Surface water resource and effect of weather parameters in estimating the annual rainfall: A case study in Lebanon

Y Kassem1,2*, H Gökçekuş2, J Aljamal2
1Department of Mechanical Engineering, Engineering Faculty, Near East University, 99138 Nicosia (via Mersin 10, Turkey), Cyprus
2Department of Civil Engineering, Civil and Environment Engineering Faculty, Near East University, 99138 Nicosia (via Mersin 10, Turkey), Cyprus
*E-mail: youssef.kassem@neu.edu.tr

Abstract. The quality and quantity of freshwater resources are continually decreasing in the world. The objective of this paper is to review the literature on the water resource with a focus on the surface water, quality of surface water in terms of physical and chemical properties in different locations in Lebanon. Moreover, one of the most important sources influencing the surface water is rainfall. Forecasting rainfall is one of the most essential issues in the hydrological cycle. It is very challenging because is still not possible to develop an ideal model given the uncertainty and unexpected variation. In the present study, prediction models using artificial neural networks (ANN) and multiple linear regressions (MLR) are developed to estimate the annual rainfall as a function of weather parameters and geographical coordinates. The annual data used in this study are recorded in 1942 locations in Lebanon. The latitude, longitude, and altitude of the location, global solar radiation, average temperature, wind speed, and relative humidity are used as the input variables and annual rainfall is estimated as the output variable. The measured values are compared versus those predicted by the ANN and MLR models by evaluating R-squared and Root mean squared error.

1. Introduction
Water availability and use depend on several factors including increased population, energy demand, and related environmental problems [1,2]. Climate change significantly affects the environment and natural resources [2]. Air temperature and precipitation (rainfall or snow) are the major parameters of climate that influence human activities such as urban water resources [3] and agricultural production [4,5]. Precipitation is one of the most important factors in the Earth's water cycle, affecting several human activities, like agriculture, with significant impacts on the economy [6,7].

Lebanon is a small Mediterranean country (surface area 10,452 km², and average width 45 km) located in South-West Asia, between N latitude 34°42′ and 33°3′and E longitudes 35°6′ and 36°37′ [8]. Lebanon’s physiography is unique, dominated by two mountain ranges which run parallel to the sea (NNE-SSW) and are separated by the Bekaa valley. Lebanon has mild, dry summers and cold, wet winters. The heaviest rainfall occurs between November and April, with relatively minimal precipitation, if any, between July and August [9]. Lebanon is a Middle Eastern country that is fortunate to have significant water resources, unlike its neighbours. However, rain is mainly concentrated in the winter months. While water is abundant in winter, significant water shortages are still experienced around the country for the rest of the year. Besides, water quality in many areas is questionable.
Recently, various models are used to estimate the monthly or annual rainfall such as the mathematical model, Neuro-Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN).

The review aims to assess the water resources in Lebanon focused on surface water and physicochemical of the surface water. One of the primary sources surface water is rainfall, thus in the present study, four meteorological parameters including average temperature (Tav), global solar radiation (GSR); relative humidity (RH) and wind speed (WS) are selected for predicting the annual rainfall. Also, geographical coordinates in terms of latitude, longitudes, and elevations are utilized as input variables for the model. For this purpose, Artificial Neural Networks (ANN) and Multiple Linear Regressions (MLR) are developed and tested for predicting annual rainfall in Lebanon. The present study aims to estimate the rainfall at any location in Lebanon where there are no measurements.

2. Surface water resources in Lebanon

Generally, Lebanon's water resources are classified into groundwater and surface water. The sources of surface water resources in Lebanon are from 16 river systems, as shown in Figure 1. The main water resources in Lebanon are groundwater (51%), and surface water (49%). The surface water resources are principally sourced from rivers (46%) and surface storage like dams and lakes (3%) [10].

Lebanon has 40 rivers, 16 of which are permanent (Figure 1). The combined annual flow of rivers is estimated to be about 3,900 million cubic meters, where the majority of the flow (75%) occurs between January and May [11]. Surface water resources are mainly sourced from 16 river mainstream discharges in Lebanon, particularly: El Kabir, Ostuene, El Bared, Abou Ali, El Kjaouz, Ibrahim, EL Kalb, Beirut, Damour, EL Awali, El Zahrali, El Assass, Al Qasmieh, Litani, Wazzani and Hasbani (Figure 1). The Kusba and Abu Samra comprise the Abou Ali river systems. Al-Janin and Al Khodaira constitute the Ibrahim river systems. In addition, El Yamouneh, Qaraoun heights, Qaraoun EL Khaddali, and El Khardali Sea form the Litani river systems. Table 1 presents the short time-series discharge data from 1971 to 1975 and from 2005-2009 for the 16 perennial rivers in Lebanon. According to the State of the Environment Report of Lebanon, El Assi and Hasbani are the only two rivers that do not discharge into the Mediterranean Sea. Additionally, the highest river flows in Lebanon are associated with Nahr el Litani, Nahr Ibrahim, and Nahr el Assi. Rivers are mainly replenished from springs that are fed from melting snow. Over 2,000 regular springs feed into different streams in Lebanon, creating an aggregate of 1,150-1,200 Mcm/yr of water that is not completely misused [12]. Most of the surface water resources come from springs, where 637 Mcm/yr is currently used [13]. The surface water supply also comes from storage dams, namely the Qaroun dam and the Shibroh Dam, which currently provide about 45 Mcm/yr of water [13]. Table 2 shows the water resources available annually in Lebanon. In addition, exploited resources according to water source type in Mm³/y are listed in Table 3.

Water resources in Lebanon are heavily polluted, as domestic and industrial wastewater is largely untreated, and intolerable agricultural practices exacerbate the situation. The main rivers in Lebanon have very high levels of bacterial contamination due to the flow of raw sewage, which poses a real threat to public health [16].

Random disposal of solid waste also results in water contamination due to leakage of chemicals. Tamination of surface and groundwater from industrial discharges is also chemical common. Untreated wastewater containing heavy metals is often disposed [17], while leaks from underground gasoline tanks and uncontrolled pumping of oil and petroleum by-o products are also common.

Coastal waters in Lebanon are also heavily polluted by wastewater flowing from domestic sewage discharges, industrial wastewater discharges, coastal agricultural waste, and huge wasted dumps (in Tripoli, Burj hammoud, Beirut, Saida, and Tyre). Oil spills especially the large leakage that occurred after the 2006 war with Israel, and coastal power stations (in Beddawi, Zouk, Jiye, and Al-zahrani) are the other sources of pollution. Several studies non have on the coastal and marine waters in Lebanon found very high levels of pollutants, particularly in areas close to the three main cities of Tripoli,
Beirut, and Sidon, including heavy metals, which are toxic to both marine and human populations [18].

The intensive use of fertilizers and pesticides in agricultural practices, especially during the dry seasons, has led to the filtering of nitrates inside the soil and contamination of groundwater systems with high concentrations found in coastal plain[19], and the Bekaa Valley[20]. As farmers rely on wells for irrigation, health and environmental concerns are increasing. In addition, it is reported that raw sewage is used for irrigation in many areas, including Akkar and Bekaa and farmers throughout the country are likely to resort to this practice when freshwater is not available[21].

Figure 1. 16 perennial rivers of Lebanon [14].
Table 1. Flow data for the 16 perennial rivers of Lebanon (1971-1975 and 2005-2009) [15].

| River name | River length (Km) | Annual average volume (1971-75) Mm³ | Average flow (1971-75) m³/s | Maximum flow (1971-75) m³/s | Minimum flow (1971-75) m³/s |
|------------|------------------|-----------------------------------|-----------------------------|-----------------------------|-----------------------------|
| El Kabir   | 58               | 259.2                             | 9.1                         | 48.5                        | 1.5                         |
| Ostuene    | 44               | 47.0                              | 1.6                         | 6.9                         | 0.0                         |
| El Bared   | 24               | 132.8                             | 4.2                         | 24.0                        | 0.9                         |
| Abou Ali   | 45               | 148.6                             | 4.6                         | 25.2                        | 0.6                         |
| El Kjaouz  | 38               | 32.3                              | 1.0                         | 11.4                        | 0.0                         |
| Ibrahim    | 30               | 208.6                             | 6.6                         | 65.5                        | 0.1                         |
| EL Kalb    | 38               | 154.1                             | 4.9                         | 29.3                        | 0.2                         |
| Beirut     | 42               | 47.9                              | 1.5                         | 25.1                        | 0.0                         |
| Damour     | 38               | 166.9                             | 5.4                         | 51.0                        | 0.1                         |
| EL Awali   | 48               | 393.7                             | 12.5                        | 51.7                        | 1.9                         |
| El Zahran  | 25               | 19.2                              | 0.6                         | 10.6                        | 0.0                         |
| El Assi    | 46               | 326.4                             | 11.0                        | 13.8                        | 0.8                         |
| Al Qasmieh | 170              | 151.7                             | 4.8                         | 47.6                        | 0.8                         |
| Litani     | 170              | 167.8                             | 5.4                         | 43.6                        | 0.0                         |
| Wazzani    | -                | 71.9                              | 2.3                         | 19.5                        | 0.5                         |
| Hasbani    | 21               | 38.4                              | 1.2                         | 9.9                         | 0.0                         |

Table 2. Annual available resources in Mm³

| Source               | Ministry of Energy and Water 2012 | Ministry of Environment / ECODIT 2002,3 | Ministry of Energy and Water 2010 |
|----------------------|-----------------------------------|----------------------------------------|----------------------------------|
| Precipitation        | 8,600                             | 8,600                                  | 8,200                            |
| Evapotranspiration   | -4,500                            | -4,300                                 | -4,100                           |
| **Losses**           |                                   |                                        | **Total renewable resources**    |
| Rivers to neighbors  | -700                              | -670                                   | -1,333                           |
| Groundwater          | -700                              | -1,030                                 | -685                             |
| **Total renewable resources** | **2,700**             | **2,000**                              | **2,767**                        |
| Surface water        | 2,200                             | 2,200                                  | 567                              |
| Groundwater          | 500                               |                                        | 567                              |
| **Net exploitable resources** | **2,700**             | **2,000**                              | **2,767**                        |

Table 3. Exploited resources according to source type in Mm³/y

| Source                                         | Beirut and Mount-Lebanon Water Establishment | North Lebanon Water Establishment | South Lebanon Water Establishment | Bekaa Water Establishment | Total   |
|------------------------------------------------|---------------------------------------------|---------------------------------|----------------------------------|---------------------------|---------|
| Surface water (springs)                        | 174                                         | 175                             | 82                               | 206                       | 637     |
| Groundwater (Wells)                           | 198                                         | 163                             | 141                              | 193                       | 695     |
| Storage (dams and lakes)                      | 15                                          | -                               | 20                               | 10                        | 45      |
| **Total**                                      | **387**                                     | **338**                         | **243**                          | **409**                   | **1377**|

In recent years, scientific researchers have examined the quality of surface water in different locations in Lebanon. For instance, Najjar et al. [22] measured twenty-three of the physicochemical parameters of Ibrahim River. The results indicated that the quality water was considered as medium to good water quality with an average value of 69.0± 1.9. Haydar et al. [23] measured the physicochemical parameters including pH, T°, TDS, EC, Na+, Ca2+, Mg2+, Clí, SO2í4, NH3+, NOí3, PO2í4, K+ and Heavy metals of Upper Litani River Basin for different seasons. The results demonstrated that the degree of pollution depends on the location and the season. Also, they concluded that the presence of pollution in terms of mineral and anthropogenic came from municipal wastewater and agricultural purposes.
discharged into the river. Kabbara et al. [24] evaluated the water quality in the coastal area of Tripoli using Landsat 7 ETM+ data. They found that the coastal area of Tripoli is described as moderate eutrophic conditions with fluvial and wastewater runoff sources. Massoud [25] evaluated the water quality index of the small Mediterranean river in Southern Lebanon (Damour River). The results show that the index of water quality is classified as good and anthropogenic activities are mainly source of pollution affect the river. Saadeh et al. [26] assessed the groundwater quality of the Upper Litani River Basin with nearly 300,000 persons depends on it for their daily domestic needs. The authors found that Total Dissolved Solids (TDS) of the river was above the normal range of 100–500 mg/L in the summer season, which indicated that the river received runoff from all other tributaries including the heavily polluted Berdawni. Daou et al. [27] measured the physicochemical and microbiological parameters of the surface water samples taken from the Arka River located in the Akkar District, north of Lebanon. The analysis showed that the most polluted sources in the river come from flatland and the surrounding villages. Therefore, an effective surface water quality management system could be established enabling the proper use of water for irrigation purposes. Fadel and Slim [28, 29] analyzed the physicochemical parameters in terms of pH, electrical conductivity, TDS, turbidity, alkalinity, Ca, Mg, TH, Cl−, SO2 4−, NH3, NO− 3, PO3 4−, Fe, Al, Na, Zn, Cr, Cu and As of Qaraaoun reservoir and the results are compared with water standards. The results showed that suboptimal quality would probably be remediated through customary water treatment processes. Korfali et al. [30] evaluated the water quality of the Qaraaoun reservoir that considered as having three water quality zones and measured the parameters (pH, Eh, DO and temperature) of 15 samples collected from different site. The authors found that the sediment data showed higher metal contents where the river entered the reservoir which matched higher concentrations of water parameters at the influx site. Korfali and Davies [31] investigate the variation of the total metal content (Fe, Mn, Zn, Cu, Pb, and Cd) in bed sediments and water of River Nahr-Ibrahim. The results indicated that the decreasing in water pH caused by the decrease in precipitation rate, lowering the level of water and the dilution of industrial discharges. Korfali and Jurdi [32] examined the quality of domestic water in Beirut city. The results showed deterioration patterns in domestic water quality. Korfali and Jurdi [33] measured the physicochemical and bacteriological parameters of domestic water collected from three household water sources. They found a high frequency of water-borne diseases in the collected water. Korfali and Jurdi [34] determined metal speciation sediment chemical fractions and metal speciation in reservoir water. The measured data indicated that the highest percentages of total metal content in sediment fractions were for Fe in residual followed by reducible, Cr and Ni in residual and is reducible, Cu in organic followed by exchangeable, Zn in residual and inorganic, Pb in organic and carbonate, Cd was mainly in carbonate. Kouzayha et al. [35] analyzed chemically the water quality of drinking water collected from the major cities in Lebanon. The authors found that high pesticide ecotoxicological risk determined by diazinon, chlorpyrifos, fenpropathrin and bifenthrin insecticides in many surface waters. Semerjian [36] analyzed physicochemical and bacterial water quality parameters of domestic bottled water collected from shops and supermarkets throughout Lebanon. The results showed negative growth for fecal Coliforms and positive results for total coliforms. Houri et al. [37] studied the chemical and microbiological properties of Lebanese perennial coastal rivers during the dry season. They found that the most polluted rivers in most categories were Abu Ali and Antelias.

Table 4 summarizes the physical parameters for selected rivers in the dry season (July, August, and September). It is found that pH values for all rivers with exception Damour river are within the limit range of limit drinking water. In addition, it is observed that the lowest value of saturation was recorded in Abu Ali and Antelias rivers and the highest value was obtained in the Damour river. Increase algal growth produced oxygen from photosynthesis led to an increase in the level of dissolved oxygen. In the dry season, the highest average TDS (Total dissolved solids) was found in the Awali river (1863 g/s) and the lowest was found in the Damour river (44 g/s) as shown in Table 5.
Table 4. Characteristics of selected rivers in the dry season [37].

| Month | River   | pH  | Temperature [°C] | Dissolved oxygen [mg/l] | Saturation [%] | Biological oxygen demand [mg/l] | Conductivity [µS/cm] | Flow [m³/s] | Total coliform | E. coli |
|-------|---------|-----|-----------------|-------------------------|----------------|---------------------------------|---------------------|-----------|----------------|--------|
| July  | Kabir   | 8.32| 28.4            | 5.7                     | 64             | -                              | 550                 | 5         | 230            | 10     |
|       | Bared   | 8.42| 24.9            | 6.90                    | 78             | -                              | 456                 | 2.3       | 350            | 90     |
|       | Abu Ali | 8.37| 22.0            | 5.55                    | 63             | -                              | 498                 | 7.2       | 12000          | 5000   |
|       | Ibrahim | 8.34| 21.5            | 7.05                    | 80             | -                              | 338                 | 2.9       | 4900           | 50     |
|       | Antelies| 8.01| 22.0            | 5.84                    | 65             | -                              | 638                 | 1.32      | 105000         | 3400   |
|       | Damour  | 8.98| 30.5            | 7.05                    | 79             | -                              | 370                 | 0.2       | 470            | 6      |
|       | Awali   | 8.18| 20.7            | 6.00                    | 66             | -                              | 462                 | 4.8       | 140            | 0      |
|       | Kassmieh| 8.20| 29.4            | 6.15                    | 68             | -                              | 576                 | 0.3       | 40             | 9      |

Table 5. Pollutant loading from active coastal rivers in the dry season [37].

| River      | BOD [g/s] | Nitrate [g/s] | Phosphate [g/s] | Sulfate [g/s] | TDS [g/s] | E.Coli 10⁵ [CFU/sec] | Coliform 10⁵ [CFU/sec] |
|------------|-----------|---------------|-----------------|--------------|-----------|----------------------|-----------------------|
| Kabir      | 69.4      | 13.6          | 1.1             | 86.7         | 1360      | 68                   | 2052                  |
| Bared      | 63        | 5.3           | 0.4             | 66.3         | 578       | 109                  | 881                   |
| Abu Ali    | 115.1     | 11            | 1.6             | 76.8         | 1146      | 11662                | 56004                 |
| Ibrahim    | 86.5      | 1.1           | 0.3             | 17.4         | 322       | 166                  | 5546                  |
| Antelies   | 37.3      | 2             | 1.4             | 27.5         | 290       | 4693                 | 46928                 |
| Damour     | 6.8       | 0.4           | 0.03            | 8.3          | 44        | 2                    | 83                    |
| Awali      | 281       | 34.9          | 1.3             | 191          | 1863      | 6.2                  | 2759                  |
| Kassmieh   | 5.4       | 1             | 0.04            | 5.1          | 76.5      | 2                    | 36                    |
| Total      | 664.5     | 69.3          | 6.17            | 479.1        | 5679.5    | 16708.2              | 114889                |

3. Material and method
Climate change affects water resources through changes in temperature, rainfall, runoff, and groundwater recharge. Furthermore, the changes in air temperature and rainfall could affect river flows, and hence, the mobility and dilution of contaminants [38]. Consequently, this study aims to study is to
predict the annual rainfall using an Artificial Neural Network (ANN) and Multi-linear regression (MLR) approaches in Lebanon.

3.1. Study region and data
In the current study, the used data consist of the annual rainfall, average temperature, relative humidity, global solar radiation and wind speed. The data are recorded in 1942 locations in Lebanon. The geographical area of the selected location is bounded by the latitude of 34.691° and 33.060° and by the longitudes of 36.575° and 35.179° (see Figure 2), whose elevations range from 1 to 2300 m above mean sea level.

Figure 2. Lebanon map.
3.2. Artificial neural networks
The most widespread technique used in calculating outputs of many systems is the artificial neural networks (ANN) model. A large number of academicians in many different fields have used ANN in their studies [39-42]. The artificial neural networks (ANN) model, also known as the black-box model, is composed of interconnected processing units called artificial neurons or nodes [43]. Generally, the multilayer feed-forward neural network is widely used for solving engineering problems. It consists of three layers, namely the input layer(s), Hidden layer(s) and output layer(s). Besides, the number of these layers depends on the nature of the problem.

In this study, the feed-forward architecture with the three layers is used. TRAINLM is used as a training function that updates the weight and bias values of the neuron connections according to Levenberg-Marquardt (LM) optimization. The back-propagation algorithm is used as a learning algorithm and it is a gradient descent algorithm. The activation function for the neurons can be linear or non-linear. The logistic-sigmoid (logsig) and tangent-sigmoid (tansig) were used as an activation function whose output lies between 0 and 1. By trial and error, the optimum number of nodes in the hidden layers, the most suitable transfer function and the number of neurons are determined. To obtain the best performance results, various ANN models are designed.

In this research, a conventional data division technique was used to divide the data, whereby the sets were divided on an arbitrary basis and the statistical properties of the respective data sets were not considered [44]. Approximately 80% of the data was used for training, while the remaining 20% was reserved for testing. The training data was used to train the ANN models with the LM algorithm. The testing data do not affect training and provide an independent measure of network performance during and after training. Moreover, normalization of the data is required for improving the performance of the ANN model. The minimum (min) and maximum (max) values of the inputs and output parameters are shown in Table 6. In general, the number of hidden layers and the number of neurons are the most factors that can affect the performance of the ANN model. Figure 3 shows the structure of the ANN model used in this study. In this study, the number of epochs and performance goal were 100,000 and 0.001, respectively. In addition, the number of the hidden layers varied between 1 and 10, while the number of neurons varied between 5-50 neurons.

| Parameters | Type                     | Parameter description                       | Abbreviation | Minimum | maximum | Unit  |
|------------|--------------------------|--------------------------------------------|--------------|---------|---------|-------|
| Input 1    | Meteorological parameters| Annual average temperature                 | Tav          | 12.49   | 23.56   | °C    |
| Input 2    |                          | Annual relative humidity                    | RH           | 55.33   | 76.50   | %     |
| Input 3    |                          | Annual global solar radiation              | GSR          | 184.93  | 230.62  | kWh/m² |
| Input 4    |                          | Annual wind speed                          | WS           | 1.74    | 2.75    | m/s   |
| Input 5    | Geographical coordinates | Latitude                                   | La           | 33.69   | 33.06   | °     |
| Input 6    |                          | Longitudes                                 | Lo           | 35.18   | 36.58   | °     |
| Input 7    |                          | Elevations                                 | El           | 1       | 2300    | m     |
| Output 1   |                          | Annual rainfall                            | R            | 90      | 1650    | mm    |
3.3. Multiple linear regressions (MLR)

Multiple linear regressions are described as the relationship dependent \((y)\) and independent variables \((x)\). It can be expressed as

\[
y_i = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i \quad i = 1, 2 \ldots n
\]

where \(y_i\) denotes the dependent variable (rainfall) and \(x_i\) where \(i=1,2,\ldots,n\), denotes the explanatory or independent variables and \(\beta\) is called the intercept. Minitab 17 was used for the regression and testing of the data.

4. Results and discussions

The annual values of rainfall and the other parameters (Tav, RH, GSR, WS) at 1942 locations for 2016 are recorded and La, Lo and El of each location are used as explanatory input variables. First, the data are randomly split into 80% training data (1554 data) and 20% testing data (388). The result of the ANN model is compared with the MLR model. The statistics of the data are summarized in Table 7. Different statistical measures, including the mean, standard deviation (SD), coefficient of variation (CV), minimum, maximum, skewness and kurtosis are calculated for each variable. It is found that the annual mean rainfall varied from 90 mm to 165 mm. The maximum and minimum annual rainfall recorded in Choueifat and El Khraïbé locations, respectively. The CV values are high, ranging from 0.76 to 68.32.

During the investigation period, the Skewness value for rainfall is negative, which indicates that all distributions are right-skewed. In addition, Lebanon has a maximum and minimum average temperature of 23.56\(^\circ\)C and 12.487\(^\circ\)C, respectively. Moreover, it is found that the annual mean wind speed in the country was 2.04 m/s. Additionally, the global solar radiation and relative humidity values ranged between 184.93-230.62 kWh/m\(^2\) and 55.326-76.501%, respectively. Consequently, it can be established that this country has considerable solar potential. Generally, the mean and standard deviation values suggest that there is good consistency in the meteorological parameter behaviour.

| Variable | Mean   | SD    | CV   | Minimum | Maximum | Skewness | Kurtosis |
|----------|--------|-------|------|---------|---------|----------|----------|
| La       | 33.923 | 0.361 | 1.07 | 33.06   | 34.691  | 0.07     | -0.47    |
| Lo       | 35.737 | 0.271 | 0.76 | 35.18   | 36.575  | 0.98     | -0.14    |
| El       | 647.8  | 442.6 | 68.32| 1       | 2300    | 0.45     | -0.41    |
| TAV      | 16.488 | 1.894 | 11.49| 12.487  | 23.561  | 1.52     | 1.59     |
| RH       | 71.55  | 3.619 | 5.06 | 55.326  | 76.501  | -1.91    | 5.02     |
| GSR      | 200.7  | 11.54 | 5.75 | 184.93  | 230.62  | 1.11     | 0.14     |
| WS       | 2.0449 | 0.2937| 14.36| 1.7427  | 2.7431  | 1.08     | -0.2     |
| R        | 812.13 | 223.84| 27.56| 90      | 1650    | -0.63    | 0.32     |

The La, Lo, El, Tav, RH, GSR, WS are utilized in the input layer as input data for the feed forward architecture with a back propagation algorithm (Figure 3). The annual rainfall is the outcome of the output layer. In this study, various ANN configurations were designed and the number of hidden layers and neurons was determined by trial and error for obtaining the best performance results. The logistic-sigmoid and the tangent-sigmoid functions are tried in the hidden layer and output layer. The best performance of the network was obtained by training the developed ANN architecture several times until the MSE showed the minimum value. The same-trained network was tested with the new datasets to check the performance of the network. Table 8 shows the best number of hidden layers and neurons, training rule, activation function, epochs, R-squared and mean squared error (MSE) that were chosen for each ANN model. Also, the R-squared and RMSE for testing data are tabulated in Table 8. It is found that the best ANN model has two hidden layers with 5 neurons and having TANSIG as the activation function.
Figure 3. The structure of the ANN for estimating annual rainfall

Table 8. Evaluation of the networks and Statistical tools’ performance of the ANN models.

| Transfer function | Hidden layer | Neurons | Epoch | MSE   | R²  | R²  | RMSE (training) | RMSE (testing) |
|-------------------|--------------|---------|-------|-------|-----|-----|-----------------|----------------|
|                   |              |         |       |       |     |     |                 |                 |
| TANSIG            | 1            | 5       | 85    | 0.00458 | 0.7665 | 0.7458 | 0.0686 | 0.0756 |
|                   | 1            | 10      | 23    | 0.00462 | 0.7700 | 0.7422 | 0.0681 | 0.0761 |
|                   | 2            | 5       | 118   | 0.00333 | 0.7882 | 0.7436 | 0.0653 | 0.0759 |
|                   | 2            | 10      | 188   | 0.0047 | 0.7813 | 0.7314 | 0.0664 | 0.0777 |
|                   | 2            | 15      | 18    | 0.00448 | 0.7667 | 0.7324 | 0.0685 | 0.0776 |
| Logsig            | 1            | 5       | 28    | 0.00778 | 0.7115 | 0.6908 | 0.0811 | 0.0881 |
|                   | 1            | 10      | 110   | 0.00782 | 0.7150 | 0.6872 | 0.0806 | 0.0886 |
|                   | 2            | 5       | 45    | 0.00653 | 0.7332 | 0.6886 | 0.0778 | 0.0884 |
|                   | 2            | 10      | 73    | 0.0079 | 0.7263 | 0.6764 | 0.0789 | 0.0902 |
|                   | 2            | 15      | 10    | 0.00768 | 0.7117 | 0.6774 | 0.0810 | 0.0901 |

The MLR model is formed for the data used for training and MLR equations are checked with the testing data. The MLR equation is given below. The Minitab 17 software was applied to the model for the regression analysis of the actual data. Eq. (1) is the model equation that correlates the response (rainfall) to the independent variables in terms of La, Lo, El, Tav, RH, GSR, WS.

\[
R = 0.476 + 0.798 \cdot La - 0.976 \cdot Lo + 0.166 \cdot El - 0.128 \cdot Tav - 0.058 \cdot RH + 0.38 \cdot GSR - 0.048 \cdot WS
\]  

(1)

Figures 4 and 5 show the comparisons of the actual and predicted data of training and testing phases, respectively. It is found that the ANN model makes better predicts than the MLR model.
Figure 4. Comparisons of the predicted and actual values of the annual rainfall for training phase.

Figure 5. Comparisons of the predicted and actual values of the annual rainfall for testing phase.
In addition, it is found that the scatter diagrams, the noises of the predicted values around the best-fit lines are wider for MLR models. Furthermore, the $R^2$ for annual rainfall estimated by the ANN and MLR for test phases are found to be 0.7436 and 0.5805, respectively (see Table 9). It is concluded that the ANN model is a capable model to define a non-linear relationship as output variable and weather parameters and geographical coordinates of any location in Lebanon as input variables without needing a priori information and without having to make preliminary assumptions.

| Model | $R^2$-training | $R^2$-testing | RMSE-training | RMSE-testing |
|-------|---------------|--------------|---------------|--------------|
| ANN   | 0.7882        | 0.7436       | 0.0653        | 0.0759       |
| MLR   | 0.5505        | 0.5805       | 0.0950        | 0.0971       |

5. Conclusions
The paper has highlighted that water resources in Lebanon focused on surface water and the quality of the water. Since the main surface water sources are rainfall thus, annual climate data in terms of rainfall, average temperature relative humidity, global solar radiation, and wind speed were analyzed statistically to show the effect of climate parameters on the rainfall. This study has shown the power of ANN to evaluate the most influencing input parameters in the prediction of monthly rainfall. ANN model using a back-propagation algorithm was developed. Out of the ANN and MLR models, the ANN model has given the best prediction with the highest $R$-squared and minimum RMSE. These models can be used for determining the level of groundwater based on the amount of rainfall and rainfall distribution at any site in Lebanon. Therefore, it can be used for the assessment of trends in groundwater levels across Lebanon.

References
[1] M. Song, R. Wang, and X. Zeng, Water resources utilization efficiency and influence factors under environmental restrictions. Journal of Cleaner Production, 184, (2018) 611-621.
[2] S. Kundu, D. Khare, and A. Mondal, Future changes in rainfall, temperature and reference evapotranspiration in central India by least square support vector machine. Geoscience Frontiers, 8(3) (2017) 583-596.
[3] N. Seino, T. Aoyagi, and H. Tsuguti, Numerical simulation of urban impact on precipitation in Tokyo: How do urban temperature rise affect precipitation? Urban Climate, 23 (2018) 8-35.
[4] Y. Kang, S. Khan, and X. Ma, Climate change impacts on crop yield, crop water productivity, and food security – A review. Progress in Natural Science, 19(12) (2009) 1665-1674
[5] T. Iizumi, and N. Ramankutty, How do weather and climate influence cropping area and intensity? Global Food Security, 4 (2015) 46-50.
[6] C. P. McMullen, and J. R. Jabbour, Climate change science compendium 2009. Nairobi: United Nations Environment Programme, (2009).
[7] OECD (Organization for Economic Co-Operation and Development), The Land-Water-Energy nexus biophysical and economic consequences. Paris: OECD Publishing, (2017).
[8] ECODIT, National Action Plan for the Reduction of Pollution into the Mediterranean Sea from Land-Based Sources, Technical report for UNEP and Ministry of Environment, Lebanon, (2015).
[9] K. J. Sene, T. J. Marsh, and A. Hachache, An assessment of the difficulties in quantifying the surface water resources of Lebanon. Hydrological Sciences Journal, 44(1) (1999) 79-96.
[10] P. Schuler, and A. Margane, Water Balance for the Groundwater Contribution Zone of Jeita Spring using WEAP Including Water Resources Management Options & Scenarios, (2013).
[11] F. Comair, Water Management and Hydrodiplomacy in Lebanon. Notre Dame University Press, Zouk Mikayel, (2009).
[12] Fanack Water, Retrieved November 5, 2018, from https://water.fanack.com/ar/lebanon/water-resources-in-lebanon/
[13] World Bank, Republic of Lebanon - Water sector: Public expenditure review. Retrieved November 5, 2018, from http://documents.worldbank.org/curated/en/965931468265767738/Republic-of-Lebanon-Water-sector-public-expenditure-review

[14] El-Fadel, M. (2001). Water resources management in Lebanon: institutional capacity and policy options. Water Policy, 3(5), 425–448. doi: 10.1016/s1366-7017(01)00079-4

[15] Ministry of Environment, Lebanon’s Initial National Communication to the United Nations Framework Convention on Climate Change. Retrieved November 5, 2018, from http://climatechange.moe.gov.lb/national-communications

[16] Nehme, N., Haydar, C., Koubaiassy, B., Fakih, M., Awad, S., Toufaily, J., … Hamieh, T. (2014). The Distribution of Heavy Metals in the Lower River Basin, Lebanon. Physics Procedia, 55, 456–463. doi: 10.1016/j.phpro.2014.07.066

[17] Raven, P. H., Berg, L. R., & Johnson, G. B. (2001). Environment. Fort Worth: Harcourt College

[18] Fallah, R. E., Olama, Z., & Holail, H. (2016). Marine Quality Assessment of Northern Lebanese Coast: Microbiological and Chemical Characteristics and their Impact on the Marine Ecosystem. International Journal of Current Microbiology and Applied Sciences, 5(1), 389-376

[19] Saad, Z., Kazpard, V., Kazpard, K., & Nabhan, P. (2003). Natural and anthropogenic influence on the quality of Ibrahim river water, Lebanon. Journal European D’Hydrologie, 34(1), 85-99.

[20] Darwish, T., Atallah, T., Francis, R., Saab, C., Jomaa, I., Shaaban, A., … Zdruli, P. (2011). soil and groundwater contamination with nitrate: A case study Observations on from Lebanon-East Mediterranean. Agricultural Water Management, 99(1), 74-84.

[21] Farajalla, N., El Hajj, R., Kerkezian, S., Farhat, Z. and Matta, M. (2015). The Way Forward to Safeguard Water in Lebanon: National Water Integrity Risk Assessment. American University of Beirut, Lebanon

[22] Najjar, P. E., Kassouf, A., Probst, A., Probst, J.-L., Ouaini, N., Daou, C., & Azzi, D. E. (2019). High-frequency monitoring of surface water quality at the outlet of the Ibrahim River (Lebanon): A multivariate assessment. Ecological Indicators, 104, 13–23. doi: 10.1016/j.ecolind.2019.04.061

[23] Haydar, C. M., Nehme, N., Awad, S., Koubaiassy, B., Fakih, M., Yaacoub, A., … Hamieh, T. (2014). Water Quality of the upper Litani River Basin, Lebanon. Physics Procedia, 55, 279–284. doi: 10.1016/j.phpro.2014.07.040

[24] Kafbara, N., Benkhellil, J., Awad, M., & Barale, V. (2008). Monitoring water quality in the coastal area of Tripoli (Lebanon) using high-resolution satellite data. ISPRS Journal of Photogrammetry and Remote Sensing, 63(5), 488–495. doi: 10.1016/j.isprsjprs.2008.01.004

[25] Massoud, M. A. (2011). Assessment of water quality along a recreational section of the Damour River in Lebanon using the water quality index. Environmental Monitoring and Assessment, 184(7), 4151–4160. doi: 10.1007/s10661-011-2251-z

[26] Saadeh, M., Semerjian, L., & Amacha, N. (2012). Physicochemical Evaluation of the Upper Litani River Watershed, Lebanon. The Scientific World Journal, 2012, 1–8. doi: 10.1100/2012/462467

[27] Daou, C., Nabout, R., & Kassouf, A. (2016). Spatial and temporal assessment of surface water quality in the Arka River, Akkar, Lebanon. Environmental Monitoring and Assessment, 188(12). doi: 10.1007/s10661-016-5686-4

[28] Fadel, A., & Slim, K. (2018). Evaluation of the Physicochemical and Environmental Status of Qaraouin Reservoir. Water Science and Technology Library The Litani River, Lebanon: An Assessment and Current Challenges, 71–86. doi: 10.1007/978-3-319-76300-2_5

[29] Shaban, A., & Hamzé, M. (2019). Litani River, Lebanon: an assessment and current challenges. S.l.: Springer.

[30] Korfali, S. I., Jurdi, M., & Davies, B. E. (2006). Variation of Metals in Bed Sediments of Qaraouin Reservoir, Lebanon. Environmental Monitoring and Assessment, 115(1-3), 307–
Korfali, S., & Davies, B. (2003). A comparison of metals in sediments and water in the river Nahr- Ibrahim, Lebanon: 1996 and 1999. Environmental Geochemistry and Health, 25, 41–50.

Korfali, S. I., & Jurdi, M. (2007). Assessment of domestic water quality: case study, Beirut, Lebanon. Environmental Monitoring and Assessment, 135(1-3), 241–251. doi: 10.1007/s10661-007-946-x

Korfali, S. I., & Jurdi, M. (2008). Provision of safe domestic water for the promotion and protection of public health: a case study of the city of Beirut, Lebanon. Environmental Geochemistry and Health, 31(2), 283–295. doi: 10.1007/s10653-008-9218-1

Korfali, S. I., & Jurdi, M. S. (2010). Speciation of metals in bed sediments and water of Qaraaoun Reservoir, Lebanon. Environmental Monitoring and Assessment, 178(1-4), 563–579. doi: 10.1007/s10661-010-1713-z

Kouzayha, A., Ashi, A. A., Akoum, R. A., Iskandarani, M. A., Budzinski, H., & Jaber, F. (2013). Occurrence of Pesticide Residues in Lebanon’s Water Resources. Bulletin of Environmental Contamination and Toxicology, 91(5), 503–509. doi: 10.1007/s00128-013-1071-y

Semerjian, L. A. (2010). Quality assessment of various bottled waters marketed in Lebanon. Environmental Monitoring and Assessment, 172(1-4), 275–285. doi: 10.1007/s10661-010-1337-7

Houri, A., & Jeblawi, S. W. E. (2007). Water quality assessment of Lebanese coastal rivers during dry season and pollution load into the Mediterranean Sea. Journal of Water and Health, 5(4), 615–623. doi: 10.2166/wh.2007.047

Whitehead, P. G., Wilby, R. L., Battarbee, R. W., Kernan, M., & Wade, A. J. (2009). A review of the potential impacts of climate change on surface water quality. Hydrological Sciences Journal, 54(1), 101–123. doi: 10.1623/hysj.54.1.101

Kalogirou, S. A. (2001). Artificial neural networks in renewable energy systems applications: a review. Renewable and Sustainable Energy Reviews, 5(4), 373–401. doi: 10.1016/s1364-0321(01)00006-5

Budcema, M., & Sacco, P. L. (2000). Feedforward networks in financial predictions: the future that modifies the present. Expert Systems, 17(3), 149–170. doi: 10.1111/1468-0394.00137

Cobaner, M., Unal, B., & Kisi, O. (2009). Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydro-meteorological data. Journal of Hydrology, 367(1-2), 52–61. doi: 10.1016/j.jhydrol.2008.12.024

Parlak, A., Islamoglu, Y., Yasar, H., & Egrisogut, A. (2006). Application of artificial neural network to predict specific fuel consumption and exhaust temperature for a Diesel engine. Applied Thermal Engineering, 26(8-9), 824–828. doi: 10.1016/j.applthermaleng.2005.10.006

Nourani, V., Mousavi, S., Dabrowska, D., & Sadikoglu, F. (2017). Conjunction of radial basis function interpolator and artificial intelligence models for time-space modeling of contaminant transport in porous media. Journal of Hydrology, 548, 569–587. doi: 10.1016/j.jhydrol.2017.03.036

Bowden, G. J., Maier, H. R., & Dandy, G. C. (2002). Optimal division of data for neural network models in water resources applications. Water Resources Research, 38(2). doi: 10.1029/2001wr000266