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Research Article

Rainfall and Atmospheric Temperature against the Other Climatic Factors: A Case Study from Colombo, Sri Lanka

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Climate prediction is given a high priority by many countries due to its importance in mitigation of extreme weather conditions. However, the prediction is not an easy task as the climatic parameters not only show spatial variations but also temporal variations. In addition, the climatic parameters are interrelated. To overcome these difficulties, soft computing techniques are widely used in prediction of climate variables with respect to the other variables. On the other hand, Colombo, Sri Lanka, is experiencing adverse or extreme weather conditions over the last few years. However, a climate prediction study is yet to be carried out in this tropical climatic zone. Therefore, this paper presents a study, identifying relationships between the two most impacted climate parameters (atmospheric temperature and rainfall) and other climatic parameters. Artificial neural network (ANN) models are developed to define the relationships and then to predict the atmospheric temperature as a function of other parameters including monthly rainfall, minimum and maximum relative humidity, and average wind speed. Same analysis is carried out to define the prediction model to the monthly rainfall. The best algorithm out of several other ANN algorithms is chosen for the analyses. Results revealed that the atmospheric temperature in Colombo can be presented with respect to the other climatic variables. However, the rainfall does not show a greater relationship with the other climatic parameters.

1. Introduction

Soft computing techniques in climate predictions have become popular in the recent years with rapidly changing climatic patterns around the world [1–4]. In recent past, soft computing techniques such as Artificial Neural Networks (ANNs), Adaptive Neuro-Fuzzy Interference System (ANFIS), Support vector machines (SVM), Data mining (DM), and Genetic Programming (GP) have been used widely in prediction models related to climatic factors [5–9]. Advantages of these methods over the conventional models include the ability to handle large amount of noisy (distorted) data from dynamic and nonlinear systems [9]. However, out of these methods, ANN and ANFIS are found to be the most popular soft computing techniques in climate prediction. ANNs are inspired by biological neural networks and designed to build complex relationships among different variables [10–12]. ANNs do not require a preassumption of the nature of the relationship between the input and output variables, and raw data transformation is not required prior to the model generation [13, 14]. ANNs are widely used for future predictions in many real-world events, and performance of the ANNs has been evaluated in literature over the past years [7, 15, 16].

With daily increasing adverse impacts of human activities, climate change has become an important topic under the radar [17]. However, predicting the future of climatic factors such as rainfall, temperature, atmospheric pressure, and wind is a time- and space-dependent complex process.

Rainfall and atmospheric temperature have random characteristics; therefore, they are often described by a stochastic process [18]. In recent past, attempts have been taken to develop prediction models for these climatic factors by merging meteorological or satellite data with prediction models and also using prediscussed soft computing techniques such as fuzzy logic or ANN [19, 20].

Literature shows many studies to predict rainfall and atmospheric temperature, which are developed using ANNs. Nair et al. [21] have employed ANN on Global Climate Model (GCM) outputs and compared the vagaries in monthly rainfall prediction in between the GCM data obtained from the International Research Institute (IRI) for Climate and Society (https://iri.columbia.edu/) and the National Centre for Environmental Prediction (https://www.ncep.noaa.gov/). They have measured the ANN performance by analyzing the absolute error, box plots, percentile, and linear error difference in the probability space. Their results showcased that ANN models have a fairly good accuracy in prediction. Kala and Vaidyanathan [22] have used ANN and Feedforward Neural Network (FFNN) to build models to predict rainfall using four climatic factors, temperature, cloud cover, vapour pressure, and precipitation. They interestingly had a Root Mean Squared Error (RMSE) of 0.254 (<0.5), which proves that the ANN model has a good accuracy in rainfall prediction.

Arabeyyat et al. [23] have simulated and predicted rainfall in semiarid regions in Jordan using the Nonlinear Autoregressive Exogenous (NARX) input model in neural networks. A possible reduction in the average rainfall over the next decade was found from this research. Further, they discovered that 2 delay inputs and 8 neurons yield the best training in the neural network based on the Mean Square Error (MSE). Chatterjee et al. [24] have proposed a novel rainfall prediction method for the southern part of West Bengal in India using two steps, greedy forward selection algorithm. This is to reduce the featured set by finding the most promising data. They proposed a two-step prediction model Hybrid Neural Network (HNN) and compared it with MLP-FFN. Results revealed that the HNN model has performed at an acceptable accuracy in predicting rainfall.

Esteves et al. [25] have presented soft computing technique to forecast rainfall using ANN and applied it to 10 agricultural areas in Brazil. They found out that the effects of continentality, altitude, and volume of the normal precipitation have direct impact on the accuracy of the ANNs. Further, they pointed out that the model has its peak performance in well-defined seasons and less accuracy in transitional seasons. On the other hand, El-Shafie et al. [26] have developed two rainfall prediction models for Alexandria, Egypt, using ANN and Multiregression (MLR). They have developed a FFNN model to predict yearly and monthly rainfall to evaluate the two models based on statistical parameters RMSE and Mean Absolute Error (MAE). Their results clearly showed that the FFNN model has outperformed the MLR model. They also have shown that even though the ANN model is a nonlinear model, it is still potentially suitable for rainfall forecasting.

Similar studies can be found in predicting the atmospheric temperature using ANN. Altan Dombaycı and Gölcü [27] have developed an ANN model to predict daily mean ambient temperature in Denizli, Turkey, using temperature data obtained from the Turkish State Meteorological Service. They have predicted the temperature by varying the number of hidden layer neurons using Levenberg–Marquardt (LM) feedforward back propagation algorithm. The study has revealed that the ANN approach is a reliable model for ambient temperature prediction. In contrast, Baboo and Shereef [28] have built an ANN model to predict temperature with Back Propagation Neural Network (BPN). They considered the atmospheric pressure, atmospheric temperature, relative humidity, wind velocity, and wind direction data as the inputs. Their results have shown that the model has not only outperformed the forecasting numerical models but also the official local weather service forecasts also. Furthermore, Abhishek et al. [29], Devi et al. [30], and Olaiya and Adeyemo [31] are few other examples to predict future weather events and climate changes using ANN approaches.

There are several attempts in the literature for modeling the rainfall prediction to Sri Lanka. Punyawardena and Kulasiri [32] and Perera et al. [33] are couple of examples for statistical models while Kumarasiri and Sonnadara [34] and Weerasinghe et al. [35] are examples for soft computational models used in predicting rainfall. However, no comprehensive research has done to predict rainfall and atmospheric temperature in Colombo area, using soft computing techniques. Therefore, identifying that research gap, a soft computing-based ANN model was applied to Colombo city to find the relationships among the climatic parameters, including rainfall and atmospheric temperature.

2. Artificial Neural Network (ANN) Training Algorithms

ANNs are commonly used as a soft computing technique around the world to predict numerous real-world scenarios. Local or global nonlinear optimization methods are used in these ANN algorithms to optimize feedforward neural network weights. However, only local solutions are available through local searches, while global searches avoid this limitation [36]. The training algorithms used to train the proposed ANN are Levenberg–Marquardt (LM), Bayesian Regularization (BR) and Scaled Conjugate Gradient (SCG), BFGS Quasi-Newton (BFG), Resilient backpropagation (RP), Conjugate gradient with Powell–Beale restarts (CGB), Fletcher–Powell conjugate gradient (CGF), Polak–Ribiere conjugate gradient (CGP), and One-step secant (OSS) [37–39]. In an ANN, the objective of the training process is to reduce the global error (E) defined as follows [40]:

$$E = \frac{1}{P}\sum_{n=1}^{P} E_n, \tag{1}$$

where P is the total number of training patterns and E_n is the error for training pattern n. E_n is calculated using the following equation:

$$E_n = \frac{1}{2}\sum_{k=1}^{N} \left(O_k - t_k\right)^2, \tag{2}$$

where N is the total number of output nodes, O_k is the network output at the k^{th} output node, and t_k is the target output at the k^{th} output node. The global error can be reduced by adjusting the weights and biases in the training algorithms [40]. The O_k is calculated based on the user-defined algorithms whereas t_k is the observed or measured values of the same variable in O_k.

Detailed explanations of the various algorithms (Levenberg–Marquardt, BFGS Quasi-Newton backpropagation, Scaled conjugate gradient backpropagation, Resilient backpropagation, Conjugate gradient with Powell–Beale restarts, Fletcher–Reeves and Polak–Ribiere conjugate gradient, and One-step secant) used in ANN are given by Perera et al. [41]. However, LM is the most commonly used optimization algorithm for the climate predictions.

3. Levenberg–Marquardt (LM) Algorithm

The Levenberg–Marquardt (LM) optimization algorithm is identified to be more powerful than the conventional gradient descent techniques. It is the most widely used optimization algorithm and designed to approach the second-order training speed without computing the Hessian matrix [42]. The Hessian matrix can be approximated when the performance function is in the form of sum of squares and is given in the following equation:

$$H = J^T J, \tag{3}$$

where **J** is the Jacobian matrix, containing the first derivatives of the network errors with respect to the weights and biases.

The standard backpropagation technique is used to compute the Jacobian matrix, which is less complex than computing the Hessian matrix. Equation (4) gives the Newton-like update used in the LM algorithm. When $\mu = 0$, this is Newton's method, using the approximate Hessian matrix:

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e, \tag{4}$$

where $\boldsymbol{e}$ is a vector of network errors, μ is a scalar quantity, $\mathbf{x_{k+1}}$ is the predicted minimizer, and $\mathbf{x_k}$ is the current point.

4. BFGS Quasi-Newton Backpropagation (BFG) Algorithm

The BFGS Quasi-Newton algorithm uses Newton's method given in equation (5), where H^{-1} is the Hessian matrix of the performance index at the current values of the weights and biases (usual notations are used here).

$$x_{k+1} = x_k - H^{-1} g. \tag{5}$$

BFGS method does not calculate the 2^{nd} derivatives. However, an approximate Hessian matrix is updated in each iteration of the algorithm. This update is calculated as a function of the gradient. Superlinear convergence rate is observed in the BFGS method on most practical problems, even though the algorithm requires more computations and storage in each of the iterations performed. The Bayesian regularization is also widely used in the ANN architecture. It is a mathematical process which transfers a nonlinear regression into a statistical problem [43]. Overfitting and overtraining are two major issues in the backpropagation neural networks; therefore, the Bayesian regularization reduces these errors [35, 44].

4.1. Other Algorithms Considered. Resilient backpropagation (RP) is a backpropagation algorithm which is used to train the neural network. It is faster and does not need to specify any free parameter values. However, it is a complex algorithm. Conjugate gradient backpropagation with Powell–Beale (CGB) uses Powell–Beale algorithm which is an improvement of the Beale algorithm. Fletcher–Powell conjugate gradient (CGF) belongs to the conjugate gradient method of training neural networks similar to the CGB; however, it follows Fletcher–Powell algorithm. Polak–Ribiere Conjugate Gradient (CGP) is another conjugate gradient method which uses a different algorithm. Therefore, conjugate algorithms are further developed using several algorithms to train the neural networks. Scaled Conjugate Gradient (SCG) is used in feedforward neural networks. The algorithm is a supervised learning algorithm and also uses principles of conjugate gradient methods. On the other hand, One-Step Secant algorithm (OSS) is similar to BFGS Quasi-Newton backpropagation; however, it does not need to store a large Hessian matrix.

4.2. ANN in MATLAB Environment. ANN models were developed using MATLAB numerical computing environment (version 8.5.0.197613—R2015a) to predict atmospheric temperature and rainfall using the above stated training algorithms. Therefore, the dependent variables of the models are monthly average atmospheric temperature and the monthly cumulative rainfall. Atmospheric pressure, minimum and maximum relative humidity, average wind speed, and average temperature and rainfall were used as input variables to train the networks. The independent variables for the prediction of atmospheric temperature in a particular month were atmospheric pressure, relative humidities, wind speeds, and monthly cumulative rainfalls of the same month. However, the atmospheric temperatures and monthly cumulative rainfalls were swapped for the prediction of rainfall. The nonlinear autoregressive network with exogenous inputs (NARX) was used as the input model to predict $\mathbf{y(t)}$ with $\mathbf{d}$ past values of $\mathbf{y(t)}$ and $\mathbf{y(t)}$, where $\mathbf{x(t)}$ depends on different $\mathbf{x(t)}$ parameters for series of time steps, and $\mathbf{x(t)}$ is an independent parameter for different times steps, and $\mathbf{d}$ is the number of past values of $\mathbf{x(t)}$ which are used for training. The ANN was trained with 60% of target time-steps while 20% each of target time-steps was used to validate and test. In addition, 10 hidden neurons and 2 delays were used in the network as shown in Figure 1. MSE and correlation coefficient (R) were used to measure the performance of the developed models to predict average temperature and rainfall.

4.3. Case Study, Colombo, Sri Lanka. Sri Lanka, being an island having an approximate area of 65,610 km^2, is located in

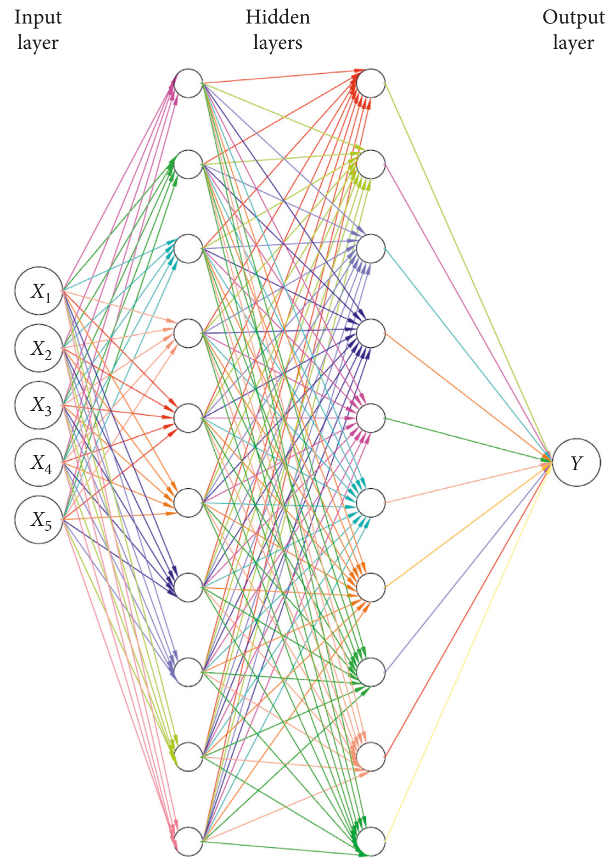


Figure 1: Architecture of the developed neural network.

the southeast of the Indian subcontinent. Climate of Sri Lanka is mainly governed by its monsoonal regime and tropical location (Kumarasiri and Sonnadara [34]). Sri Lanka experiences four rainfall seasons namely, northeast monsoon from December to February, 1st intermonsoon from March to April, southwest monsoon from May to September, and 2nd intermonsoon from October to November [5]. Colombo is the main city and the capital of Sri Lanka and it is in the west side of the island. Figure 2 shows the Google-based map of Colombo which has a land area of 37.31 km^2. Colombo is in the wet zone of Sri Lanka and receives higher annual precipitation. However, it has a warm tropical temperature pattern. Since 5 to 10 years ago, residents in Colombo have experienced impact of climate variabilities, including intensified rainfall causing floods and also higher daytime and nighttime atmospheric temperatures.

Therefore, it is highly important to understand the physics in the atmosphere in predicting the climate patterns for Colombo due to many reasons, including tourism-related aspects, control of electricity usage, and control of water supply. Therefore, we developed these ANN models to support the understanding of physics in climate variabilities in Colombo.

Monthly weather data were collected for Colombo city for 57 years spanning from 1961 to 2017 from the Department of Meteorology, Sri Lanka. Atmospheric pressure, minimum and maximum relative humidity, average wind speed, average temperature, and monthly rainfall data were collected for the analysis. These data were fed to the developed ANN algorithms to predict rainfall and average temperature as functions of other climatic parameters.

The analysis has also been carried out to the extreme weather conditions. There were no extreme temperature records in the temperature measurements to the city of Colombo over the past years. In other words, average monthly temperatures were below 30°C. However, there were several extreme rainfall events. A threshold value of 500 mm per month was considered as the lower margin of the extreme event for the demonstration purposes. There were 38 extreme rainfall months in total out of 684 months. The maximum rainfall of them is 971.5 mm occurred in November 2010. These extreme rainfall events were developed as a function corresponding to other climatic parameters.

5. Results and Discussion

5.1. Atmospheric Temperature as a Function of Other Climatic Parameters. Table 1 shows the correlation coefficients (R values) depicting the performance of the neural networks trained to predict atmospheric temperature using different training algorithms. It shows that BFG and LM training algorithms (highlighted) have performed slightly better compared with other algorithms with R values (>0.7). However, other algorithms also have shown fairly successful in predicting atmospheric temperature with higher R values

Figure 2: Map of Colombo, Sri Lanka (source: Google maps).

Table 1: Correlation coefficients for different algorithms for atmospheric temperature.

ANN algorithm	Correlation coefficient			
	Training	Validation	Test	All
BFG	**0.71**	**0.72**	**0.82**	**0.73**
CGB	0.67	0.6	0.66	0.65
CGF	0.71	0.77	0.41	0.67
CGP	0.6	0.72	0.67	0.62
LM	**0.75**	**0.76**	**0.57**	**0.72**
OSS	0.65	0.72	0.76	0.68
RP	0.78	0.58	0.52	0.68
SCG	0.72	0.59	0.54	0.63

in acceptable range. Nevertheless, the BFG algorithm shows the best result.

Figures 3(a)–3(d) give the results of the ANN model trained using the BFG algorithm. The figures show the predicted atmospheric temperature values against the observed data. It can be clearly seen that the predicted temperature values are underpredicted due to the lowering gradient of the trend line. However, the algorithm shows acceptable results in validation process. It has a correlation coefficient of 0.721. Therefore, the developed model using the BFG algorithm produces acceptable results for the atmospheric prediction.

Similar observations can be seen in CGF and LM algorithms (refer Figures 4 and 5). Both show the underpredicting behavior of the atmospheric temperature from the analysis. Therefore, the prediction provides a slight decreased atmospheric temperature value than the real value. Therefore, the people in Colombo city should be ready for increased atmospheric temperatures than those were predicted. This can be clearly seen in the real world as well, thus, the feelable atmospheric temperature around Colombo is more than the expected.

Table 2 shows the validation performance of different training algorithms used for atmospheric temperature prediction. CGB, CGP, and LM have converged to better

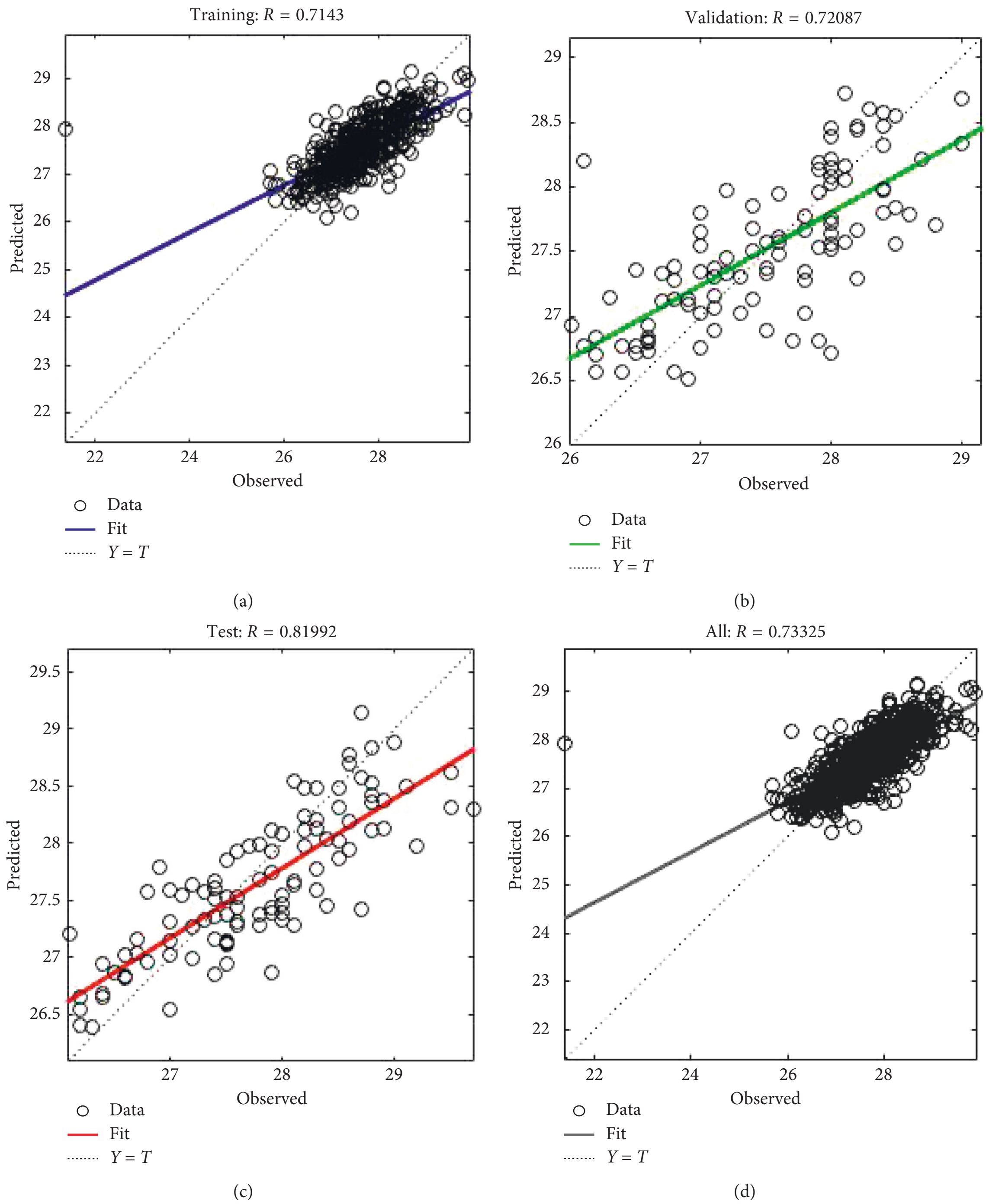


FIGURE 3: Correlation coefficients for the BFG algorithm for the atmospheric temperature case. (a) For training. (b) For validation. (c) For test. (d) For all.

perform faster than the other algorithms. However, the mean square error (MSE) of CGB is higher than the BFG, CGF, and LM algorithms. It can be summarized that the BFG and LM algorithm produce better solutions in lowered computational time by comparing the MSE values and number of epochs. Therefore, as a conclusion, it is clear that BFG and LM have outperformed other algorithms in predicting atmospheric temperature.

Furthermore, the graphical representation of the validation performance for the BFG and LM training algorithms is shown in Figure 6. It is clear that the developed ANN architecture for BFG and LM algorithms performs effectively in predicting atmospheric temperature since MSE has approached close to zero in lesser number of epochs while having an acceptable correlation coefficient.

5.2. Monthly Rainfall as a Function of Other Climatic Factors. Monthly rainfall was clustered into 12 months and then analyzed to identify the relationship among other climatic

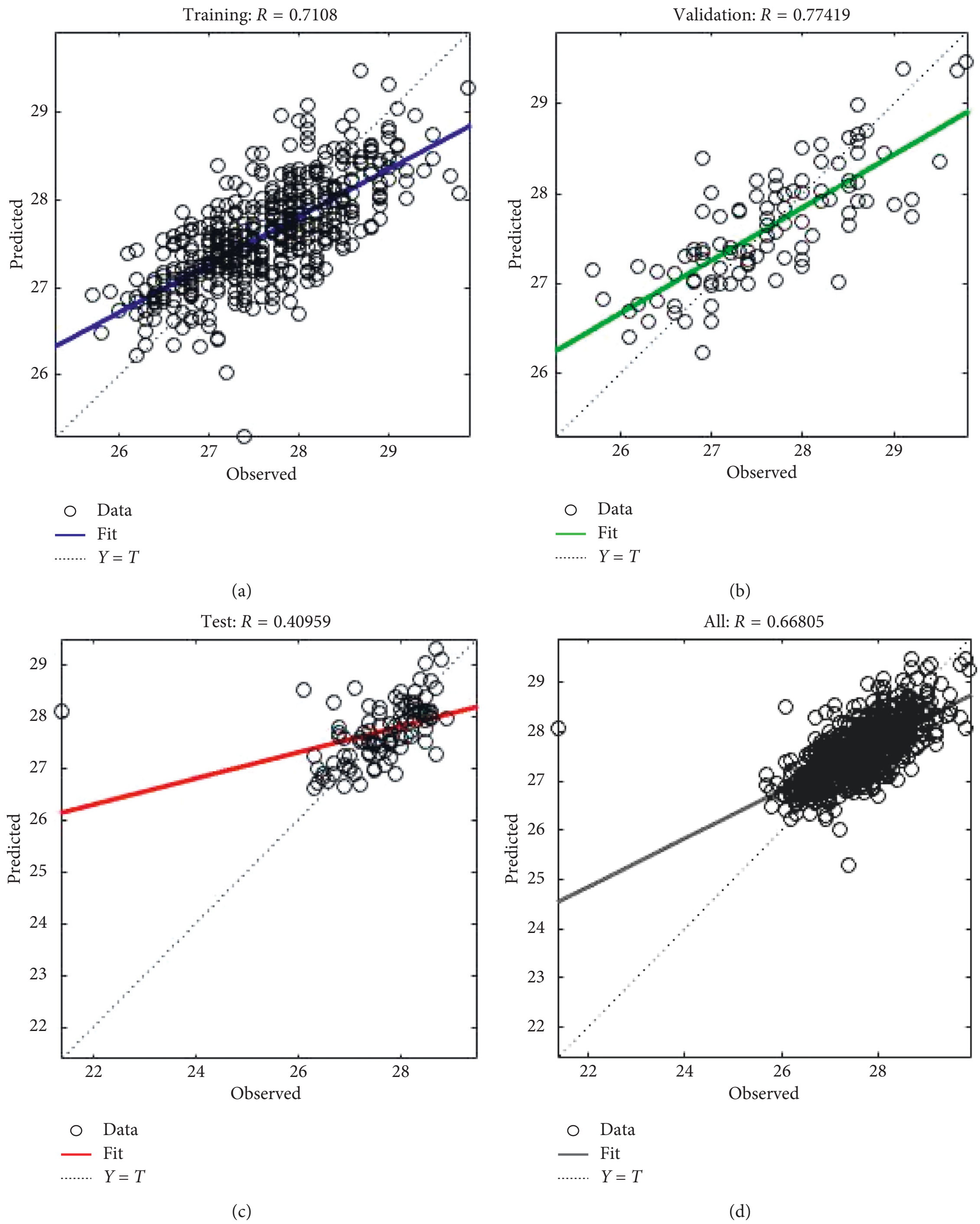


Figure 4: Correlation coefficients for the CGF algorithm for the atmospheric temperature case. (a) For training. (b) For validation. (c) For test. (d) For all.

parameters (12 ANN analyses for 12 months). However, the results are not promising. A direct link among the other climatic parameters (atmospheric temperature, relative humidity, atmospheric pressure, and wind) was not found. For some months like January with the LM algorithm (refer Figures 7(a) and 7(b)) and July with the SCG algorithm have shown slight agreement on a relationship among other climatic parameters; however, in general, the relationship is inconclusive. The correlation coefficients are around 0.4–0.6.

Figure 8 presents the July rainfall analysis performance for the SCG training algorithm. As it was stated above, a marginal acceptance can be seen with correlation coefficients (0.4–0.6). These were the best results obtained for the rainfall prediction using ANN for Colombo city. Even though we

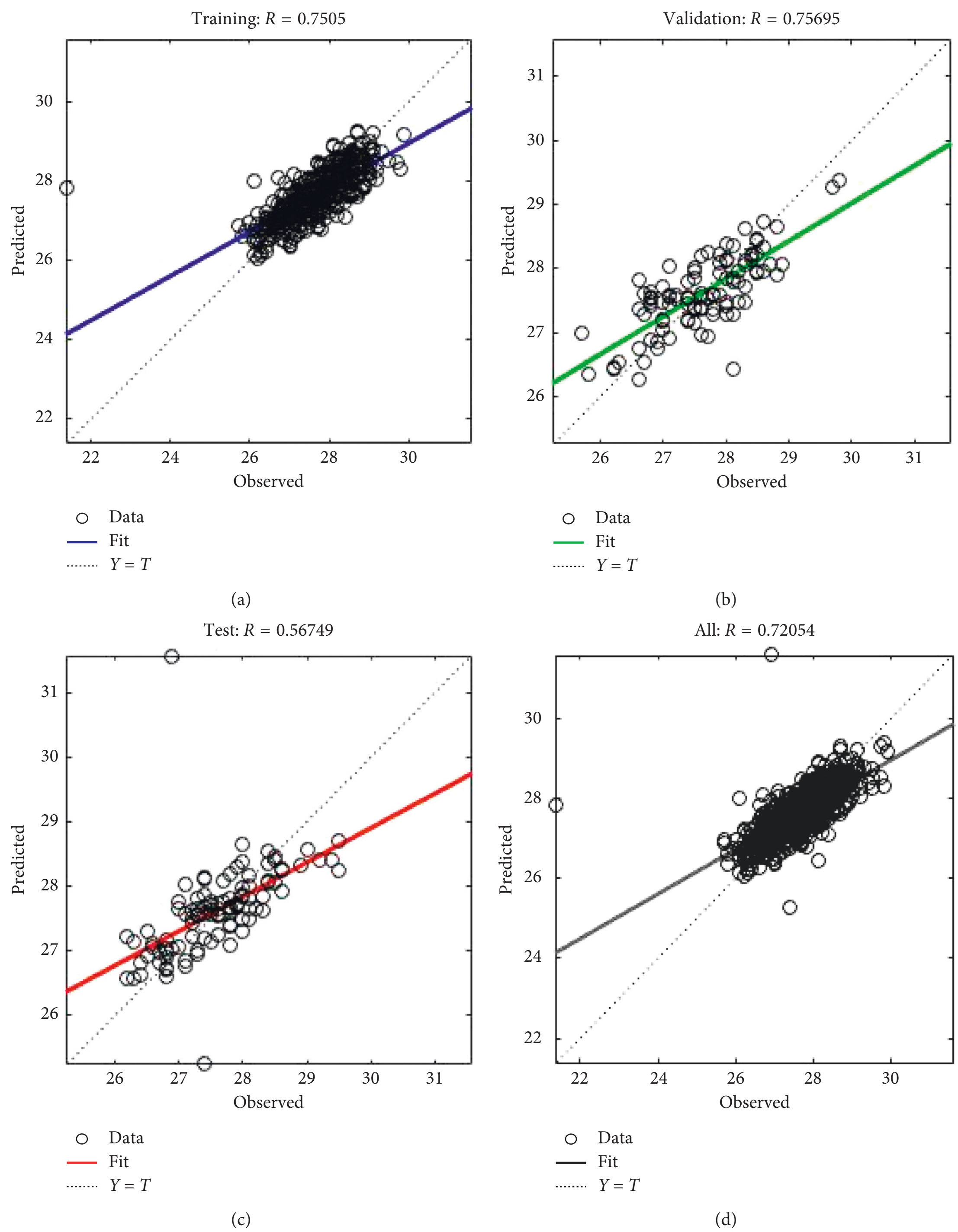


Figure 5: Correlation coefficients for the LM algorithm for the atmospheric temperature case. (a) For training. (b) For validation. (c) For test. (d) For all.

have marginal correlation coefficients, the MSE values for these analyses are unacceptable. LM algorithm gives 11908 of MSE for the month of January while SCG gives 5052 of MSE for the month of July. Average monthly rainfall for Colombo in January and July is **75 mm** and **135 mm**, respectively. Therefore, the errors are unacceptable for the rainfall measurements and predictions.

Figures 9(a)–9(f) illustrate some of the unsuccessful results from the analysis in predicting rainfall as a function of other climatic variables. Figure 9(a) shows a good correlation coefficient to the LM algorithm in the month of November; however, the validation correlation coefficient is -0.32 (refer Figure 9(b)). Therefore, this is an unacceptable test result. Even though the model is ready to predict the

Table 2: Validation performance.

ANN algorithm	MSE	Number of epoch
BFG	0.26	17
CGB	0.36	5
CGF	0.3	19
CGP	0.38	2
LM	0.25	6
OSS	0.28	10
RP	0.67	68
SCG	0.55	49

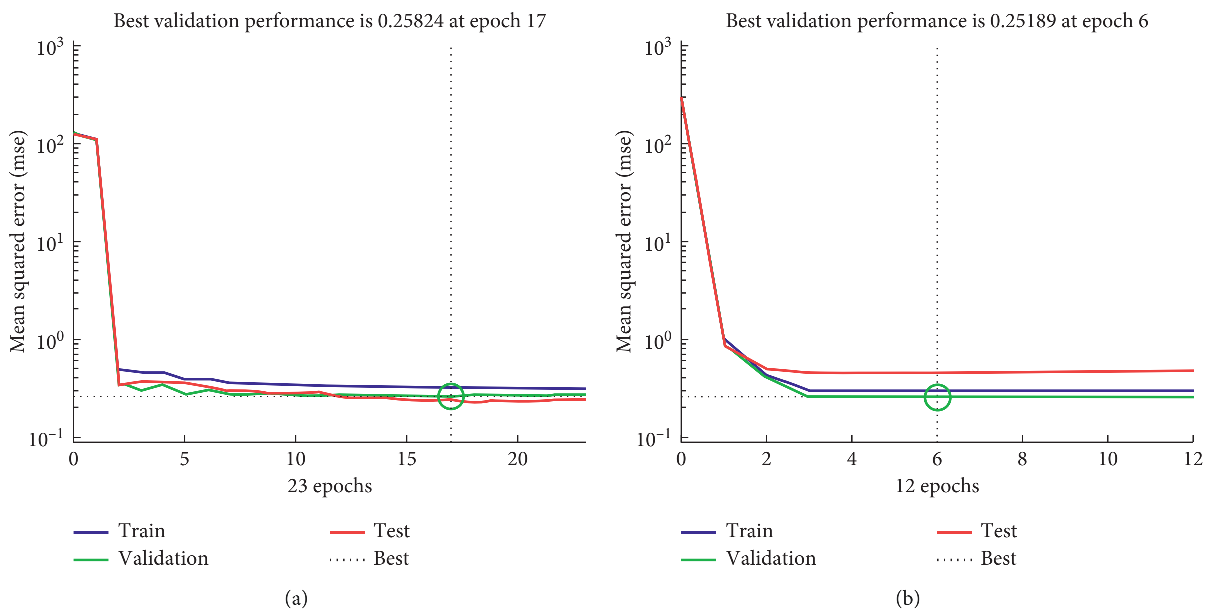


Figure 6: Performance for BFG and LM algorithms. (a) For the BFG algorithm. (b) For the LM algorithm.

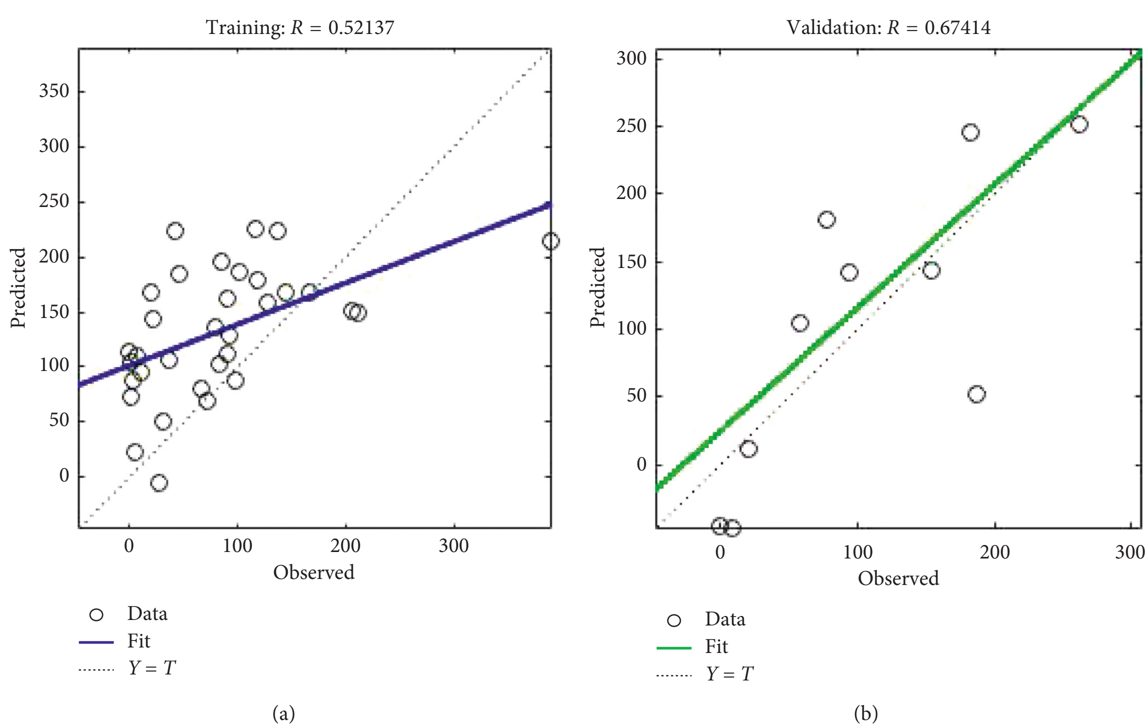


Figure 7: Monthly rainfall analyses for January under the LM algorithm. (a) For training. (b) For validation.

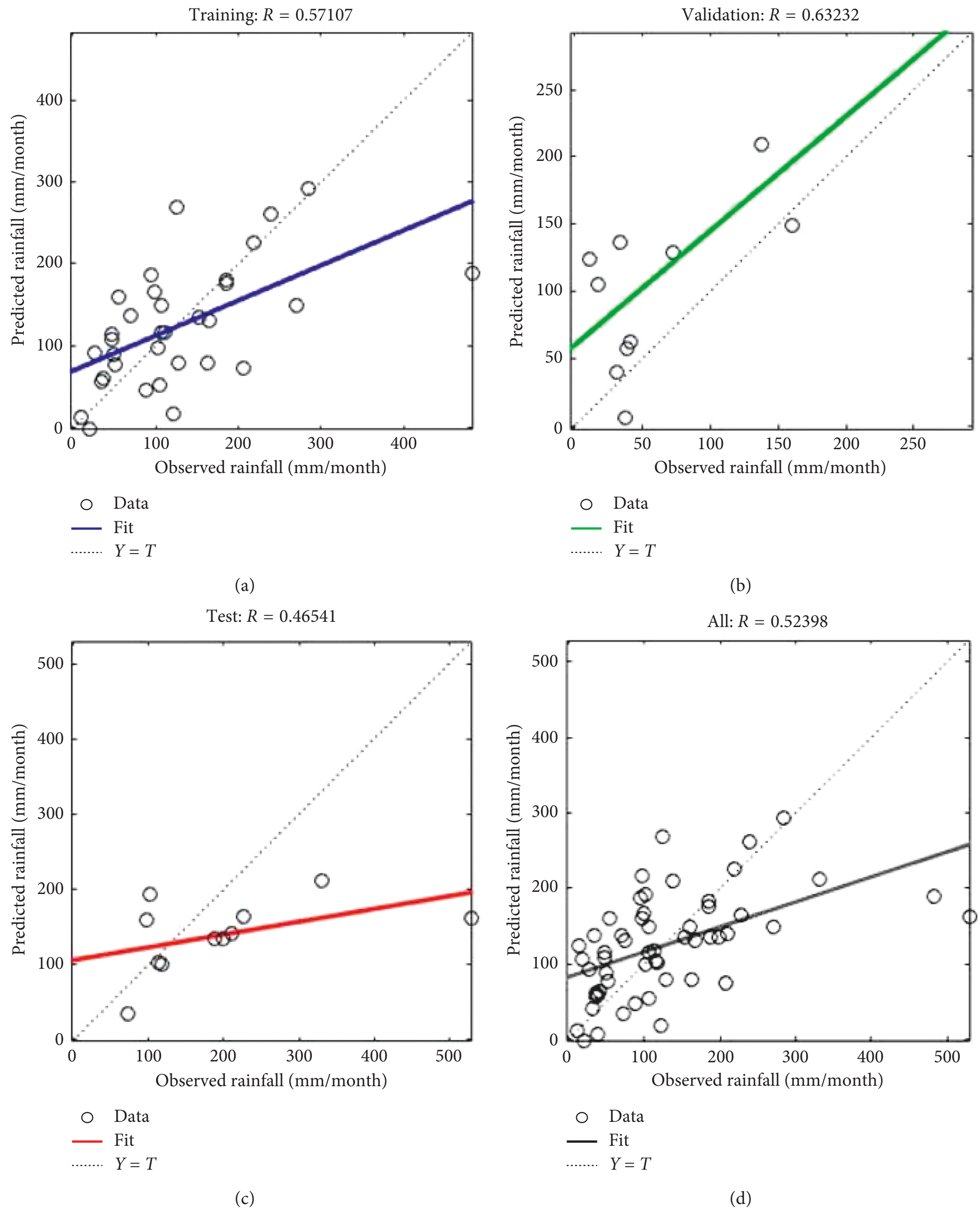


FIGURE 8: Monthly rainfall analysis for July under the SCG algorithm. (a) For training. (b) For validation. (c) For test. (d) For all.

rainfall in the month of November, and it cannot be validated. Therefore, this is a failure. Figures 9(c)–9(f) show similar results for different algorithms in different months. Failures can be observed even in the training of the neural network.

5.3. Extreme Rainfall Events as a Function of Other Climatic Factors. Figure 10 illustrates the correlation coefficients for the predicted and observed extreme rainfall events over the 57 years. The presented correlation coefficients are for the LM algorithm. However, unlike the regular rainfalls, there is an acceptable correlation for the extreme rainfall events. Therefore, the extreme rainfall events can be predicted using the other climatic parameters to some extent. This is interesting as the authorities are more concerned on the extreme events rather than the regular events.

However, there were no extreme events recorded for the last 57 years for the monthly average atmospheric temperatures for Colombo. There may be few extreme events in

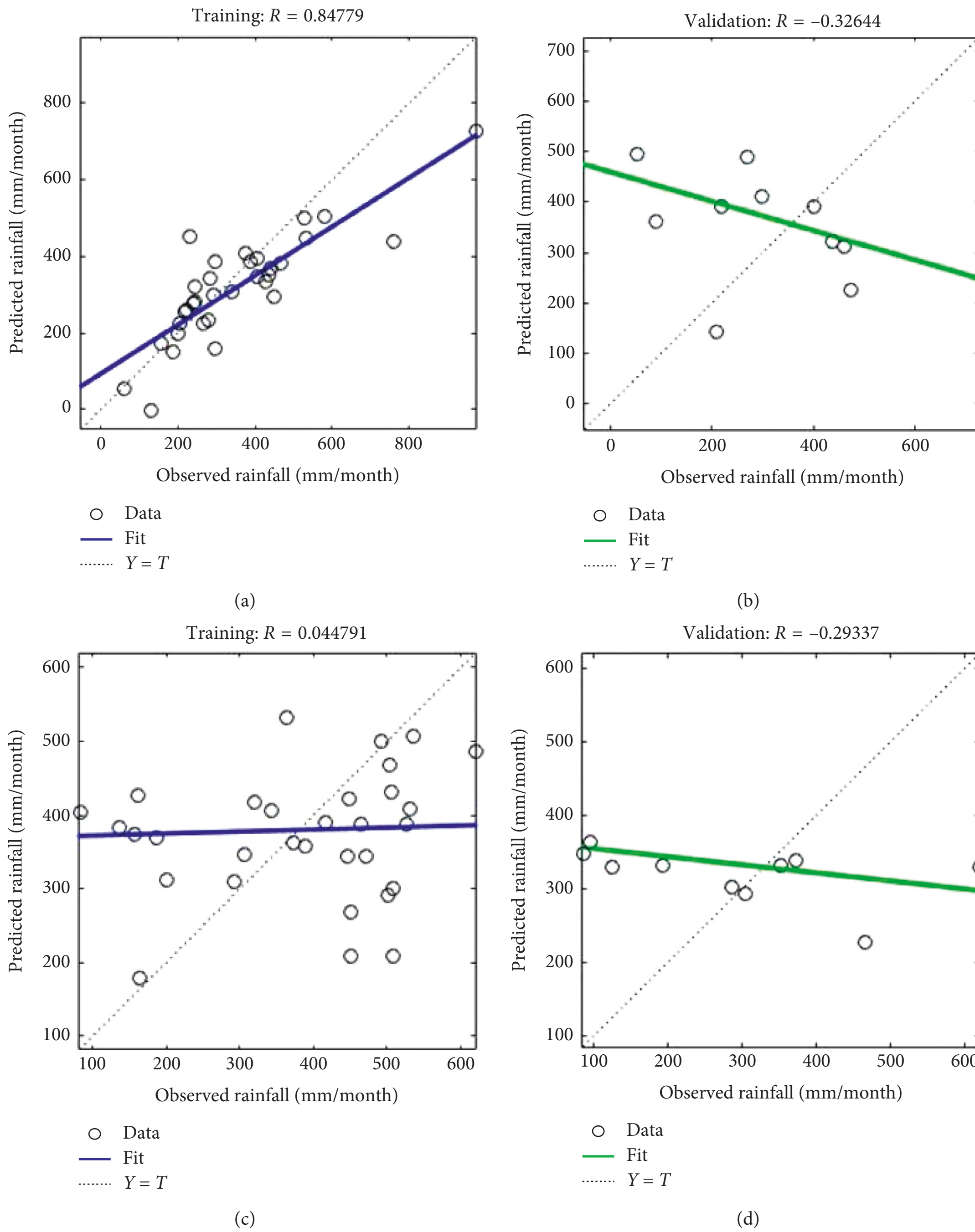


FIGURE 9: Continued.

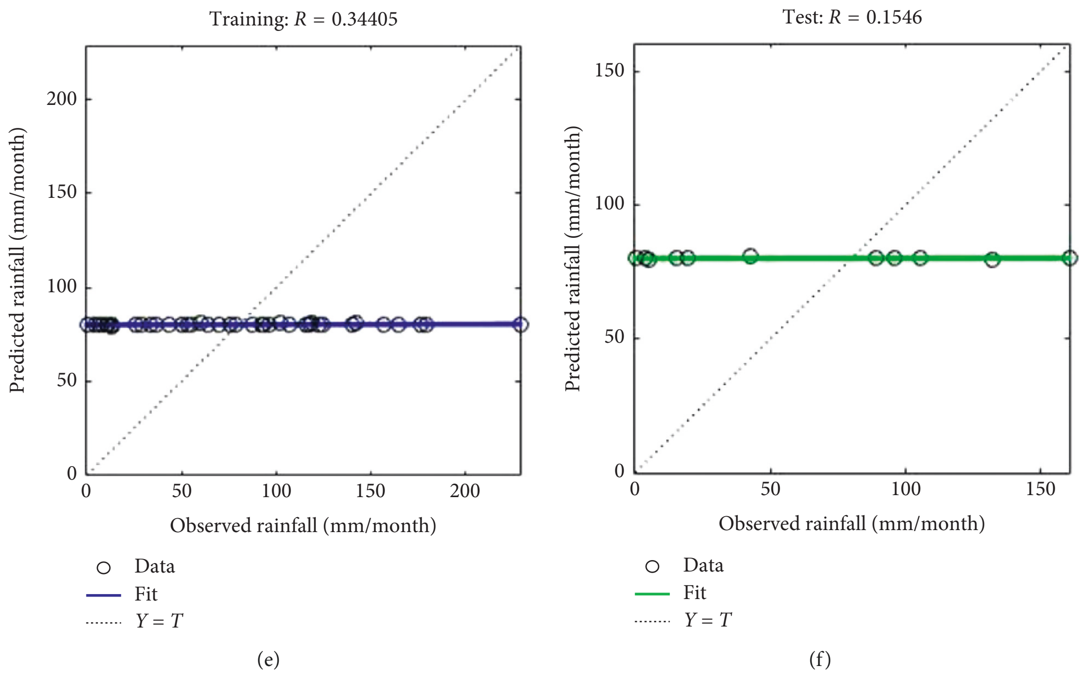


Figure 9: Unsuccessful results from several analyses. (a) Training (LM, Nov). (b) Validation (LM, Nov). (c) Training (SCG, Oct). (d) Validation (SCG, Oct). (e) Training (BFG, Feb). (f) Test (BFG, Feb).

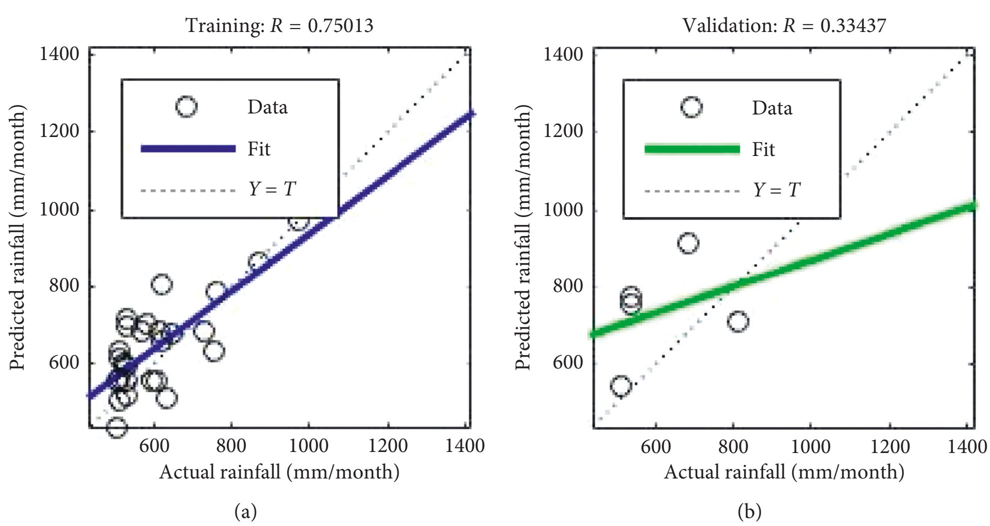
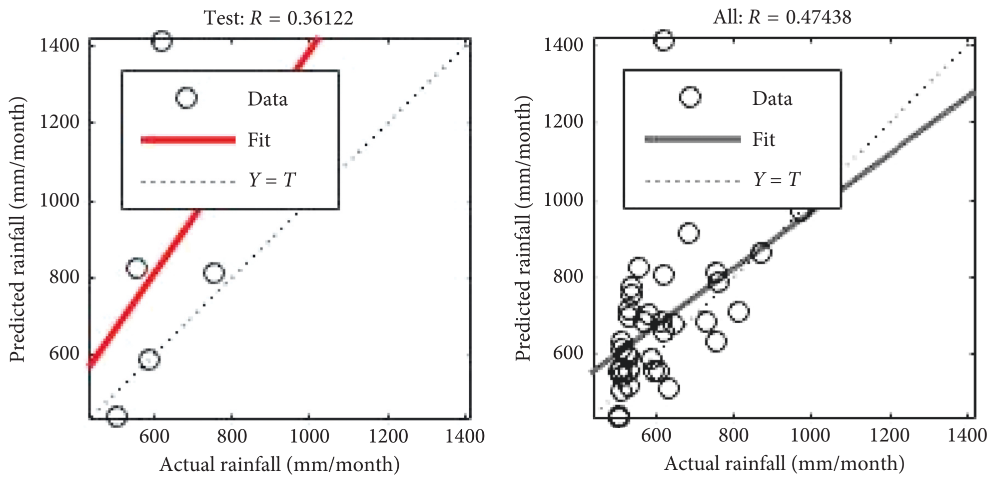


Figure 10: Continued.



(c) (d)

FIGURE 10: Extreme rainfall analyses under the LM algorithm. (a) Training. (b) Validation. (c) Test. (d) All.

atmospheric temperature for higher resolutions in the durations; for example, in daily temperatures or hourly temperatures.

6. Conclusions

Soft computing techniques were applied in identifying the climatic variables in a tropical environment, Colombo, Sri Lanka. Atmospheric temperature and monthly rainfall were identified as the two most important climatic parameters to predict as functions of other climatic parameters. The results show a good correlation in predicting atmospheric temperature with respect to other climatic parameters, including monthly rainfall, atmospheric pressure, minimum and maximum relative humidity, and average wind speed. LM and BFG algorithms produce better results, and BFG is the best out of them. Therefore, the neural model is ready for the future predictions in atmospheric temperature, and the results are highly important for the future energy demand, specifically in controlling the air conditions in the working environments at the energy crisis in Sri Lanka. However, a clear link between the monthly rainfall and the other climatic parameters could not be found. Results revealed that none of the algorithms produces acceptable results at a better computational cost. Therefore, it can be concluded herein that the monthly rainfall does not correlate with the considered other climatic parameters. However, future research is highly encouraged to find the better relationships. It would be better to incorporate the climate of the Indian Ocean to predict the rainfall in Colombo. However, the extreme rainfall events can be predicted with the usage of other climatic parameters. This is important. The controllers, environmentalists, and even the generic public are concerned on extreme rainfall events in Colombo due to flash floods in roads.

In addition, the model can be further implemented for the future climate prediction. The climate data can be obtained from various prediction models (global climate models-GCMs), and then the required climatic parameter can be predicted using the same model. For example, the future temperature in Colombo can be predicted using the GCM data for future years.

Data Availability

The climatic data and the analysis data are available from the corresponding author upon request.

Disclosure

The research was carried out in the Sri Lanka Institute of Information Technology environment.

Conflicts of Interest

The authors declare that there are no conflicts of interest. The first author was a bachelor's student of the Civil Engineering Degree Program, while the corresponding author is a senior lecturer in the Faculty of Engineering, Sri Lanka Institute of Information Technology, Sri Lanka.

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References

[1] N. Acharya, N. Shrivastava, B. Panigrahi, and U. Mohanty, "Development of an artificial neural network based multi-model ensemble to estimate the northeast monsoon rainfall over south peninsular India: an application of extreme learning machine," *Climate Dynamics*, vol. 43, no. 5-6, pp. 1303–1310, 2013.

[2] A. Belayneh, J. Adamowski, B. Khalil, and B. Ozga-Zielinski, "Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models," *Journal of Hydrology*, vol. 508, pp. 418–429, 2014.

[3] S. Moghim and R. L. Bras, "Bias correction of climate modeled temperature and precipitation using artificial neural networks," *Journal of Hydrometeorology*, vol. 18, no. 7, pp. 1867–1884, 2017.

[4] N. Mishra, H. Kumar Soni, S. Sharma, and A. K. Upadhyay, "Development and analysis of artificial neural network models for rainfall prediction by using time-series data," *International Journal of Intelligent Systems and Applications*, vol. 10, no. 1, pp. 16–23, 2018.

[5] D. A. K. Fernando and A. W. Jayawardena, "Runoff forecasting using RBF networks with OLS algorithm," *Journal of Hydrologic Engineering*, vol. 3, no. 3, pp. 203–209, 1998.

[6] G. Tayfur and V. P. Singh, "ANN and fuzzy logic models for simulating event-based rainfall-runoff," *Journal of Hydraulic Engineering*, vol. 132, no. 12, pp. 1321–1330, 2006.

[7] Ö. Kişi, "River flow forecasting and estimation using different artificial neural network techniques," *Hydrology Research*, vol. 39, no. 1, pp. 27–40, 2008.

[8] O. Kisi, J. Shiri, and M. Tombul, "Modeling rainfall-runoff process using soft computing techniques," *Computers & Geosciences*, vol. 51, pp. 108–117, 2013.

[9] Z. He, X. Wen, H. Liu, and J. Du, "A comparative study of artificial neural network, adaptive neuro fuzzy inference system and support vector machine for forecasting river flow in the semiarid mountain region," *Journal of Hydrology*, vol. 509, pp. 379–386, 2014.

[10] E. Betiku, S. S. Okunsolawo, S. O. Ajala, and O. S. Odedele, "Performance evaluation of artificial neural network coupled with generic algorithm and response surface methodology in modeling and optimization of biodiesel production process parameters from shea tree (Vitellaria paradoxa) nut butter," *Renewable Energy*, vol. 76, pp. 408–417, 2015.

[11] H. Ebrahimi and T. Rajaee, "Simulation of groundwater level variations using wavelet combined with neural network, linear regression and support vector machine," *Global and Planetary Change*, vol. 148, pp. 181–191, 2017.

[12] M. Ravansalar, T. Rajaee, and O. Kisi, "Wavelet-linear genetic programming: a new approach for modeling monthly streamflow," *Journal of Hydrology*, vol. 549, pp. 461–475, 2017.

[13] S. Agatonovic-Kustrin and R. Beresford, "Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research," *Journal of Pharmaceutical and Biomedical Analysis*, vol. 22, no. 5, pp. 717–727, 2000.

[14] S. Ibrić, M. Jovanović, Z. Djurić et al., "Artificial neural networks in the modeling and optimization of aspirin extended release tablets with eudragit L 100 as matrix substance," *AAPS PharmSciTech*, vol. 4, no. 1, pp. 62–70, 2003.

[15] P. Nayak, K. Sudheer, D. Rangan, and K. Ramasastri, "A neuro-fuzzy computing technique for modeling hydrological time series," *Journal of Hydrology*, vol. 291, no. 1-2, pp. 52–66, 2004.

[16] X. Wang, F. Liu, Y. Gao, C.-h. Xue, R. W. Li, and Q.-j. Tang, "Transcriptome analysis revealed anti-obesity effects of the Sodium Alginate in high-fat diet -induced obese mice," *International Journal of Biological Macromolecules*, vol. 115, pp. 861–870, 2018.

[17] R. Field, M. Luo, D. Kim, A. Del Genio, A. Voulgarakis, and J. Worden, "Sensitivity of simulated tropospheric CO to subgrid physics parameterization: a case study of Indonesian biomass burning emissions in 2006," *Journal of Geophysical Research: Atmospheres*, vol. 120, no. 22, pp. 11,743–11,759, 2015.

[18] R. Venkata Ramana, B. Krishna, S. R. Kumar, and N. G. Pandey, "Monthly rainfall prediction using wavelet neural network analysis," *Water Resources Management*, vol. 27, no. 10, pp. 3697–3711, 2013.

[19] C. W. Dawson and R. L. Wilby, "Hydrological modelling using artificial neural networks," *Progress in Physical Geography*, vol. 25, no. 1, pp. 80–108, 2001.

[20] P. Hettiarachchi, M. J. Hall, and A. W. Minns, "The extrapolation of artificial neural networks for the modelling of rainfall-runoff relationships," *Journal of Hydroinformatics*, vol. 7, no. 4, pp. 291–296, 2005.

[21] A. Nair, G. Singh, and U. C. Mohanty, "Prediction of monthly summer monsoon rainfall using global climate models through artificial neural network technique," *Pure and Applied Geophysics*, vol. 175, no. 1, pp. 403–419, 2017.

[22] A. Kala and S. Vaidyanathan, "Prediction of rainfall using artificial neural network," in *Proceedings of the International Conference on Inventive Research in Computing Applications (ICIRCA 2018)*, pp. 339–342, Coimbatore, India, June 2018.

[23] O. Arabeyyat, N. Shatnawi, and M. Matouq, ""Nonlinear multivariate rainfall prediction in Jordan using NARX-ANN model with GIS techniques'," *Jordan Journal of Civil Engineering*, vol. 12, no. 3, pp. 359–368, 2018.

[24] S. Chatterjee, B. Datta, S. Sen, N. Dey, and N. C. Debnath, "Rainfall prediction using Hybrid neural network approach," in *Proceedings of the 2nd International Conference on Recent Advances in Signal Processing, Telecommunications & Computing (SigTelCom)*, pp. 67–72, Ho Chi Minh City, Vietnam, January 2018.

[25] J. Esteves, G. de Souza Rolim, and A. Ferraudo, "Rainfall prediction methodology with binary multilayer perceptron neural networks," *Climate Dynamics*, vol. 52, no. 3-4, pp. 2319–2331, 2018.

[26] A. El-Shafie, H. G. El-Mazoghi, A. A. A. S. Abou-Kheira, and M. R. Taha, "Artificial neural network technique for rainfall forecasting applied to Alexandria, Egypt," *International Journal of the Physical Sciences*, vol. 6, no. 6, pp. 1306–1316, 2011.

[27] Ö Altan Dombaycı and M. Gölcü, "Daily means ambient temperature prediction using artificial neural network method: a case study of Turkey," *Renewable Energy*, vol. 34, no. 4, pp. 1158–1161, 2009.

[28] S. S. Baboo and I. K. Shereef, "An efficient weather forecasting system using artificial neural network," *International Journal of Environmental Science and Development*, vol. 1, no. 4, pp. 321–326, 2010.

[29] K. Abhishek, M. P. Singh, S. Ghosh, and A. Anand, "Weather forecasting model using artificial neural network," *Procedia Technology*, vol. 4, pp. 311–318, 2012.

[30] C. Devi, B. S. P. Reddy, K. V. Kumar, B. M. Reddy, and N. R. Nayak, "ANN approach for weather prediction using back propagation," *International Journal of Engineering Trends and Technology*, vol. 3, no. 1, pp. 19–23, 2012.

[31] F. Olaiya and A. B. Adeyemo, "Application of data mining techniques in weather prediction and climate change studies," *International Journal of Information Engineering and Electronic Business*, vol. 4, no. 1, pp. 51–59, 2012.

[32] B. V. R. Punyawardena and D. Kulasiri, "On development and comparative study of two Markov models of rainfall in the Dry Zone of Sri Lanka," in *Proceedings of the Joint International Conference on Agricultural Engineering & Technology*, pp. 231–238, Dhaka, Bangladesh, 1997.

[33] H. Perera, D. Sonnadara, and D. Jayewardene, "Forecasting the occurrence of rainfall in selected weather stations in the wet and dry zones of Sri Lanka," *Sri Lankan Journal of Physics*, vol. 3, p. 39, 2002.

[34] A. D. Kumarasiri and U. J. Sonnadara, "Performance of an artificial neural network on forecasting the daily occurrence and annual depth of rainfall at a tropical site," *Hydrological Processes*, vol. 22, no. 17, pp. 3535–3542, 2008.
[35] H. D. P. Weerasinghe, H. L. Premaratne, and D. U. J. Sonnadara, "Performance of neural networks in forecasting daily precipitation using multiple sources," *Journal of the National Science Foundation of Sri Lanka*, vol. 38, no. 3, p. 163, 2010.
[36] J. Ilonen, J.-K. Kamarainen, and J. Lampinen, "Differential evolution training algorithm for feed-forward neural networks," *Neural Processing Letters*, vol. 17, no. 1, pp. 93–105, 2003.
[37] M. T. Hagan and M. B. Menhaj, "Training feedforward networks with the marquardt algorithm," *IEEE Transactions on Neural Networks*, vol. 5, no. 6, pp. 989–993, 1994.
[38] M. Liang, S. X. Wang, and Y. H. Luo, "Fast learning algorithms for multi -layered feed-forward neural network," in *Proceedings of National Aerospace and Electronics Conference (NAECON'94)*, pp. 787–790, Dayton, OH, USA, May 1994.
[39] N. Japkowicz and S. J. Hanson, "Adaptability of the backpropagation procedure," in *Proceedings of International Joint Conference on Neural Networks, IJCNN'99*, pp. 1710–1715, Washington DC, USA, July 1999.
[40] Ö. Kişi, "Streamflow forecasting using different artificial neural network algorithms," *Journal of Hydrologic Engineering*, vol. 12, no. 5, pp. 532–539, 2007.
[41] A. Perera, U. S. Rathnayake, and H. M. Azamathulla, "Comparison of different Artificial Neural Network (ANN) training algorithms to predict atmospheric temperature in Tabuk, Saudi Arabia," *Journal of Earth System Science*, 2019.
[42] J. J. Moré, "The Levenberg-Marquardt algorithm: implementation and theory," in *Lecture Notes in Mathematics*, vol. 630, pp. 105–116, Springer, Berlin, Heidelberg, Germany, 1978.
[43] F. Burden and D. Winkler, "Bayesian regularization of neural networks," in *Artificial Neural Networks. Methods in Molecular Biology*™, D. J. Livingstone, Ed., Vol. 458, Humana Press, Totowa, NJ, USA, 2008.
[44] D. J. C. MacKay, "A practical Bayesian framework for backprop networks," *Advances in Neural Information Processing Systems*, vol. 4, no. 3, pp. 839–846, 1992.