International Journal of Design & Nature and Ecodynamics
Vol. 19, No. 3, June, 2024, pp. 1043-1049
Journal homepage: http://iieta.org/journals/ijdne

Modeling Surface Runoff in Al-Mohammadi Valley: Influence of Climate and Soil Parameters

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https://doi.org/10.18280/ijdne.190333

Received: 22 March 2024
Revised: 17 May 2024
Accepted: 24 May 2024
Available online: 25 June 2024

Keywords:
ANN, Al-Mohammadi Valley, Euphrates Basin, forecasting, climate change

ABSTRACT

The use of artificial neural networks (ANNs) is becoming increasingly common in the analysis of hydrology and water resources problems. In this research, an ANN was developed and used to model the rainfall-runoff relationship, in a catchment located in a arid climate in western part of Iraq. The aim of this paper is to model the rainfall-runoff relationship in the Al-Mohammadi Valley using a black box type model based on ANN methodology. The multilayer perceptron (MLP) neural network was chosen for use in the current study. Six parameters were considered as independent parameters in the model: daily precipitation, evaporation, temperature, with soil surface properties such as profile soil moisture, root zone soil wetness in addition to soil surface wetness. The Data had been used for about thirty-one years from 1990 up to 2015. The results and comparative study indicate that the artificial neural network method is more suitable to predict river runoff than classical multi linear regression model with a correlation coefficient of 0.61. The results show that the proposed ANN prediction model had a great probability to simulate and predict Runoff. It was observed that the predicted Runoff were close to the observed values with (R = 0.995) for. The significant values of 0.712, and 0.707 for the t-test and F-test respectively indicated the capability of these models to predicate data and there were no significantly different between predicated and observed values. The most variable affecting Runoff values among the runoff input variables is the precipitation as 100% normalized importance analysis, followed by the temperature 85.7%, then soil surface wetness is 72.1%, and the evaporation is 43.4%.

1. INTRODUCTION

The consequences of climate change on Iraq's land are a major significant concern due to its effect on runoff within its catchment. Both natural and human-caused factors contribute to climate change because greenhouse gas emissions occur. Climate change impacts humans and their environment and constantly modifies temperature and precipitation, consequently altering both the quantity and quality of runoff in the river basin. Floods or a lack of rainfall may result from climate change in the ecosystem. According to the IPCC, "climate change" is defined as changes in the state of the climate that can be seen over extended periods of time, typically decades or longer, and are manifested through variations in the value and variation of its characteristics. It covers all variations in climate over time, whether brought on by human activity or natural variability [1]. According to the fifth assessment report of the Intergovernmental Panel on Climate Change, the primary impact of climate change has been on water resources. Therefore, any change that is projected in precipitation and temperature can result in an adjustment of climate zones in arid/humid regions [2].

The summers in Iraq are hot and humid, with highs of 50°C and 150–200 mm of precipitation on average annually. As one moves further south, the average annual precipitation decreases to less than 50 mm, and the climate becomes increasingly arid [3]. Through its effects on the elements of the hydrological cycle, climate change has the potential to significantly affect water resources. For instance, evapotranspiration and the volume and quality of runoff can be directly impacted by variations in temperature and precipitation. As a result, control of the runoff should begin at the most miniature area, such as a household, or what is known as "site control and regional control" [4].

A thorough understanding of the surface water supply provided by the river basin is necessary for the management of water resources. Sudden surface runoff puts rainy plants and the population at risk because it is difficult to forecast runoff events due to a lack of hydrological data. Surface runoff is random due to the variety of the terrain and abrupt climate changes, which are reflected in abrupt and uneven rainfall. The runoff surface of various basin areas is significantly impacted by soil texture heterogeneity in addition to climate change [5].

According to Wang et al. [6], the precipitation runoff relationship (PRR) is crucial to engineering hydrology, water resource planning and management, and the evolution of watershed systems. Surface runoff and soil loss processes are influenced by two major factors: land use and rainfall characteristics [7, 8].

To help planners better modify land uses in order to accomplish the objectives of conserving water and soil, understanding the dynamics of soil loss and runoff across a range of land uses is crucial. In ecohydrological processes, precipitation duration and frequency are crucial factors [9]. Higher intensity or longer-lasting rainfall caused runoff to peak earlier, increasing the overall amount of runoff in basins [10]. Fortunately, we can estimate runoff using mathematical techniques based on easily accessible rainfall data because of the link between runoff and rainfall. Numerous studies have been published that use ANN to address hydrology-related issues. In order to analyze hydrology and water resource problems, artificial neural networks (ANNs) are being used more and more. ANN models' ability to model both linear and nonlinear systems without the need for any assumptions has also led to an increase in their use in a variety of scientific and engineering fields, as is generally assumed in conventional statistical methods. At present, ANNs have shown success in river flow prediction for several hydrologic problems [11].

Solaimani [12] evaluated rainfall-runoff forecasts in Iran's Jarahi Watershed using artificial neural networks. Through the use of monthly hydro-meteorological data, such as temperature, precipitation, and runoff, the study aimed to model the rainfall-runoff correlation in the catchment area over a seventeen-year for the period (1983–2000). Poff et al. [13] utilized ANN to examine two streams' hydrological responses using different hydro-climatological data in the northeastern United States of America. Harun et al. [14] conducted an analysis of the rainfall-runoff relationships in Malaysia's Sungai Lui catchment using artificial neural networks (ANN). For a five-year period (1993–1997), daily precipitation and runoff data from hydrometeorology were used. Two sets of data were used in the analysis: the first set contains the data used for model calibration during the first three years (1993–1995), and the second set contains the data used for model validation during the next two years (1996–1997). The outcome showed how well the ANN model predicts runoff. Dozier [15] investigated how rainfall-runoff modeling using artificial neural networks is affected by spatial variation in precipitation. Using varying amounts of spatial precipitation data, an Elman-type recurrent artificial neural network (ANN) was created to replicate the observed stream flow for Fountain Creek at Pueblo. They found that spatial variability in precipitation data makes the ANN more effective.

Olomoda [16] mentioned that a number of climatic changes have affected the Niger basin over the past 50 years, resulting in extremely low river flows. Niamey's Niger River, for example, was completely dry in 1985. In 2002, when the flow was recorded at one of the lowest levels in fifty years, this incident nearly happened again. Furthermore, the approximately 2,500,000 km^2 potential area of the Niger basin has been reduced to a 1,500,000 km^2 active catchment area. Ojoye [17] pointed out that a study had also shown how the Niger River's annual yield at Kainji Reservoir was steadily declining, indicating that the river was experiencing the effects of climate change. The Kainji hydropower station has also seen a sharp decline in the production of electricity over time, which may be caused, among other things, by a depletion of the reservoir's water level.

Therefore, it is essential to research how climate change affects runoff, and the hydrological parameters effects on it with an artificial neural network (ANN) model. This method allows numerous factors to be evaluated simultaneously. The purpose of this study was to predict the runoff at Al-Mohammadi Valley based on six parameters: daily precipitation, evaporation, temperature, soil surface wetness, profile soil moisture, and root zone soil wetness.

2. MATERIAL AND METHODS

2.1 Study area

The objective of this section is to simply describe the study area and the framework of the applied ANN model. The suggested methodologies were employed to Al-Mohammadi valley as shown in Figure 1.

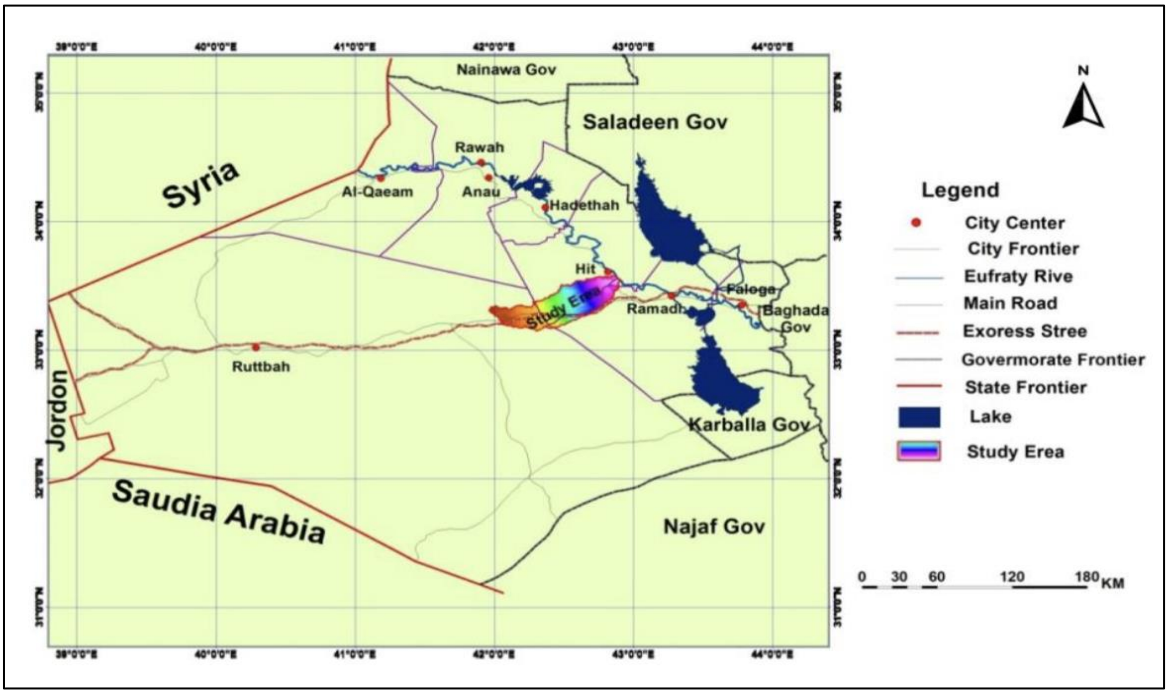

Figure 1. The map of the study area [18]

One of the transient valleys in the Western Desert that empties into the Euphrates River is Al-Mohammadi Valley. It's situated between the Hit and Ramadi towns. The basin is bounded by the following coordinates: Latitudes 33° 34′ 18.1″–33° 4′ 44.4″ and longitudes 41° 55′ 3.8″ –42° 56′ 31.6″. The western boundary of the basin is illustrated by the area of Kilo-160, whereas the eastern border is illustrated by the Euphrates River from the West Bank. The Kubaisa watershed's Hajiya valley forms the basin's northern boundary, while the Abu-Jir valley serves as its southern boundary. From the oldest to the youngest, the geology of the examined area is based on studies [19, 20]. Within an approximate 96 km^2 area, the Msaad Formation (late Cretaceous, Cenomanian-Turonian) is located, about 591 km^2 make up the Euphrates Formation, which goes back to the Early Miocene, approximately 56 km^2 is covered by the Middle Miocene Fatha Formation, the roughly 939 km^2 Nfayil Formation (Middle Miocene). A region of roughly 594 is found in the Pliocene–Pleistocene Zahra Formation. Additionally, quaternary sediments covering an approximate 10 km^2 area.

The investigation area is situated within the Western Desert of Iraq, with humid, dry conditions in the summer and a cold, rainy climate in the winter. The temperature limitations for the warmest and coldest months are 49 and 4℃, respectively. The greatest recorded value of evaporation in July was 517.1 mm, and the smallest value in December was 60.1mm. The precipitation starts yearly from (October to May) and has an average rainfall of 104.6 mm, whereas the humidity ranges from 13% to 47%. Wind speeds range between 3.3 m/s and 4.5 m/s [21].

2.2 Land use/ Land cover

Land uses in the study area have a low percentage, where the residential cover is almost non-existent most of the land is barren land with seasonal plants their growth depends on the amount of rainfall, rainfall season, temperatures, and surface nature. An increase in the vegetation cover contributes to reducing soil erosion by increasing the cohesion of soil particles, as well as reduces the intensity of raindrops falling on the soil surface furthermore plants can act as a barrier to flowing water thus contributes to the increase of groundwater. Plants in the study area are divided into two types: perennial plants that can resist drought and high-temperature conditions (such as reed, thistle, Sidr, etc.). The other type is annual plants that grow only during the rainy season (such as anemone, shamrock, etc.). However, vegetation cover in the study area has a low effect on surface runoff by considering its low density its low-density comparing with the whole area [22].

Although land-use and rainfall characteristics are two important factors that affect runoff and soil loss processes, nested watersheds in unstable geo-ecosystems have received less attention. In one of the nested basins, which consists of six sub-basins with diverse land uses, by examining the characteristics of rainfall and its effects on runoff and sediments [23].

2.3 Data collection

The climatic data was taken from Iraqi Meteorological Organization, Ministry of Transport. (2021) as Excel file, including daily data of the precipitation, evaporation, temperature was obtained for the period 1990 to 2015, in addition to soil surface wetness, profile soil moisture, root zone soil wetness taken from Nasa Website for the period (1990-2015), and the runoff (mm) data from National center of water resources management\ Ministry of water resources, Baghdad.

2.4 Data analysis

2.4.1 Artificial neural networks model

Multi-layer non-linear mapping frameworks that mimic the functioning of the human brain are called artificial neural network (ANN) models. When the relationship between the foundational data is unknown, they are particularly effective modeling tools. From the set of input data and the corresponding desired values, the model can identify and create patterns of correlation. It is made up of highly interconnected neurons, which are basic computational units. In situations where training data is easily accessible, the model performs admirably and is now receiving more attention in the field of prediction and classification, where the traditional use of regression models and other related statistical techniques has been prevalent [24].

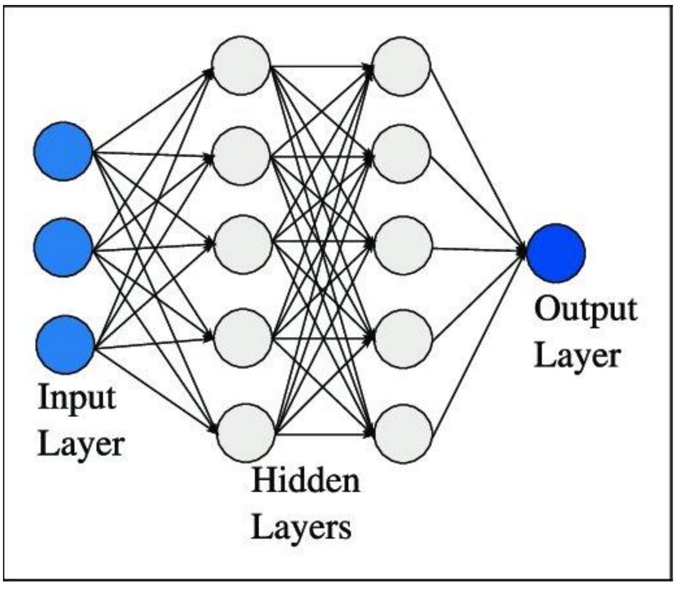

Figure 2. An artificial neural network with three layers of input and neural variables is represented by the ANN model

ANNs have a number of interconnected processing elements (Pes) that usually operate in parallel and are configured in regular architectures. The collective behavior of ANN, like a human brain, demonstrates the ability to learn, recall, and generalize from training patterns or data. The advantage of neural networks is they are capable of modelling linear and nonlinear systems. In the present study, we use an MLP trained with a backpropagation algorithm to predict the drainage basin runoff. The MLP consists of an input layer consisting of node (s) representing various input variable(s), the hidden layer consisting of many hidden nodes, and an output layer consisting of output variable(s) [25]. The input nodes pass on the input signal values to the nodes in the hidden layer unprocessed. The values are distributed to all the nodes in the hidden layer depending on the connection weights Wij and Wjk (24-26) between the input node and the hidden nodes. Connection weights are the interconnecting links between the neurons in successive layers. Each neuron in a certain layer is connected to every single neuron in the next layer by links having an appropriate and an adjustable connection weight. The architecture of the neural network used in this study and the schematic representation of a neuron are shown in Figure 2.

Each node j receives incoming signals from every node i in the previous layer. Associated with each incoming signal (Xi) is a weight (Wij). The effective incoming signal (Sj) to node j is the weighted sum of all the incoming signals and bj is the neuron threshold value.

$$Sj = \sum_{t=1}^{n} \mathrm{XiWij} + \mathrm{bj} \tag{1}$$

The effective incoming signal, Sy, is passed through a nonlinear activation function to produce the outgoing signal (yj) of the node. The most commonly used in this type of networks is the logistic sigmoid function. This transfer function is continuously differentiable, monotonic, symmetric, bounded between 0 and 1 [26]. It is expressed mathematically as:

$$f(Sj)^n = \frac{1}{1+e-sj} \tag{2}$$

ANNs are acknowledged as effective data analysis tools. The multiple-layer ANNs are built using layers of units. Components that carry out comparable tasks make up a layer of units. The associated variables are mapped onto three layers in the ANN model: the input, hidden, and output layers. The unit that generates the results of a particular input is known as the output layer; it is the unit that receives data from the model, processes it in the hidden layer, and then outputs it [14]. Before analyzing information, ANN models typically simulate it using learning techniques. The amount of data required for the validation, testing, and prediction of the ANN model is usually less than that needed for its calibration. In general, approximately two thirds of the input and output data are needed to calibrate the model, whereas the remainder is used for testing and validation [27].

2.4.2 Multi linear regression model

The linear regression model fit the runoff as a function of six parameters annual rainfall, mean evaporation, mean temperature, mean soil surface wetness, mean profile soil moisture and root zone soil wetness [26]. The software used is (SPSS) Statistical Package for the Social Sciences. A multi linear egression is fitted, yield the equation no 10 with a correlation coefficient of 0.614. This correlation coefficient is much lower than the ANN model. This indicate the superette of the ANN over the multiple linear Following is the obtained expression for the Runoff equation [28]:

$$\begin{gathered}\text{Runoff} = [187.304 + 166 * \text{Annual Rainfall} - 0.003 * \\ \text{Mean Evaporation} + 3.360 * \text{Mean} \\ \text{Temperature} + 703.604 * \text{Mean Soil Surface Wetness}]\end{gathered} \tag{3}$$

3. RESULTS AND DISCUSSIONS

Before application of the ANN modeling, the data are checked and reduced to full measurements cases only, i.e., if any set of the data of the water quality parameters measured in a certain date has missing value or values the whole set is removed and only the complete sets are considered in the analysis.

The full dataset reached from 1990 to September 2015 (26 years) as indicated in Table 1.

Table 1. Descriptive statistics for the investigated parameters

Parameters		Annual Rainfall	Mean Evaporation	Mean Temperature	Mean Soil Surface Wetness	Mean Profile Soil Moisture	Root Zone Soil Wetness	Runoff (MM)
N	Valid	30.00	26.00	32.00	32.00	31.00	32.00	30.00
	Missing	2.00	6.00	0.00	0.00	1.00	0.00	2.00
Mean		101.23	228.89	22.92	0.23	0.40	0.41	92.42
Std. Deviation		54.22	46.97	0.70	0.02	0.01	0.01	34.33
Variance		2939.33	2205.98	0.49	0.00	0.00	0.00	1178.77
Range		228.50	184.78	3.81	0.12	0.03	0.03	125.64
Minimum		12.60	133.50	20.73	0.18	0.39	0.40	38.58
Maximum		241.10	318.28	24.54	0.30	0.42	0.44	164.22
%	25	65.48	199.11	22.59	0.21	0.39	0.41	65.36
	50	87.05	224.85	22.99	0.23	0.40	0.41	88.92
	75	133.13	263.14	23.33	0.24	0.40	0.42	114.86

The differences in means between the variables is relatively high, hence this will justify the use of standardized variables instead of the original in the ANN modeling in order to avoid the order of magnitude effect. The standardization process of each variable is obtained by subtracting the mean value and dividing by the standard deviation of this variable, which transform the data to a zero mean and unit variance sets.

Many trials had been done for obtaining the best ANN model to predict the runoff from the proposed data set. The trial involved many different numbers of nodes of a hidden layer, with different learning rates, concepts of momentum, in addition to a variety of activation functions. There are a many numbers of data sets were which subdivided for training, testing and holding out. Figure 3 shows a normalized relative important analyze of the input parameters on the output variable Runoff (mm), indicates the highest importance of precipitation 100% then the evaporation is 43.4%, the temperature 85.7%, and soil surface wetness is 72.1%. The best performance of the distribution of data was found corresponding to a ratio 69.2%; 7.7%; 23.1% for training, testing and holdouts. For the training set, the relative error and total square error are :0.006 and 0.001, respectively. The values used to test the data are found to be (0.048 and 0.531), respectively, whereas the relative error for the holdout is found to be (1.975).

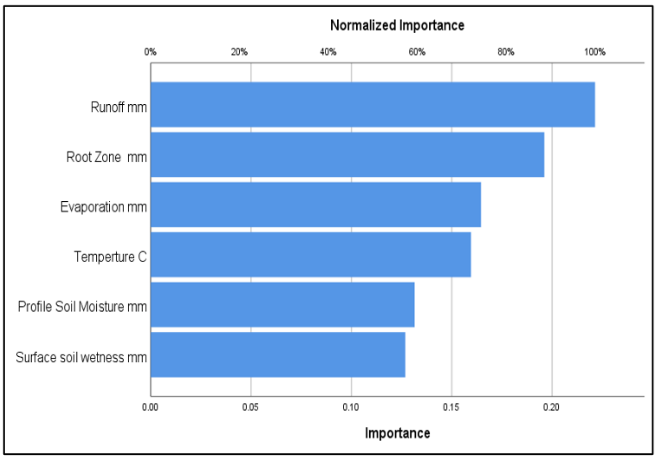

Figure 3. The normalized importance analysis on Runoff of Al-Mohammadi valley

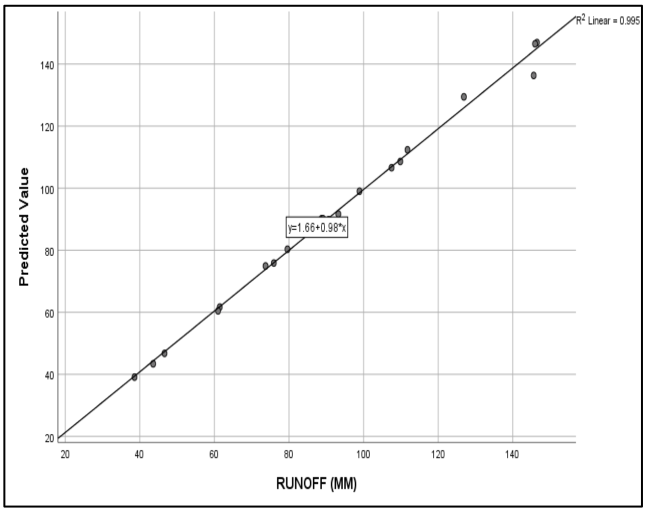

Figure 4. The predicated Runoff values vs the observed runoff values of Al-Mohammadi valley

The best structure of an ANN for runoff is composed of five nodes as the number in the hidden layer with an initial learning rate of 0.4, a term for momentum that is 0.9, the hidden layer activation function using a hyperbolic tangent, and an identify method for the output layers that is illustrated in Figure 4. Finally, Figure 5 shows the architecture of the final neural network obtained.

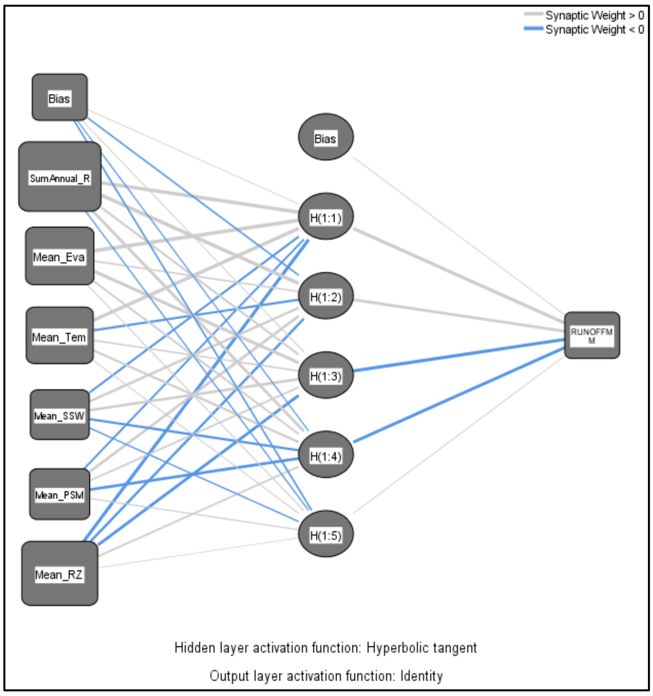

Figure 5. Three layers feed forward neural network for runoff of Al-Mohammadi valley

There will be an expectation of the amount of runoff that can be stored and used to increase the quantity of river water or reservoirs in industrial or natural lakes and then invest them for municipal consumption or irrigation when the amount of runoff is subtracted under different climatic conditions.

4. CONCLUSION

From this analysis, this study's findings could lead to the following conclusions:

1. The developed ANN model that is capable of predicting Runoff values from daily precipitation, evaporation, temperature, soil surface wetness, profile soil moisture, root zone soil wetness as input values with correlation coefficient of 0.995.
2. The most variable affecting Runoff values among the runoff input variables is the precipitation as 100% normalized importance analysis, followed by the temperature 85.7%, then soil surface wetness is 72.1%, and the evaporation is 43.4%. The best performance of the distribution of data was found corresponding to a ratio 69.2 %; 7.7%; 23.1% for training, testing and holdouts. For the training set, the relative error and total square error are :0.006 and 0.001, respectively.
3. The test values for the data were discovered to be (0.048 and 0.531), respectively, on the other hand, the holdout's relative error is discovered to (1.975).
4. The best-fit equation is ANN model with a correlation coefficient of 0.99 while the classical linear regression gives a correlation coefficient of 0.61.
5. The future research directions of the study are to

determine how climatic factors affect runoff amounts, and as a result, surface runoff amount can be predicted under any climate conditions based on the elements of the climate, such as temperature and precipitation in various locations or under varying combinations of those elements.

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