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Analysis of different combinations of meteorological parameters in predicting rainfall with an ANN approach: a case study in Morphou, Northern Cyprus

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ABSTRACT

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. Therefore, the objective of the study is to predict the monthly rainfall using an artificial neural network (ANN) approach. In this study, 25 ANN models are developed by varying the weather parameters. A 33-year database (1985–2017) comprising monthly rainfall, minimum temperature, maximum temperature, average temperature, global solar radiation (GSR), sunshine duration, and wind speed have been used in the ANN models. All the models are validated and the performances of the models are analyzed by using different statistical tools such as the *R*-squared, root mean squared error, and mean absolute error value. Out of the 25 ANN models, ANN-13, ANN-17, and ANN-23 have given the best prediction with the combinations of (Tmin, Tmax, W), (Tmin, Tmax, SD, GSR) and (Tmin, Tmax, Tav, W, SD), respectively. The proposed approach illustrates how the ANN modeling technique can be used to identify the key meteorological variables required to the most significant meteorological parameters affecting rainfall.

Keywords: Artificial neural network; Temperature; Global solar radiation; Sunshine duration; Rainfall; Wind speed

1. Introduction

Cyprus is the third largest island in the Mediterranean Sea and it has a typical Mediterranean climate. Climate conditions on the island vary based on geographical factors. Cyprus has a total surface area of 9,250 km^2 and the area of the north of the island is 3,355 km^2 [1,2]. The land distribution of the Northern part of Cyprus constitutes 56.7% of agricultural, 19.5% of forestry, 5.0% of grass areas, 10.7% is covered by towns, villages, rivers, and reservoirs and nearly 8.2% is bare land, with 87 km^2 of irrigable land [3]. Northern Cyprus has very limited water resources. Rainfall is considered as the main source of water in North Cyprus. Generally, in Cyprus, more than two-thirds of the rainfall occurs between October and April. The increased population, energy demands, and related environmental problems are the main factors affecting the availability of water [4,5]. Climate change has significant effects on the environment and natural resources [5]. Air temperature rainfalls are the major parameters of climate that influence human activities such as urban water resources [6] and agricultural production [7,8]. Precipitation (rainfall and snow) is one of the most important factors in the Earth's water cycle, affecting a number of human activities, like agriculture, with significant impacts on the economy [9].

Several studies have been carried out to predict the rainfall or precipitation using artificial intelligence approaches [10–24]. For example, Mislan et al. [10] estimated the monthly

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rainfall at Tenggarong station in Indonesia using an artificial neural network (ANN) with a backpropagation neural network (BPN) algorithm. They found that the BPN algorithm could be used as a predictive algorithm that provided good predictive accuracy. Kashiwao et al. [11] developed two ANN models called multi-layer perceptron neural network (MLPNN) and radial basis function neural network (RBFNN) to predict the total precipitation in Japan. The input variables for the models were atmospheric pressure, precipitation, temperature, vapor pressure, humidity, and wind speed. The results indicated that MLPNN performed better than RBFNN for the precipitation prediction problem. Dash et al. [12] used k-nearest neighbor (KNN), ANN, and extreme learning machine (ELM) to estimate the seasonal rainfall in Kerala state, India.They concluded that the ELM approach was more accurate than ANN and KNN for estimating the seasonal rainfall. Hashim et al. [13] applied anadaptive-neuro-fuzzy inference system (ANFIS) to identify the most significant meteorological parameters that affect rainfall. The input variables of the model were wet day frequency, vapor pressure, maximum temperature, minimum temperature, and cloud cover. The results showed that wet day frequency was found to be the most influential parameter for rainfall prediction and the best predictor of accuracy. Bagirov and Mahmood [14] examined the performance of support vector machines for regression, multiple linear regressions, KNNs, and ANN for forecasting the monthly rainfall in 24 four stations in Australia. They found that support vector machines for regression and ANN were the most accurate models for rainfall prediction compared to other models. Mohd-Safar et al. [15] used atmospheric pressure, temperature, dew point, humidity, and wind speed as input parameters for a combination of fuzzy c-means (FCM) and ANN to predict the rainfall data. The authors concluded that the accuracy of the combined model (FCM-ANN) was better than the basic ANN model. Mohammadpour et al. [16] utilized temperature, humidity, wind speed, and pressure as input variables for ANNs and learning-cellular automation for estimating the daily rainfall in Shiraz synoptic stations. The results demonstrated that average wind speed is the main parameter that affects the prediction of rainfall. Ramana et al. [17] predicted the monthly rainfall by combining the wavelet technique with ANN and utilized minimum and maximum temperatures as input variables. The results indicated that the proposed models were more effective than the ANN models. Devi et al. [18] examined the performance of different neural network models including a feed-forward backpropagation neural network (BPN), cascade-forward backpropagation neural network, distributed time-delay neural network and nonlinear autoregressive exogenous network (NARX) for daily rainfall prediction in Nigeria, in which temperature and humidity data were the input variables for the models. The results showed that NARX performed better than the other models for the rainfall prediction problem. Dubey [19] compared the performance accuracy of ANFIS and a support vector machine regression model for predicting monthly rainfall. Relative humidity, atmospheric pressure, average temperature, and wind speed were considered as inputs for the models. It was found that ANFIS had a better performance compared to the support vector machine regression model.

Based on the previous studies, it can be observed that the majority of the models utilized several meteorological parameters such as wet day frequency, vapor pressure, maximum, and minimum temperatures, cloud cover, dew point, humidity, and wind speed as input variables for the artificial intelligence model. In the present study, six meteorological parameters including minimum temperature (Tmin), maximum temperature (Tmax), mean temperature (Tav), global solar radiation (GSR); sunshine duration (SD) and wind speed (W) were selected for predicting the monthly rainfall. The current study proposed GSR and sunshine duration as extra input parameters. The ANN approach was used to perform a variable search and thereafter it was used to examine how the six input parameters influence the rainfall prediction performance. This study obtained the average monthly meteorological observations for the years between 1985 and 2017 for Morphou in Northern Cyprus. To examine the significance and performance of the developed ANN models, statistical tools including *R*-squared, root mean squared error (RMSE) and mean absolute error (MAE) were calculated for each model.

2. Methodology

In this section, the details of the selected area, the meteorological parameters, and the ANN method are described. In addition, ANN models that are used to predict the monthly rainfall are presented. Fig. 1 shows the schematic flow of this research.

2.1. Description of the study area

Morphou is located in the northwestern part of Cyprus. The location and area-specific information are shown in Fig. 2 and Table 1, respectively. The dataset consisted of seven meteorological parameters for the years between 1985 and 2017. In general, the rainfall amount varied from 300 mm in the plains to 1,200 mm on the Troodos range located entirely in the southwest part of the island, with part of its drainage area flanking into the northern part of the island, specifically replenishing the groundwater resources of the Güzelyurt aquifer, which is one of the main water supplying aquifers [25,26]. Therefore, the rainfall prediction for this area has a particular importance.

2.2. Simulation using ANN approach

The ANN models that were used to predict the monthly rainfall for the selected region are presented in this section.

2.2.1. Artificial neural network

The most widespread technique used in calculating outputs of many systems is the ANN model. A large number of academicians in many different fields have used ANN in their studies [27–32]. The ANN model, also known as the black-box model, is composed of interconnected processing units called artificial neurons or nodes [33]. 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).

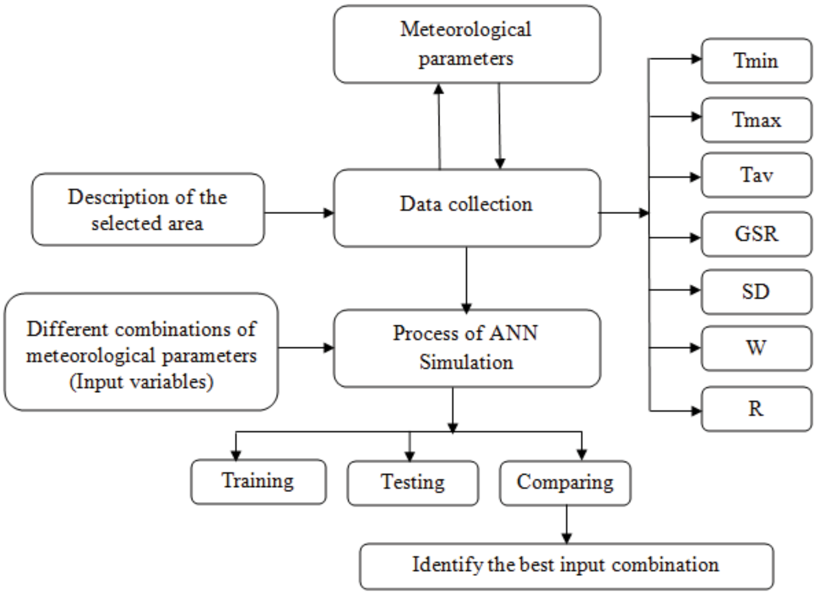

Fig. 1. Schematic flow of this research.

Fig. 2. Map of Cyprus (selected region).

Table 1
Morphou, Northern Cyprus information

Region location	
Latitude (°N)	35° 12′ 3.528″
Longitude (°E)	32° 59′ 26.808″
Elevation (m)	49

In addition, the number of these layers depends on the nature of the problem.

2.2.2. Training and testing

The feedforward architecture with the three layers (input, hidden, and output layers) is used in the present study. 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 backpropagation 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 and are defined as:

$$\log\text{sig} = \frac{1}{1+e^{-x}} \quad (1)$$

$$\tan\text{sig} = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad (2)$$

Eq. (3) is used to normalized the data in the range of 0–1 and Eq. (4) is used to return the data to the original values after the simulation.

$$x_n = \frac{x_{\text{actual}} - x_{\min}}{x_{\max} - x_{\min}} \quad (3)$$

$$x_{\text{actual}} = x_n \left(x_{\max} - x_{\min} \right) + x_{\min} \quad (4)$$

2.2.3. Input and output variables

Previous research works have estimated the rainfall by using several meteorological parameters such as wet day frequency, vapor pressure, maximum, and minimum temperatures, cloud cover, dew point, humidity, and wind speed [13,15,16,34–39]. In the present study, six meteorological parameters were selected for predicting the monthly rainfall, as shown in Table 2. The current study also proposed GSR and sunshine duration as extra input parameters. The reason for choosing these parameters is due to the relationship between solar radiation and weather data including rainfall, and sunshine duration has been investigated by several scientific researchers [40–43].

2.2.4. Rainfall prediction with selected inputs

The methodology is used to estimate the monthly rainfall is shown in Fig. 3. The ANN method uses minimum temperature (Tmin), maximum temperature (Tmax) average temperature (Tav), GSR, sunshine duration (SD), and wind speed (W) as inputs. 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 (1985–2010) was used for training, while the remaining 20% (2011–2017) 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, Eq. (3) was used to normalize the data for improving the performance of the ANN model. The minimum (min) and maximum (max) values of the climate variables are shown in Table 3. Therefore, Table 4 lists the number of inputs used to develop the ANN models. 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. Fig. 4 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.

Table 2
Input and output parameters

Parameters	Parameter description	Abbreviation
Input 1	Monthly minimum temperature	Tmin
Input 2	Monthly maximum temperature	Tmax
Input 3	Monthly average temperature	Tav
Input 4	Monthly global solar radiation	GSR
Input 5	Monthly sunshine duration	SD
Input 6	Monthly wind speed	W
Output 1	Monthly rainfall	R

2.2.5. Appraisal of the developed models

The developed ANN models were evaluated comprehensively for predicting the monthly rainfall. The following statistical indicators were employed: coefficient of determination (R^2), mean squared error (MSE), RMSE and mean relative error (MAE).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(a_{a,i} - a_{p,i} \right)^2}{\sum_{i=1}^{n} \left(a_{p,i} - a_{a,\text{ave}} \right)^2} \quad (5)$$

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} \left(a_{a,i} - a_{p,i} \right)^2 \quad (6)$$

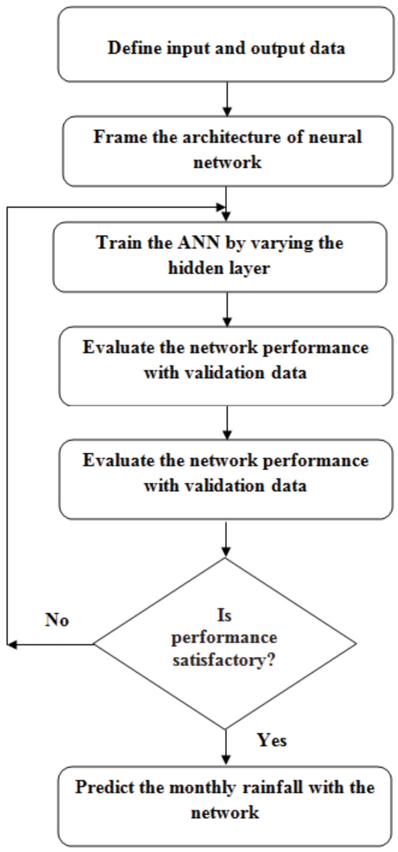

Fig. 3. Proposed ANN model for predicting the monthly rainfall at the selected area.

Table 3
Limit values for the input and output variables on the ANN model

Input	Parameter description	Limit		Unit
		Minimum	Maximum	
Tmin	Monthly minimum temperature	22.0	1.5	°C
Tmax	Monthly maximum temperature	36.3	14.1	°C
Tav	Monthly average temperature	29.0	7.3	°C
GSR	Monthly global solar radiation	703.8	0	Cal/cm^2-d
SD	Monthly sunshine duration	12.7	0	h/d
W	Monthly wind speed	4.8	0.4	m/s
Output				
R	Monthly rainfall	159.0	0	Mm

Table 4
ANN models developed in this study

No.	Number of inputs	No.	Number of inputs
ANN-1.	Tmin	ANN-2.	Tmax
ANN-3.	Tav	ANN-4.	GSR
ANN-5.	SD	ANN-6.	W
ANN-7.	Tmin, Tmax	ANN-8.	Tav, GSR
ANN-9.	Tav, SD	ANN-10.	Tav, W
ANN-11.	Tmin, Tmax, GSR	ANN-12.	Tmin, Tmax, SD
ANN-13.	Tmin, Tmax, W	ANN-14.	Tav, SD, GSR
ANN-15.	Tav, SD, W	ANN-16.	Tav, GSR, W
ANN-17.	Tmin, Tmax, SD, GSR	ANN-18.	Tmin, Tmax, SD, W
ANN-19.	Tmin, Tmax, Tav, GSR	ANN-20.	Tmin, Tmax, Tav, SD
ANN-21.	Tmin, Tmax, Tav, W	ANN-22.	Tmin, Tmax, Tav, W, GSR
ANN-23.	Tmin, Tmax, Tav, W, SD	ANN-24.	Tmin, Tmax, Tav, SD, GSR
ANN-25.	Tmin, Tmax, Tav, W, SD, GSR		

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(a_{a,i} - a_{p,i}\right)^2} \tag{7}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|a_{a,i} - a_{p,i}\right| \tag{8}$$

where n is the number of data, $a_{p,i}$ is the predicted values, $a_{a,i}$ is the actual values, $a_{a,\mathrm{ave}}$ is the average actual values and i is the number of input variables.

3. Results and discussion

3.1. Analysis of measurement data

Different statistical measures, including the mean, standard deviation (SD), coefficient of variation (CV), minimum, median, maximum, skewness and kurtosis are calculated for each meteorological parameter. Table 5 shows a statistical summary of monthly rainfall for theyears 1985 to 2017. It is found that the monthly mean rainfall varied from 0.0 to 159.0 mm. The maximum monthly rainfall occurred in February 2003 with a value of 159.0 mm. The CV values are high, ranging from 86.25 to 173.16. Moreover, Table 6 presents the annual descriptive statistics of each meteorological parameter computed from 1985 to 2016 for the selected area. It is noticed that the selected region received an average annual rainfall of 283.5 mm, while the maximum annual

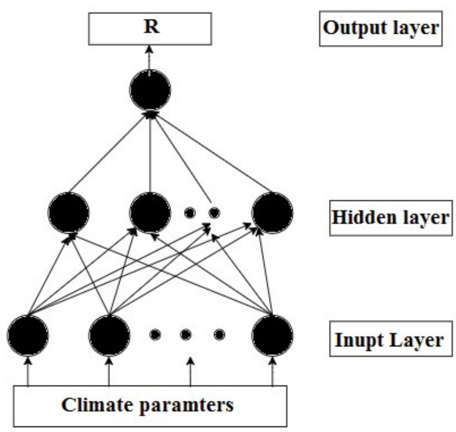

Fig. 4. Architecture of the ANN.

Table 5
Statistical analysis of monthly rainfall from 1985 to 2017

Year	Mean (mm)	SD (mm)	CV	Minimum (mm)	Median (mm)	Maximum (mm)	Skewness	Kurtosis
1985	18.95	25.23	133.14	0	9.7	84.2	1.77	3.41
1986	25	36.3	145.24	0	11.9	131.1	2.61	7.62
1987	26.13	32.39	123.96	0	9.9	89.3	0.99	–0.47
1988	39.2	45.2	115.48	0	21.1	116.5	0.89	–0.72
1989	11.75	15.46	131.55	0	5.1	50.3	1.52	2.48
1990	12.49	20.25	162.07	0	3.75	70.5	2.46	6.74
1991	26.5	37.5	141.54	0	11.8	128.3	2.07	4.83
1992	25.23	34.49	136.68	0	7.15	99.8	1.37	0.71
1993	17.23	19.8	114.89	0	8.95	51.8	0.78	–1.16
1994	40.4	34.8	86.25	0	39.5	99.3	0.25	–1.04
1995	12.33	12.21	99.04	0	11.75	37	0.86	0.01
1996	26.27	25.57	97.36	0	26.5	65.4	0.36	–1.47
1997	23.18	25.05	108.08	0	18.16	82.5	1.44	1.89
1998	18.32	26.11	142.54	0	6.56	86.4	1.84	3.58
1999	21.56	30.09	139.58	0	9.8	102.9	1.96	4.63
2000	29.22	33.58	114.92	0	17.2	99.8	1.06	0.05
2001	26.91	31.93	118.66	0	16.15	87	1.18	–0.04
2002	31.68	34.6	109.23	0	20.52	107.11	0.99	0.28
2003	33.3	46.3	139.09	0	18.7	159	2.05	4.84
2004	27.7	40.6	146.18	0	5.7	135.3	1.89	4.02
2005	17.66	17.81	100.83	0	14.6	46.31	0.37	–1.58
2006	18.78	22.6	120.34	0	9.15	70.6	1.23	1.03
2007	25.29	29.81	117.87	0	17.46	84.1	1.02	0.01
2008	11.28	17.27	153.17	0	4	57.7	2.13	4.6
2009	29.94	33	110.22	0	18.31	90.71	0.96	–0.64
2010	29.3	50.8	173.16	0	3.4	154.7	1.94	2.93
2011	26.03	23	88.36	0	30.2	51.9	–0.08	–2.11
2012	38.7	42.8	110.59	0	19.9	135	1.17	0.74
2013	14.28	16.97	118.9	0	8.7	53.1	1.27	1.04
2014	15.45	13.93	90.14	0	9.8	35.2	0.36	–1.64
2015	26.32	24.92	94.69	0	16.8	67.5	0.65	–1.06
2016	22.25	30.19	135.67	0	9.8	96.6	1.62	2.31
2017	10.94	13.93	127.35	0	4.65	41.6	1.47	1.2

Table 6
Annual statistical analysis of each meteorological parameter

Parameter	Mean	SD	CV	Minimum	Median	Maximum	Skewness	Kurtosis
R (mm)	283.50	97.20	34.27	131.30	302.80	484.80	0.22	–0.46
Tmin (°C)	11.50	5.57	48.47	4.74	10.91	19.67	0.22	–1.56
Tmax (°C)	25.57	6.73	26.32	16.43	25.94	34.50	–0.03	–1.60
Tav (°C)	18.49	6.45	34.85	10.27	18.34	27.39	0.11	–1.61
GSR (Cal/cm^2-d)	412.80	151.50	36.70	195.20	423.80	612.80	–0.09	–1.54
SD (h/d)	8.99	2.17	24.11	5.55	8.91	11.97	–0.07	–1.19
W (m/s)	2.65	0.27	10.01	2.28	2.57	3.13	0.55	–0.76

rainfall was 484.8 mm. During the investigation period, the skewness value is positive, which indicates that all distributions are left-skewed, as shown in Table 6. In addition, this area had a maximum and minimum air temperature of 34.5°C and 4.74°C, respectively. Moreover, it is found that the annual wind speed in this region was 2.65 m/s. Additionally, the GSR and sunshine duration values ranged between 195.2–612.80 Cal/cm^2 d and 5.55–11.97 h/d, respectively. Consequently, it can be established that this region has considerable solar potential. Generally, the mean and standard deviation values suggest that there is good consistency in the meteorological parameter behavior.

Moreover, the variation of the rainfall during the investigated period is shown in Fig. 5. It is observed that the monthly rainfall varied between 0 and 159 mm. In addition, as shown in Fig. 6, the total annual rainfall ranged between 131.3 and 484.8 mm, with an average of 283.5 mm. Furthermore, the mean annual temperature, wind speed, GSR, and sunshine duration are shown in Figs. 6–9, respectively. It is noticed that the highest and lowest maximum temperatures occurred in 2016 and 1992, with values of 26.4°C and 24°C, respectively, as shown in Fig. 7. In addition, the average temperature in the selected location was approximately 18.5°C. The averaged wind speed was 2.76 m/s, as shown in Fig. 8. Furthermore, GSR and sunshine duration during the investigation period ranged between 134.7 and 240.6 Cal/cm^2-d and 8.5 and 9.6 h/d as shown in Figs. 9 and 10, respectively. Additionally, the average GSR and sunshine duration was 195.2 Cal/cm^2-d and 8.99 h/d, respectively.

3.2. Results of ANN analysis

This section aims to determine the optimal combination set of the input parameters. In the present study, 25 ANN models (ANN-1 to ANN-25) were developed with a different

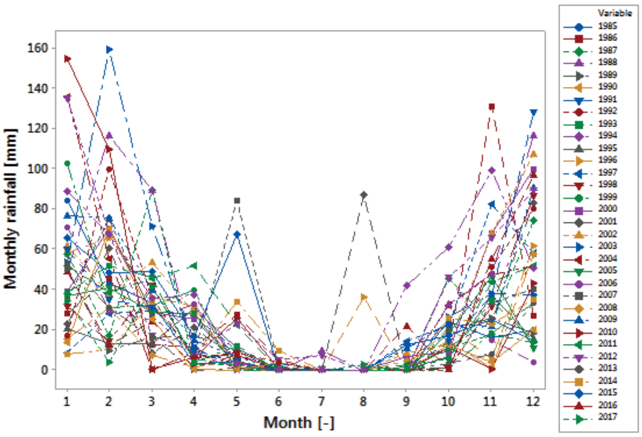

Fig. 5. Monthly mean rainfall over 33 years.

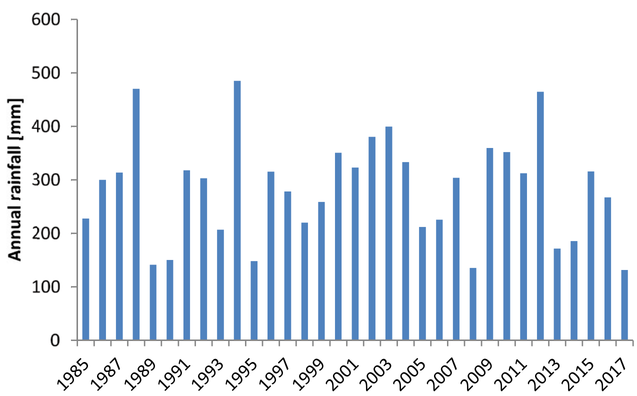

Fig. 6. Total rainfall (1985–2017).

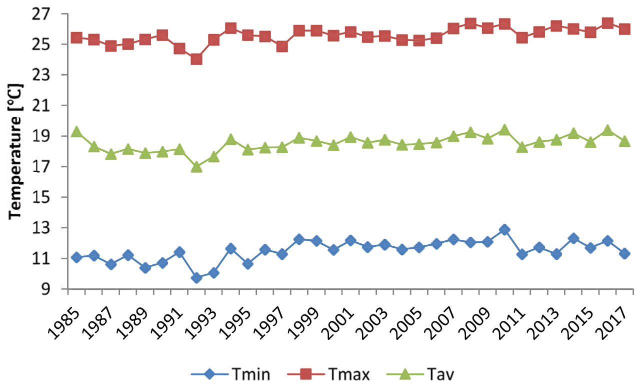

Fig. 7. Mean annual temperature (1985–2017).

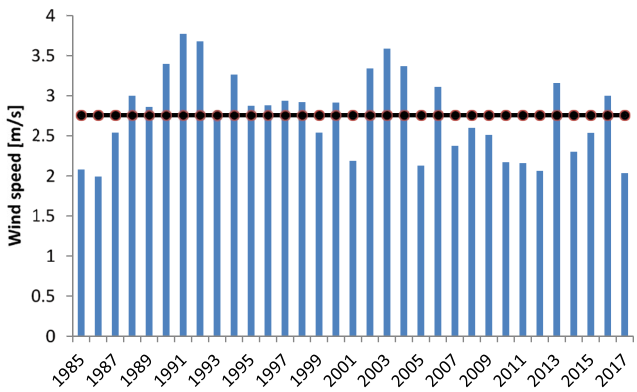

Fig. 8. Mean annual wind speed (1985–2017).

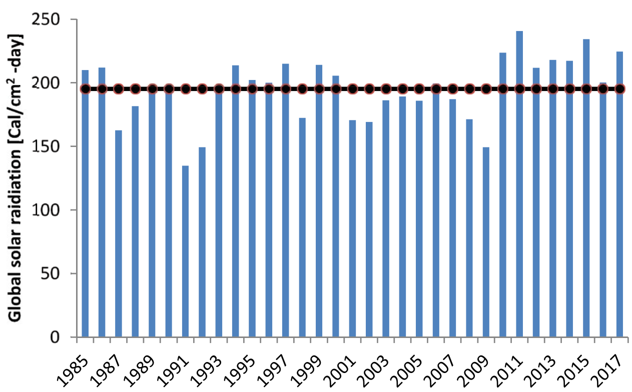

Fig. 9. Mean annual global solar radiation (1985–2017).

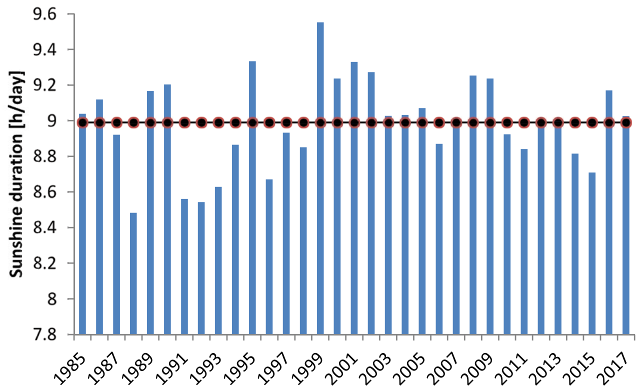

Fig. 10. Mean annual sunshine (1985–2017).

combination of inputs and the target for all the models was to predict the monthly rainfall. The developed ANN models were trained and tested using MATLAB 2015a. Different numbers of hidden layers and neurons were used to develop the ANN model to select the best architecture of the developed ANN model. Moreover, the network with the minimum MSE invalidation is called the trained ANN model [45].

3.2.1. ANN model with one input

Out of the six selected inputs, each input was individually applied to the ANN (see Table 4). The effect of each input on the monthly rainfall was identified. The best performance of the network was obtained by training the developed ANN architecture a number of 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 7 shows the best number of hidden layers and neurons, training rule, activation function, epochs, *R*-squared and MSE that were chosen for each ANN model. In addition, the *R*-squared, RMSE, and MAE for testing data are tabulated in Table 7. Based on the statistical tool performance (R^2, RMSE, and MAE) for testing, both GSR and SD have shown high prediction performance compared to the other inputs.

3.2.2. ANN model with two inputs

The performance of four ANN models (ANN-7, ANN-8, ANN-9, and ANN-10) with different two input combinations for predicting the monthly rainfall is examined. The statistical tools' performance of the ANN model for selecting the best combination effect on monthly mean rainfall is shown in Table 8. Out of all the formed combinations, the ANN with the combination of ANN-7 (Tmin, Tmax) produced the highest R^2 and least error (RMSE, MAE) in estimating the monthly mean rainfall. In addition, the combination of ANN-8 (Tav, GSR) had the lowest errors and highest *R*-squared, as shown in Table 8. The combinations of ANN-9 (Tav, SD) and ANN-10 (Tav, W) gave the highest error values and minimum R^2 values compared to the other models.

3.2.3. ANN model with three inputs

A total of six combinations were formed with three combinations to train and test the ANN. Table 9 shows the evaluation of the network and the statistical tools' performance of ANN models. It is noticed that the ANN-12 and ANN-13 with the combination of (Tmin, Tmax, SD) and (Tmin, Tmax, W), respectively, produced almost the same R^2, RMSE and MAE values in predicting the monthly mean rainfall. The ANN-14 with a combination of (Tav, SD, GSR) gave the highest error values.

Table 7
Evaluation of the networks and statistical tools' performance of the ANN model with one input

Model	Transfer function	Hidden layer	Neurons	Epoch	MSE (training)	R^2 (training)	R^2 (testing)	RMSE (testing)	MAE (testing)
ANN-1	TANSIG	1	20	3	1.35E-02	0.3565	0.3168	0.1699	0.1060
ANN-2	LOGSIG	2	30	3	1.23E-02	0.4645	0.3720	0.1737	0.1066
ANN-3	LOGSIG	2	30	129	1.47E-02	0.3990	0.2418	0.1863	0.0991
ANN-4	TANSIG	1	30	79	9.18E-03	0.5403	0.4578	0.1611	0.0992
ANN-5	LOGSIG	1	40	20	8.87E-03	0.5888	0.4345	0.1637	0.1021
ANN-6	TANSIG	2	20	4	2.88E-02	0.1567	0.0074	0.2144	0.1531

Table 8
Evaluation of the networks and Statistical tools' performance of the ANN model with two inputs

Model	Transfer function	Hidden layer	Neurons	Epoch	MSE (training)	R^2 (training)	R^2 (testing)	RMSE (testing)	MAE (testing)
ANN-7	LOGSIG	2	20	51	1.12E-02	0.7075	0.5842	0.1339	0.0755
ANN-8	LOGSIG	3	20	10	2.13E-02	0.5431	0.5680	0.1359	0.0761
ANN-9	TANSIG	2	20	53	9.20E-03	0.6378	0.3575	0.1759	0.0972
ANN-10	LOGSIG	3	10	39	1.26E-02	0.4690	0.2524	0.1890	0.1067

3.2.4. ANN model with four inputs

Four ANN models with four different combinations of inputs are developed to predict the monthly rainfall and the statistical tools' performance of these models are listed in Table 10. The ANN-17 tested with the combination of (Tmin, Tmax, SD, GSR) has given the highest R^2. In addition, it is noticed that the ANN-19 and ANN-20 with the combination of (Tmin, Tmax, Tav, GSR) and (Tmin, Tmax, Tav, SD), respectively, have produced the same RMSE and MAE values. The ANN-21 with a combination of (Tmin, Tmax, Tav, W) has given the highest RMSE and the lowest value of MAE and R^2.

3.2.5. ANN model with five inputs

Table 11 presents an evaluation of the four ANN models with five different combinations of inputs and the statistical tools' performance of these models. The ANN-22, -23, -24 tested with the combination of (Tmin, Tmax, Tav, W, GSR), (Tmin, Tmax, Tav, W, SD) and (Tmin, Tmax, Tav, SD, GSR), respectively, have produced almost the same R^2, RMSE, and MAE values.

3.2.6. ANN model with six inputs

All six input variables are applied to train and test the developed ANN, named as ANN-25. The statistical tools' performance during training and testing is shown in Table 12. The ANN-25 has shown good prediction accuracy with an R^2 value of 0.5530 and an MAE of 7.7%.

3.3. Observations from the developed ANN models

The predictions of the monthly rainfall value using different input combinations are compared with the actual value. Table 13 presents the R^2, RMSE, and MAE of the testing data for the optimum models used to predict the monthly rainfall data of the selected area. Moreover, Table 14 presents the ranking of the ANN models that are used for predicting the monthly rainfall based on thethree statistical tools. Based on the R-squared value, it is found that ANN-17 with a combination of (Tmin, Tmax, SD, GSR) has the maximum value compared to other models. In addition, it is observed that ANN-13 with a combination of (Tmin, Tmax, W) produced the least error with a value of 0.1316 for RMSE and 0.0763 for MAE. Moreover, it is observed that ANN-6 with

Table 9
Evaluation of the networks and statistical tool's performance of the ANN model with three inputs

Model	Transfer function	Hidden layer	Neurons	Epoch	MSE (training)	R^2 (training)	R^2 (testing)	RMSE (testing)	MAE (testing)
ANN-11	LOGSIG	1	10	15	8.37E-03	0.7367	0.5697	0.1389	0.0758
ANN-12	LOGSIG	3	30	8	6.26E-03	0.7350	0.6009	0.1337	0.0810
ANN-13	LOGSIG	2	10	6	9.26E-03	0.7037	0.6247	0.1261	0.0705
ANN-14	TANSIG	1	20	8	2.56E-02	0.5841	0.4667	0.1638	0.0949
ANN-15	LOGSIG	2	30	14	1.60E-02	0.5772	0.4564	0.1535	0.0892
ANN-16	LOGSIG	1	30	3	2.19E-02	0.4852	0.5017	0.1481	0.0833

Table 10
Evaluation of the networks and statistical tools' performance of the ANN model with four inputs

Model	Transfer function	Hidden layer	Neurons	Epoch	MSE (training)	R^2 (training)	R^2 (testing)	RMSE (testing)	MAE (testing)
ANN-17	LOGSIG	1	10	4	6.52E-03	0.6966	0.6488	0.1301	0.0872
ANN-18	TANSIG	1	10	8	5.05E-03	0.7213	0.5465	0.1427	0.0871
ANN-19	TANSIG	2	10	19	7.77E-03	0.6720	0.5788	0.1337	0.0767
ANN-20	TANSIG	3	10	15	6.22E-03	0.7146	0.5860	0.1343	0.0782
ANN-21	TANSIG	3	10	26	1.78E-02	0.6844	0.5243	0.1432	0.0776

Table 11
Evaluation of the networks and statistical tools' performance of the ANN model with four inputs

Model	Transfer function	Hidden layer	Neurons	Epoch	MSE (training)	R^2 (training)	R^2 (testing)	RMSE (testing)	MAE (testing)
ANN-22	TANSIG	3	30	1	1.28E-02	0.6397	0.6405	0.1346	0.0899
ANN-23	LOGSIG	2	10	11	7.41E-03	0.7057	0.6217	0.1259	0.0776
ANN-24	LOGSIG	2	30	2	1.38E-02	0.5966	0.5593	0.1441	0.0857

Table 12
Evaluation of the networks and statistical tool's performance of the ANN model with four inputs

Model	Transfer function	Hidden layer	Neurons	Epoch	MSE (training)	R^2 (training)	R^2 (testing)	RMSE (testing)	MAE (testing)
ANN-25	TANSIG	2	20	9	1.51E-02	0.6710	0.5530	0.1379	0.0770

Table 13
R^2, RMSE and MAE of testing data for the optimum ANN models and the selected best model (in bold) for predicting the monthly rainfall

Input number	Model	R^2	RMSE	MAE
1	ANN-1	0.3168	0.1699	0.1060
	ANN-2	0.3720	0.1737	0.1066
	ANN-3	0.2418	0.1863	0.0991
	ANN-4	0.4578	0.1611	0.0992
	ANN-5	0.4345	0.1637	0.1021
	ANN-6	0.0074	0.2144	0.1531
2	ANN-7	0.5842	0.1339	0.0755
	ANN-8	0.5680	0.1359	0.0761
	ANN-9	0.3575	0.1759	0.0972
	ANN-10	0.2524	0.1890	0.1067
3	ANN-11	0.5697	0.1389	0.0758
	ANN-12	0.6009	0.1337	0.0810
	ANN-13	0.6247	0.1261	**0.0705**
	ANN-14	0.4667	0.1638	0.0949
	ANN-15	0.4564	0.1535	0.0892
	ANN-16	0.5017	0.1481	0.0833
4	ANN-17	**0.6488**	0.1301	0.0872
	ANN-18	0.5465	0.1427	0.0871
	ANN-19	0.5788	0.1337	0.0767
	ANN-20	0.5860	0.1343	0.0782
	ANN-21	0.5243	0.1432	0.0776
5	ANN-22	0.6405	0.1346	0.0899
	ANN-23	0.6217	**0.1259**	0.0776
	ANN-24	0.5593	0.1441	0.0857
6	ANN-25	0.5530	0.1379	0.0770

the combination of (W) gave the lowest R-squared and the highest RMSE and MAE, as shown in Table 6.

The predictions of the monthly mean rainfall values using the best-input combination of all the ANN models, which were chosen based on the highest value of R^2, least value of RMSE and MAE, are compared with the actual values and are shown in Fig. 11. Out of the 25 ANN models, ANN-13, ANN-17 and ANN-23 have given the best prediction with the combinations of (Tmin, Tmax, W), (Tmin, Tmax, SD, GSR) and (Tmin, Tmax, Tav, W, SD), respectively. From the developed ANN models, it can be observed that the combinations consisting of Tmin and Tmax outperformed the other combinations. It can be concluded that temperature is the only parameter considered in all the ANN models and this confirms that the temperature of a particular location is one of the key parameters for estimating the rainfall.

4. Conclusions and future work

This study has shown the power of ANN to evaluate the most influencing input parameters in the prediction of monthly rainfall. Twenty-five ANN models using a back-propagation algorithm were developed with different input combinations. The most important input variables for predicting the monthly rainfall were found to be minimum temperature and maximum temperature. Out of the 25 ANN models, ANN-13, ANN-17, and ANN-23 have given the best prediction with the combinations of (Tmin, Tmax, W), (Tmin, Tmax, SD, GSR) and (Tmin, Tmax, Tav, W, SD), respectively. These models can be used for determining the level of groundwater based on the amount of rainfall and rainfall distribution at any site in Northern Cyprus. Therefore, it can be used for the assessment of trends in groundwater levels across Northern Cyprus. Moreover, these input variables are

Table 14
Ranking of ANN models for estimating the monthly mean rainfall based on the R^2, RMSE, and MAE for testing data

Statistic	Rank of the ANN model									
R^2	Rank	1	2	3	4	5	6	7	8	9
	Model	ANN-17	ANN-22	ANN-13	ANN-23	ANN-12	ANN-20	ANN-7	ANN-19	ANN-11
	Rank	10	11	12	13	14	15	16	17	18
	Model	ANN-8	ANN-24	ANN-25	ANN-18	ANN-21	ANN-16	ANN-14	ANN-4	ANN-15
	Rank	19	20	21	22	23	24	25		
	Model	ANN-5	ANN-2	ANN-9	ANN-1	ANN-10	ANN-3	ANN-6		
RMSE	Rank	1	2	3	4	5	6	7	8	9
	Model	ANN-23	ANN-13	ANN-17	ANN-19	ANN-12	ANN-7	ANN-20	ANN-22	ANN-8
	Rank	10	11	12	13	14	15	16	17	18
	Model	ANN-25	ANN-11	ANN-18	ANN-21	ANN-24	ANN-16	ANN-15	ANN-4	ANN-5
	Rank	19	20	21	22	23	24	25		
	Model	ANN-14	ANN-1	ANN-2	ANN-9	ANN-3	ANN-10	ANN-6		
MAE	Rank	1	2	3	4	5	6	7	8	9
	Model	ANN-13	ANN-7	ANN-11	ANN-8	ANN-19	ANN-25	ANN-21/ ANN-23	ANN-21/ ANN-23	ANN-20
	Rank	10	11	12	13	14	15	16	17	18
	Model	ANN-12	ANN-16	ANN-24	ANN-18	ANN-17	ANN-15	ANN-9	ANN-14	ANN-9
	Rank	19	20	21	22	23	24	25		
	Model	ANN-3	ANN-4	ANN-5	ANN-1	ANN-2	ANN-10	ANN-6		

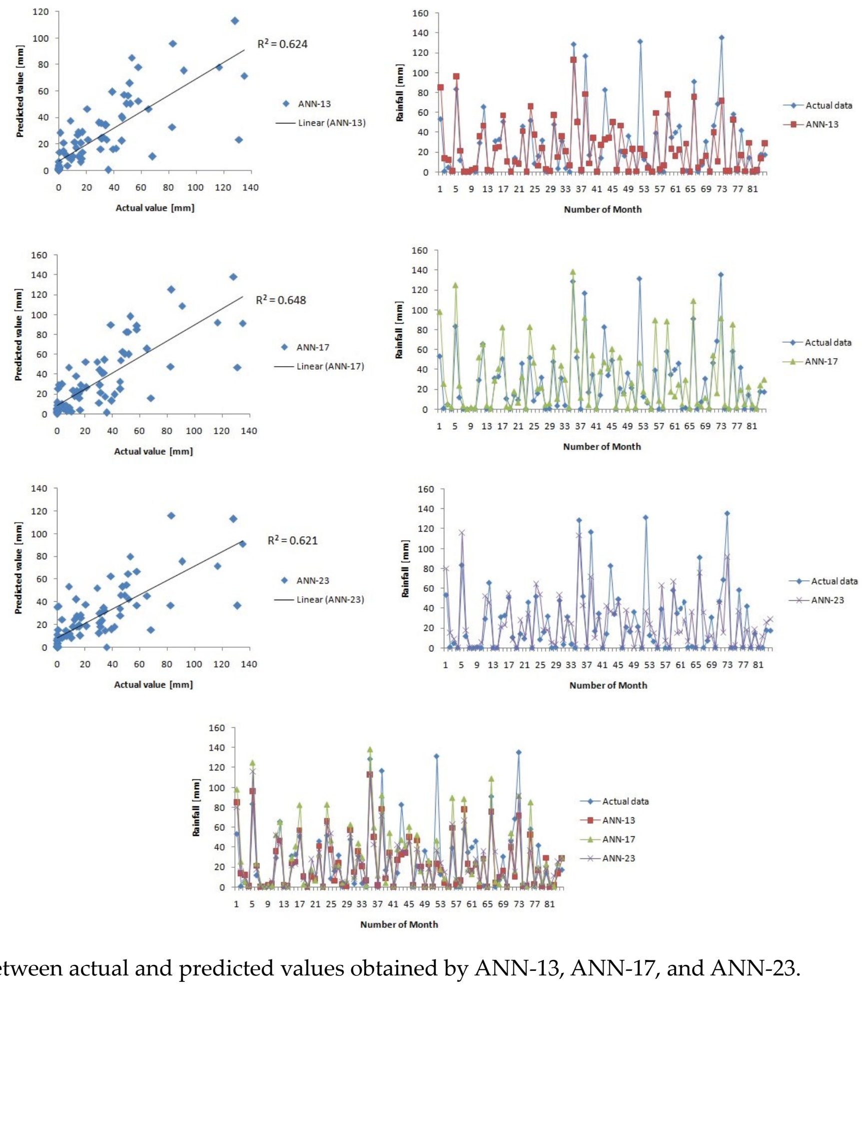

Fig. 11. Comparison between actual and predicted values obtained by ANN-13, ANN-17, and ANN-23.

easily obtainable from monitoring stations and hence, the developed models are practically applicable to any site in Northern Cyprus. Consequently, the results revealed that the temperature is considered as the most important parameter that has a greater impact on the estimated rainfall. It is found that wind speed has a minimum effect on rainfall prediction.

Further studies to estimate the rainfall of the Northern part of Cyprus with greater accuracy can be undertaken. Future research should focus on finding the most relevant input parameters from other meteorological variables with improved prediction accuracy of different ANN models. In addition, the effects of latitude and longitude as extra inputs on the prediction of the rainfall will be investigated.

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