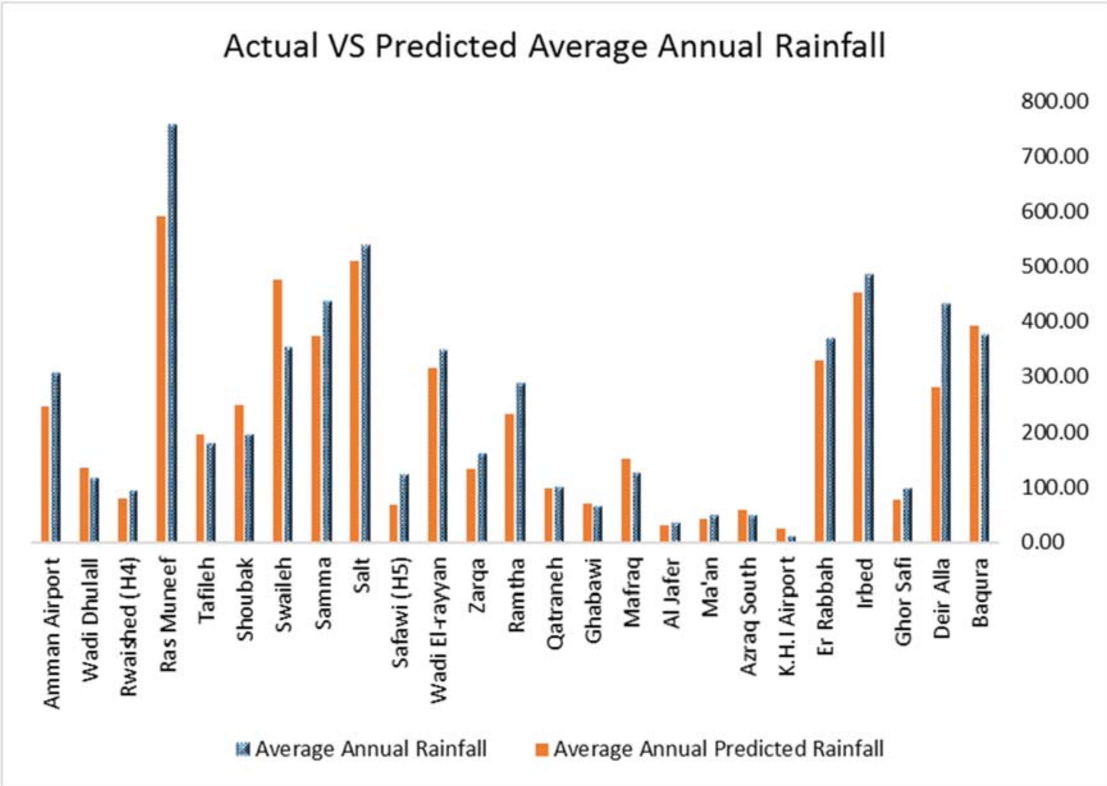

Figure (6): Actual *vs.* predicted average annual rainfall of the study area

CONCLUSIONS

ANN was developed and applied for rainfall data simulation and prediction in Jordan. The developed ANN model with Levenberg-Marquardt training algorithm (TrainLM) was applied to simulate rainfall values collected from 26 stations in Jordan. This data was then used to predict rainfall patterns for the same stations in the coming ten years. The results showed a reduction in rainfall amounts in the next 10 years, which means a direct impact on Jordanian economy, which is severely dependent on rain-fed agriculture for income and employment.

It is clear from the prediction model that the total rainfall will be reduced in the coming decade, especially in areas where the rainfall amount used to be high, like the northern part of the Kingdom (Ramtha and Ras Muneef), while the southern part of the country will either keep its total amount of rainfall (Maan, Qatraneh and Al-Jafer) or even receive more rainfall than usual (Qatraneh and Shoubak). Another part in the eastern region of the country (Al-Mafraq and Al-Azraq) will also have more rainfall than usual. These areas are in the desert region, which means that more rainfall is expected to fall in comparison to the whole regions of the country. These areas usually have an average annual rainfall below 100 mm, representing a semi-arid zone.

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