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Forecasting of daily rainfall at Ercan Airport Northern Cyprus: a comparison of linear and non-linear models

Rabiu Aliyu Abdulkadir[a], Shaban Ismael Albrka Ali[b,*], S.I. Abba[c], Parvaneh Esmaili[a]

[a]*Department of Electrical and Electronic Engineering, Near East University, Nicosia - North Cyprus, via Mersin 10 Turkey, Tel. +905338773111; email: rabiukk@gmail.com (R.A. Abdulkadir), Tel. +9054288225801; email: parvaneh.esmaili@neu.edu.tr (P. Esmaili), Tel. +905338717889*
[b]*Department of Civil Engineering, Near East University, Nicosia - North Cyprus, via Mersin 10 Turkey, Tel. +905428880237; email: shabarofking10@gmail.com*
[c]*Department of PPD and M, Yusuf Maitama Sule University, Kano - Nigeria, Tel. +2348031334033; email: saniisaabba86@gmail.com*

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ABSTRACT

Forecasting of complex and chaotic phenomena such as rainfall is very challenging. Prediction of precipitation in airports helps agencies responsible for air traffic control in terms of planning and decision making. Conventional methods often provide imprecise forecasts, which may lead to flight delays and economic losses. This paper presents a comparison of linear and non-linear models for the forecasting of daily rainfall at Ercan Airport, Northern Cyprus. The study uses daily meteorological data consisting of relative humidity, minimum and maximum temperature, wind speed, solar radiation, and rainfall for 10 years (2008–2018) for Ercan Airport. The accuracy of the model is evaluated using the determination coefficient, mean square error and mean absolute percentage error performance indices. Simulation results indicate that the performance of the non-linear models is more accurate. The developed model could serve as a reliable rainfall forecasting tool for Ercan Airport.

Keywords: MLR; ANN; ANFIS; Northern Cyprus; Rainfall

1. Introduction

Precise prediction of rainfall is one of the most crucial and challenging tasks. Rainfall affects human civilization and developments in many ways. Correct information on rainfall is essential for water resources management and the prevention of floods, which helps in protecting properties, lives and economic activities [1]. Furthermore, rainfall has a significant effect on agricultural activities, sewer systems, traffic, and other human activities, especially in urban areas. Inaccurate forecasting of rainfall at airports may lead to flight delays. Flight delays at one airport usually propagate to other airports because of flight connectivity. Such delays lead to passenger dissatisfaction, poor airport performance and economic losses [2–4]. However, like other natural phenomena, rainfall is difficult to comprehend and model because of the inherent non-linearity and complexity of the atmospheric processes that generate the rainfall. Therefore, successful prediction of rainfall requires advanced and well-established modeling approaches [5]. In the literature, various linear and non-linear techniques are available for rainfall prediction, including statistical methods, regression models, numerical weather prediction (NWP) models, and artificial intelligence techniques. Regression models such as ARMA and ARX belong to a family of linear models, which are commonly used in forecasting due to their ability to deal with

* Corresponding author.

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large data samples and may yield better prediction; however, they show poor performance for samples with fewer data [6–8]. Statistical models fit the given data by generating random numbers to resemble the data [9], but their major disadvantage is that they are dependent on a large number of implicit assumptions concerning the system. However, chaotic processes like rainfall cannot be constrained by any assumptions. It has also been proved by many studies that NWP models developed for rainfall forecasting are disposed to biases and errors due to high uncertainties in atmospheric processes and the limitation in understanding of mathematical modeling of atmospheric dynamics [10].

Intelligent models, such as random forest, *k*-nearest neighbor, decision trees, support vector machine, Naive Bayes, artificial neural networks (ANN), extreme learning machine and fuzzy logic, are found to be more appropriate for rainfall prediction [11]. Intelligent models are precise, versatile and can learn the relationship between the parameters of real-world data. Additionally, they can effectively handle uncertain, non-linear, limited and noisy data. However, local minima, over/underfitting, in addition to choosing the membership function and selecting the structure represent challenges in using these models. The integration of neural networks and fuzzy logic within a hybrid model, referred to as an adaptive neuro-fuzzy inference system (ANFIS), has the potential to overcome the deficiencies of the individual models. ANFIS has achieved overall acceptability since its inception. In general, forecasting has become an important field of research in recent decades. In most cases, researchers have attempted to establish a linear relationship between the input weather data and the corresponding target data. However, with the discovery of nonlinearity like rainfall data, the focus has shifted towards the nonlinear prediction of the rainfall data. Although numerous studies have applied nonlinear statistics for rainfall forecasting, most of them required that the nonlinear model be specified before the estimation is done. However, since rainfall data is nonlinear and follows a very irregular trend, AI has shown to be a better technique to demonstrate the structural relationship between the various entities [12]. Research conducted by Frencha et al. [13] applied ANN to predict rainfall 1 h in advance. The data used were created through the simulation of a mathematical rainfall model. This work is considered one of the initial contributions to explore the application of ANN in the modeling of geophysical systems. Philip and Kouneiher [14] developed a prediction model to forecast the monthly rainfall in the southern Indian state of Kerala. Their model was based on a unique adaptive function neural network, which used recorded rainfall data collected over 51 months [14]. Gholizadeh and Darand [15] used a neural network and genetic algorithm (NG) to predict monthly average precipitation in Tehran one year in advance. Likewise, Bodri and Čermák [16] forecasted monthly average rainfall using ANN with recorded data obtained from two meteorological stations in the Czech Republic. The developed ANN model used observed data for the same given month from the two past consecutive years, and the data from the previous months in the present year, as predictors. A performance comparison among three ANN models, namely Elman partial recurrent NN (Elman), time delay NN and multi-later feed-forward NN (MLFN), was presented in [17]. In a similar vein, Aksoy and Dahamsheh [18] developed and compared the performance of radial basis function NN, regression-based NN and back-propagation feed-forward NN, to predict rainfall one month in advance. To establish a reliable flight schedule, the fuzzy logic rule-based approach was used in [19] to predict rainfall events at Cairo Airport. The data were collected for 25 years, with total cloud cover, relative humidity (RH), surface pressure, wind flow and temperature as inputs. For more information on the use of ANN and fuzzy logic to forecast rainfall, refer to the following studies [20–24]. The significance of variations in the precipitation patterns of Northern Cyprus has been actively debated in recent research studies. Based on [25–27], the occurrence and intensity of precipitation are increasing, thus causing flash floods in the region. Therefore, Ercan Airport has significant potential to be impacted by the consequences of climate change soon and needs detailed precipitation forecast analysis.

The main objective of this paper is to provide a performance comparison of linear and non-linear models applied in the forecasting of daily rainfall for Ercan Airport, Northern Cyprus. In this regard, a conventional multi-linear regression (MLR) technique, and two machine learning techniques, namely ANN and ANFIS techniques, are employed in the modeling process. A comprehensive comparative analysis is presented to identify the best model. Although researchers have used ANN, ANFIS, and MLR to predict daily rainfall, establishing a suitable combination of input parameters remains a challenging task, which has been addressed via sensitivity analysis. Moreover, this study considers the need to compare artificial intelligent approaches with conventional methods to determine which is more efficient in predicting daily rainfall for Ercan Airport, Northern Cyprus. The remaining sections are arranged as follows: Section 2 presents the material and methodology adopted in the study, while the results and discussions are given in Section 3 and the paper ends with a conclusion in Section 4.

2. Material and method

2.1. Study area and data collection

The island of Cyprus is located in the Eastern Mediterranean and is the third-largest island in the Mediterranean in terms of population and landmass. It is positioned in a strategic location, north of the Arab Republic of Egypt, south of Turkey, west of Lebanon, southeast of Greece and northwest of Israel. Ercan Airport is located in Northern Cyprus at 35.159°N latitude and 33.504°E longitude. Presently, Ercan Airport occupies an area of 20 km^2 with an annual capacity of about 4 million passengers. Fig. 1 shows the location of the study area. For this study, the available (at 2 m above the earth's surface) daily meteorological data of RH, minimum temperature (Tmin), wind speed (WS), maximum temperature (Tmax), solar radiation (SR) and rainfall (RF) for Ercan Airport are collected from "National Aeronautics and Space Administration (NASA)", covering the 10 years from 2008 to 2018. Table 1 shows the regional statistical analysis of the data. 75% of the data were used for model calibration, while the remaining 25% were employed in the verification phase.

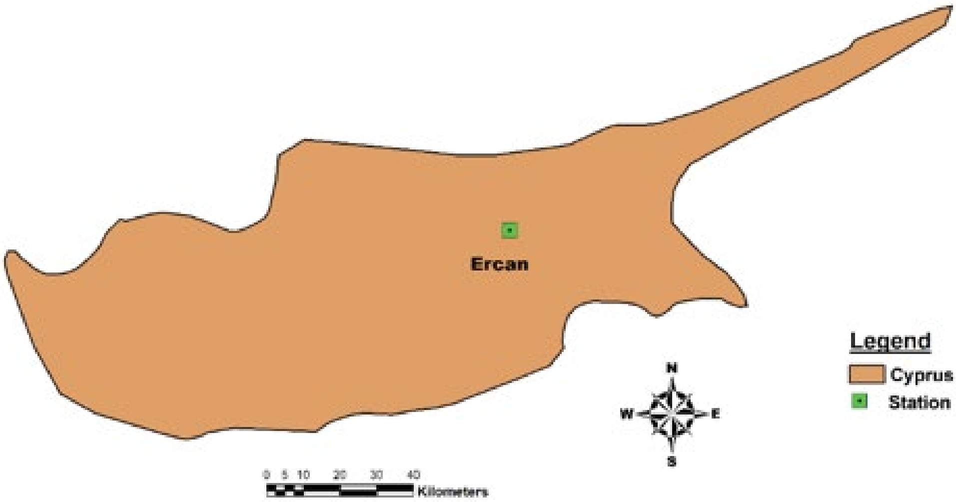

Fig. 1. Map of the study location.

Table 1
Statistical analysis of the raw data

Parameters	Mean	Standard deviation	Kurtosis	Skewness	Minimum	Maximum
WS (m/s)	3.3436	1.5387	1.5706	1.1572	0.4100	11
RH (%)	64.1622	7.7884	–0.1217	0.1722	37.5700	88.4900
SR (kWh/m²/d)	8.3199	0.84845	–0.6788	–0.0829	6.0100	10.7900
Tmax (°C)	23.9001	6.4869	–1.2332	0.0328	8.0300	37.1300
Tmin (°C)	19.5551	5.6523	–1.1859	0.0486	4.9300	30.1100
RF (mm/d)	0.8437	2.6747	42.9410	5.7061	0	35.9100

2.2. Proposed methodology

This study proposes the development of a classical MLR, ANN and ANFIS modeling techniques applied in the forecasting of daily rainfall at Ercan Airport (Fig. 2) to achieves this, daily meteorological data consisting of RH, minimum and maximum temperature, WS, SR, and rainfall were collected for the 10 years from 2008 to 2018 from Ercan Airport. From the collected data, five parameters (RH, Tmin, Tmax, WS, and SR) serve as the model inputs for predicting the rainfall RF.

The knowledge of data science is fundamental to machine learning-based modeling. Data science is used to establish the relationship and the degree of closeness between data variables [28]. As a pre-processing stage, data normalization is conducted to improve the performance accuracy and speed of the models [29]. For this work, the normalization is implemented using Eq. (1).

$$y = 0.5 + \left(0.5 \times \left(\frac{x - \bar{x}}{x_{\max} - x_{\min}}\right)\right) \tag{1}$$

where y is the normalized data, x is the measured data, and $\bar{x}$, $x_{\max}$ and $x_{\min}$ represent the mean, maximum, and minimum values of the measured data, respectively.

2.3. Multi-linear regression

Linear regression methods are widely used to determine the relationship between quantitative variables, such that the input (independent variables) can be applied to forecast the future values of the output (dependent variable). The MLR method is an extension of linear regression [8]. For detailed theory about MLR, readers are referred to [6,8].

In this study, the MLR models developed for the three sets of inputs are expressed in Eqs. (2)–(4).

$$\mathrm{RF}_i = \propto_0 + \propto_1 \mathrm{WS}_i + \propto_2 \mathrm{RH}_i \tag{2}$$

$$\mathrm{RF}_i = \propto_0 + \propto_1 \mathrm{WS}_i + \propto_2 \mathrm{RH}_i + \propto_3 \mathrm{Tmax}_i + \propto_4 \mathrm{Tmin}_i \tag{3}$$

$$\mathrm{RF}_i = \propto_0 + \propto_1 \mathrm{WS}_i + \propto_2 \mathrm{RH}_i + \propto_3 \mathrm{Tmax}_i + \propto_4 \mathrm{Tmin}_i + \propto_5 \mathrm{SR}_i \tag{4}$$

where WS, RH, SR, Tmax, Tmin, and RF are as defined in Section 2.1, $\propto_0$ is a constant, while $\propto_1$, $\propto_2$, $\propto_3$, $\propto_4$, and $\propto_5$ are the coefficients of regression to be estimated by solving the regression equations.

In general, considering an nx1 matrix of observations Y, with corresponding nx(m + 1) matrix of input variables X, a nx1 vector of regression coefficient $\propto_2$ to be estimated and

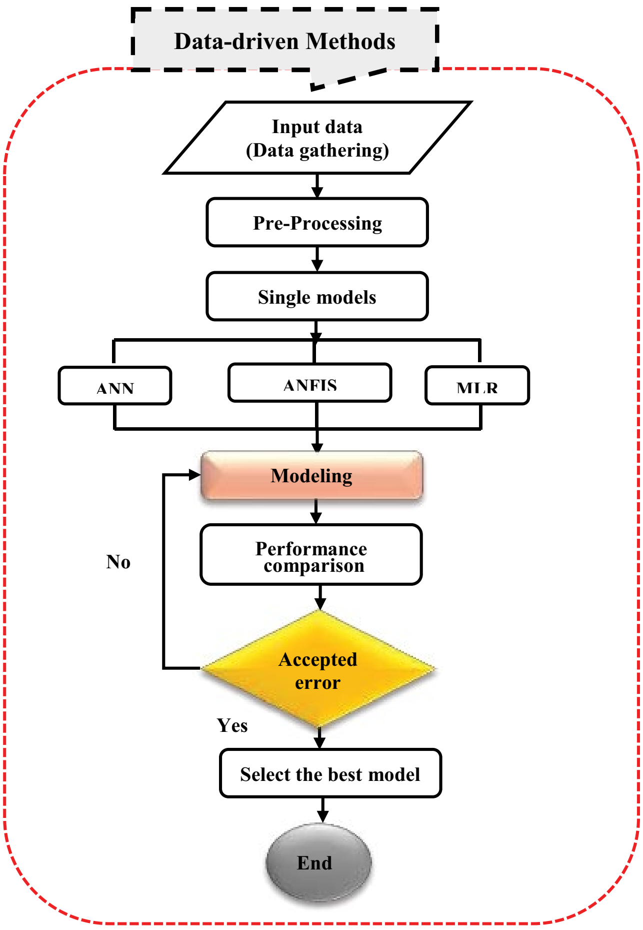

Fig. 2. Proposed flowchart of the study.

nx1 vector of irreducible error ∊, the MLR problem can be described in compact form using Eq. (5).

$$Y = \propto X + \in \tag{5}$$

where m and n are the total numbers of input variables and the data samples, respectively. The estimated regression parameters can be obtained using the least square criterion as:

$$\hat{\propto} = \left(X'X\right)^{-1} X'Y \tag{6}$$

By using the estimated values of the regression coefficients obtained from Eq. (5) with a given input X, one can obtain the predicted output $\hat{y}$ using Eq. (7).

$$\hat{y} = X\,\hat{\propto} \tag{7}$$

2.4. Artificial neural network

The ANN is a data-driven model motivated by the function of the human biological nervous system. ANN has been widely used as a function approximator to approximate complicated tasks that are difficult to model using the classical mathematical modeling approach [28]. The fundamental structure of ANN is the perceptron, which consists of a single input layer and a single output layer. All layers have a certain number of data processing equivalent to the cell body in the biological neurons. The perceptron is expanded to a multilayer perceptron by adding more layers between the input and output layers, referred to as hidden layers.

A feed-forward backpropagation neural network (FFNNBP) can be described as a composition function where each layer in the FFNNBP is a function of the previous layer's output. FFNNBP is named based on the fact that information flows from the input layer to the output layer through some intermediate layers called hidden layers, without any feedback connection [30]. Fig. 3 illustrates the basic structure of the three-layered FFNNBP. In Fig. 3, the first layer x_i presents the input data given to the neural network. The input is processed by the hidden layer h_i through the hidden layer activation function. More than one hidden layer can be used depending on the application, but at the expense of higher computational time and cost, since more parameters have to be learned. Finally, the output layer transforms the output from the last hidden layer to the desired output y. The predicted output can be written mathematically as a linear composition of the consecutive layer functions:

$$\hat{y}_k = f_0\left(\sum_{j=1}^{n} W_{jk} \times f_h\left(\sum_{i=1}^{n} W_{ij} \times x_i + b_j\right) + b_k\right) \tag{8}$$

where W_{ij} is the weight factor connecting the ith input layer neuron to the jth hidden layer neuron, x_i is the ith input variable, b_j is the bias of the jth hidden layer neuron, f_h is the hidden layer neuron activation function, n is total number of hidden neurons, b_k is bias of the kth output neuron, W_{jk} is a weighting factor connecting jth hidden layer neuron to the kth output layer neuron, while m is total number of output neurons and f_0 is output neuron activation function [1,30,31]. For this work, sigmoid activation functions are employed for both output and hidden layer neurons.

The most important stage in the development of the network is the learning stage. During the learning stage, also known as training, the recorded data consisting of input and output parameters are given to the system. The network processes the data to find the optimal weights matrix that matches the predicted output to the actual output. In this work, the backpropagation algorithm is used for the training [32].

2.5. Adaptive neuro-fuzzy inference system

ANFIS is a neuro-fuzzy hybrid system made by combining a neural network with fuzzy logic. ANFIS is proposed to enhance the performance of the individual models (ANN and FIS). Their unique features, such as high reliability, adaptation, robustness, and ability to handle limited and noisy data, make them an obvious choice for many applications. The fuzzy inference is constructed based on the given dataset, and the optimal parameters of the model are obtained through a learning process [33]. In this study, a hybrid optimization method is used, which combines the gradient-descent optimization method with the least square approach. Fig. 4 depicts the basic ANFIS structure based on the Sugeno and Takagi fuzzy model. This structure is composed of

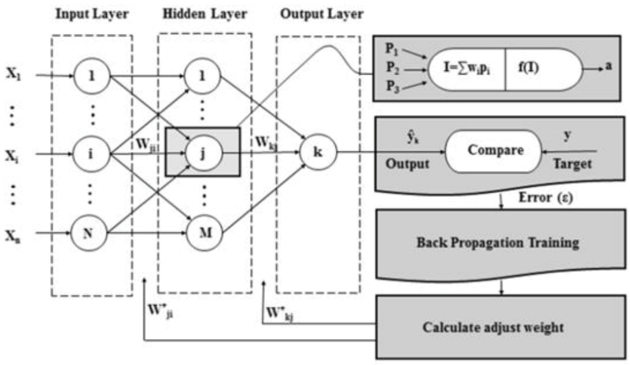

Fig. 3. Three-layer FFBP neural network [27].

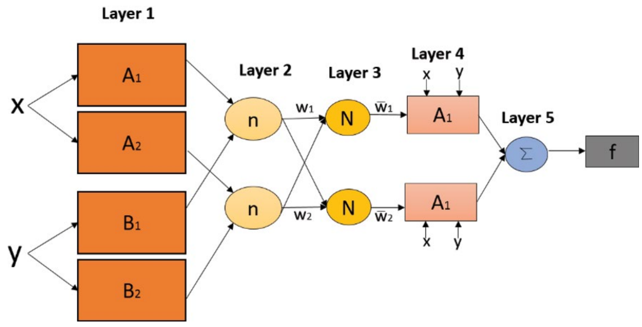

Fig. 4. ANFIS structure [28].

square nodes and round nodes (with constant parameters). In addition to the structure shown, the IF-THEN rule-based is created. The first-order Sugeno fuzzy model is used to generate the rules as illustrated below. Considering two inputs x and y with corresponding output f, the rules can be written as:

$$\text{Rule 1: IF } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ THEN } f_1 = m_1 x + n_1 y + r_1 \tag{9}$$

$$\text{Rule 2: IF } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ THEN } f_2 = m_2 x + n_2 y + r_2 \tag{10}$$

where A_i and B_i are the respective membership functions for the inputs x and y, with m_i, n_i and r_i as output function parameters.

Layer 1: Every node i is an adaptive node in this layer, which has a node function as in Eq. (10).

$$Q_i^1 = \mu_{Ai}(x) \text{ for } i = 1,2 \text{ or } Q_i^1 = \mu_{\text{Bi}}(x) \text{ for } i = 3,4 \tag{11}$$

where Q_i^1 for input x or y is the membership grade. Gaussian membership function was chosen as it has the lowest error in prediction.

Layer 2: T-norm operator connects every rule in this layer between inputs that performs as an 'AND' operator as in Eq. (11).

$$Q_i^2 = w_i = \mu_{\text{Ai}}(x), \mu_{\text{Bi}}(y) \text{for } i = 1,2 \tag{12}$$

Layer 3: ''Normalized firing strength'' is the output in this layer and every neuron is labeled as in Eq. (12).

$$Q_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,\ 2 \tag{13}$$

Layer 4: Every node i in this layer is an adaptive node and performs the consequent of the rules as in Eq. (13).

$$Q_i^4 = \overline{w}_i (p_i x + q_i y + r_i) = \overline{w}_i f_i \tag{14}$$

p_1, q_1, r_1 are irregular parameters referred to as consequent parameters.

Layer 5: In this layer, the overall output is computed as the summation of all incoming signals as in Eq. 14.

$$Q_i^5 = \overline{w}_i (p_i x + q_i y + r_i) = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{15}$$

2.6. Performance indicators

The performance efficiency of prediction models is usually evaluated using different statistical measures, including mean square error (MSE), determination coefficient (DC), root mean square error, mean absolute percentage error (MAPE), etc. Therefore, to assess the performance efficiency of the proposed models, DC, MSE and MAPE were employed in this study. The equations of MSE, DC, and MAPE are given in Eqs. (16)–(18), respectively.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(\text{RF}_{\text{obsi}} - \text{RF}_{\text{comi}}\right)^2 \tag{16}$$

$$\text{DC} = 1 - \frac{\sum_{i=1}^{N}\left(\text{RF}_{\text{obsi}} - \text{RF}_{\text{comi}}\right)^2}{\sum_{i=1}^{N}\left(\text{RF}_{\text{obsi}} - \overline{\text{RF}}_{\text{obs}}\right)^2} \tag{17}$$

$$\text{MAPE} = \frac{1}{N}\left[\sum_{i=1}^{N}\left|\frac{\text{RF}_{\text{obsi}} - \text{RF}_{\text{comi}}}{\text{RF}_{\text{obsi}}}\right|\right] \tag{18}$$

where N is the number of data samples, while RF_{obsi}, $\overline{\text{RF}}_{\text{obs}}$ and RF_{comi} are the observed data, the average value of the observed data and computed values, respectively. DC ranges between 0 and 1, with a perfect score of 1.

3. Result and discussion

This study focuses on the comparison between linear and non-linear modeling approaches for the prediction of rainfall at Ercan Airport. Considering the data correlation analysis results (Table 2), three models, M1, M2, and M3, are developed with different input combinations, as presented in Table 3. Although the correlation results suggest that SR has a minimal influence on the rainfall, M3, which comprises all the five input parameters, shows the best performance.

The backpropagation algorithm based on Levenberg–Marquardt is used for the training of the ANN. The ANN structure used in this study has only one hidden layer; the number of hidden neurons and epochs are chosen through

Table 2
Correlation analysis of data

Parameters	WS	RH	SR	Tmax	Tmin	RF
WS	1					
RH	0.192106	1				
SR	–0.23642	–0.11485	1			
Tmax	–0.32373	–0.45548	0.84115	1		
Tmin	–0.31092	–0.4352	0.875941	0.981014	1	
RF	0.051926	0.049753	0.011835	–0.01758	–0.0139	1

Table 3
Input combinations of the models

Model	Input variables	Output
M1	WS, RH	RF
M2	WS, RH, Tmin, Tmax	RF
M3	WS, RH, Tmin, Tmax, SR	RF

trial and error. The optimal number of hidden neurons is found to be 3, 5 and 6 for M1, M2, and M3, respectively. Similarly, the ANFIS technique employs a hybrid learning optimization method to update the parameters of the FIS through learning from the data set to match the predicted output to the target output. The optimal structure of the ANFIS is established by trial and error. Table 4 presents the results obtained during the calibration and verification phases. From Table 4, it is evident that ANN and ANFIS show better performance compared to MLR for all three linear regression models during both calibration and verification phases. The time series of the predicted and observed rainfall in the verification phase are shown in Figs. 5a–c. From the plots, it can be seen that the predictions made by the ANFIS technique show greater agreement with the observed values compared to the other two techniques. This could be due to its hybrid nature in that it combines the learning capability of ANN and the ability of fuzzy inference systems to handle uncertainties, which make it more robust. The poor performance of the MLR might be linked to the fact that it relies on least-square optimization, which is more suitable for linear systems and hence cannot effectively handle the complexity and non-linearity of the rainfall dynamics.

Further examination of the results indicated that all the values of DC from the three models are above 0.9, which proved the reliability of the classical (MLR) and artificial intelligence models (ANN and ANFIS) in the forecasting of rainfall at Ercan Airport. Despite the satisfactory performance of the models, the ANFIS-based model increased the average accuracy with regard to ANN and MLR. This can be justified by considering Fig. 6a and Table 4.

According to the values of MSE and MAPE, ANFIS-M3 emerged as the best with values of MSE = 0.0021 and MAPE = 0.0016; according to the various literature, the best model is the one with the minimum values of MSE and MAPE. Figs. 6b and c demonstrate the values of MSE and MAPE for all the employed models' combinations. It can be seen from the values of the performance indicators, as shown in Table 4, that M3 has the highest accuracy among the three models, followed by M2 and M1, respectively. To understand the justification of the correlation presented in Table 2, two-dimensional Taylor plots of the best three models are presented in Fig. 7. The Taylor plots describe the relationship between two sets of data in terms of different indices such as standard deviation (SD), correlation, etc. In this regard, the closer the SD of the predicted data to the SD of the observed data, the better the accuracy of the model. Hence, the ANFIS-M3 has achieved the highest accuracy. Table 5 shows the nexus between the SD of the observed and predicted rainfall.

Table 4
Performance evaluation of MLR, ANN, and ANFIS

		Calibration			Verification		
Model	Techniques	DC	MSE	MAPE	DC	MSE	MAPE
M1	MLR	0.9950	0.0032	0.0348	0.9948	0.0036	0.0034
	ANN	0.9976	0.0031	0.0349	0.9955	0.0032	0.0042
	ANFIS	0.9961	0.0031	0.0348	0.9955	0.0031	0.0036
M2	MLR	0.9914	0.0032	0.0348	0.9948	0.0036	0.0034
	ANN	0.9961	0.0031	0.0349	0.9958	0.0029	0.0047
	ANFIS	0.9961	0.0031	0.0348	0.9959	0.0028	0.0027
M3	MLR	0.9951	0.0031	0.0349	0.9956	0.0031	0.0020
	ANN	0.9972	0.0035	0.0345	0.9972	0.0020	0.0017
	ANFIS	0.9977	0.0024	0.0349	0.9970	0.0021	0.0016

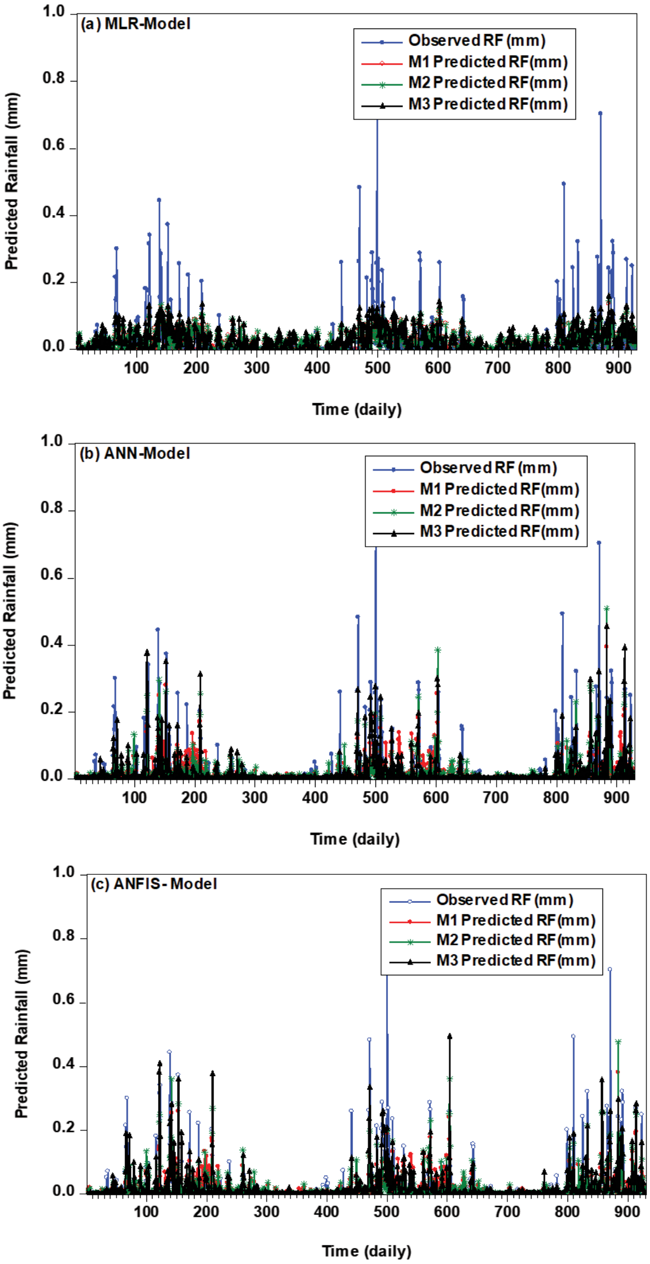

Fig. 5. Time series of the observed and predicted values for (a) MLR, (b) ANN, and (c) ANFIS.

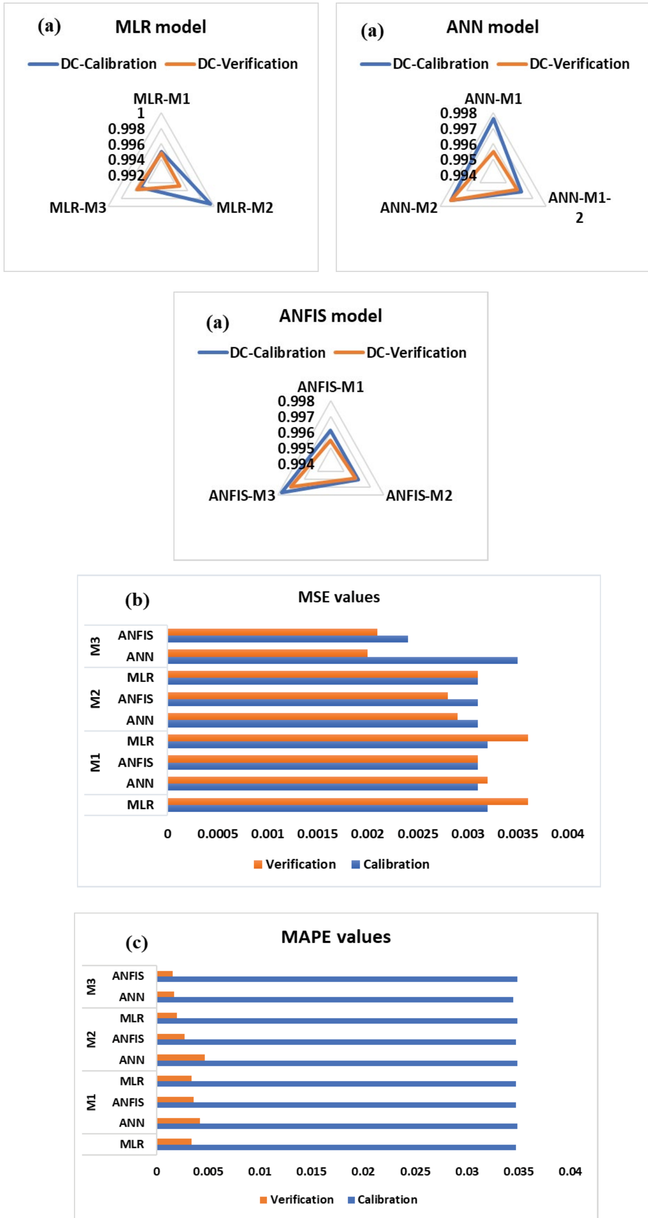

Fig. 6. Performance accuracy of (a) DC, (b) MSE, and (c) MAPE.

4. Conclusion

In this paper, a comparison of linear and non-linear modeling approaches for the prediction of daily rainfall at Ercan Airport, Northern Cyprus, has been presented. The simulation results suggest that the DC values obtained from the models are satisfactory and therefore, both the linear (MLR) and nonlinear (ANN and ANFIS) models could be applied for forecasting rainfall at Ercan Airport. However, the ANFIS model has the lowest values of MSE and MAPE and increased the average accuracy with regards to ANN and MLR. The developed ANFIS model can reliably serve as a substitute for the existing rainfall forecasting tools.

Table 5
SD values in the Taylor diagram

Techniques	Model	Predicted SD	Observed SD
MLR	M1	0.0630	0.0744
	M2	0.0652	0.0744
	M3	0.0698	0.0744
ANN	M1	0.0600	0.0744
	M2	0.0681	0.0744
	M3	0.0703	0.0744
ANFIS	M1	0.0688	0.0744
	M2	0.0708	0.0744
	M3	0.0734	0.0744

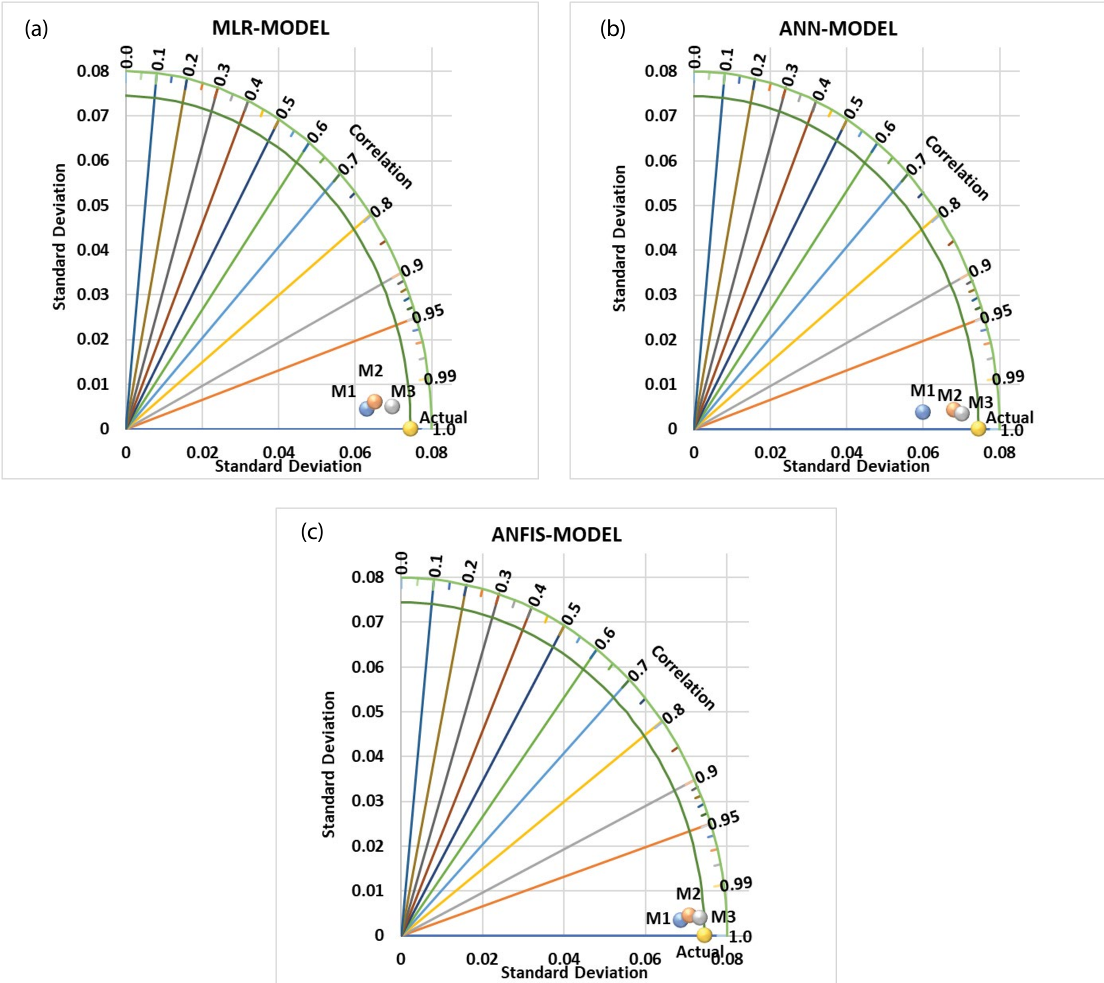

Fig. 7. Taylor plots for (a) MLR, (b) ANN, and (c) ANFIS models.

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