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Machine Language Approach for Modeling and Predicting Rainfall in Different Zones of Kerala

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SUMMARY

The forecasting of rainfall is said to be the most difficult of other hydrological processes due to sudden changes in atmospheric processes. The rainfall directly and indirectly influences agriculture and allied sectors. Sudden changes in rainfall or an uneven distribution of rainfall can lead to crop loss. In order to avoid such problems and take the necessary precautions, it is mandatory to forecast the rainfall using various models with maximum precision. In this study, rainfall for northern, central and southern Kerala, India, was predicted using an artificial neural network (ANN) with a multi-layer perceptron (MLP) feed-forward neural network and an extreme learning machine (ELM) neural network. The monthly rainfall data was collected for a period of 39 years (1982–2020) from the regional agricultural research stations (RARS), Pilicode and Pattambi, for the northern and central zones of Kerala, respectively, whereas for the southern zone of Kerala, data was collected from RARS, Vellayani, for a period of 36 years (1985–2020). For the rainfall data collected from three different zones of Kerala, the MLP and ELM were applied. The comparison and validation of MLP and ELM models was done based on the error values of mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). The results indicated that for three different zones in Kerala, ANN with MLP showed better performance in forecasting rainfall compared to the ELM model. The best-selected model was also used for forecasting the next 5 years rainfall in each zone of Kerala.

Keywords: ANN; ELM; MLP; Northern zone; Central zone; Southern zone.

1. INTRODUCTION

Rainfall forecasting is an important problem faced by scientists throughout the world. The dynamic nature of the weather phenomenon makes forecasting rainfall a cumbersome procedure. Extreme variations in rainfall predictions are largely a result of climate change. Rainfall is one of the important weather phenomena that have a direct and indirect influence on the daily lives of human beings. Exact information regarding rainfall is required to guarantee proper management of water resources. Compared to other weather parameters, rainfall shows the most variations due to unpredictable sudden changes and the complexity of atmospheric processes. Thus, modeling and forecasting rainfall with maximum accuracy is one of the main challenges faced by scientists all over the world, even though there has been a huge development in strategies for weather forecasting in recent decades. The forecasting of rainfall with maximum accuracy can help reduce the damage and also ensure proper catchment management. Qualitative and quantitative management strategies can reduce the impacts of sudden uneven rainfall, droughts, and floods and also minimize the damage caused by them.

The forecasting of rainfall directly influences agriculture and allied sectors, especially in tropical countries like India, with an annual rainfall of 1194mm. The management of irrigation strategies for various crops heavily depends on it. In India, the southwest monsoon, which lasts from June to September, is responsible for more than 75% of the country's yearly rainfall. The growth and development of India's Kharif crops depend heavily on the south-west monsoon. More than half of the crops cultivated in India are directly or indirectly affected by unexpected changes in rainfall. Kerala is one of the states that depends on both the south-west (June to September) and north-west monsoon (October to November) for various purposes,

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including basic necessities and agriculture activities. When compared to the north-west monsoon, the south-west monsoon contributes the most rainfall to Kerala. The variation or fluctuations in monsoon rainfall could disturb or affect people's livelihoods. Thus, rainfall forecasting is crucial because it enables us to take the necessary precautions to limit the negative impacts of fluctuations in rainfall.

Anctil *et al.* (2004) investigated the performance of artificial neural network (ANN) with validation of multi-layer perceptrons (MLPs) and compared it to other parsimonious models employed for rainfall-runoff prediction and the results obtained from the conceptual rainfall-runoff model were consistent, such that for shorter periods of time, conceptual models showed better results, whereas for longer periods of time, MLPs were more beneficial. For a period of five years (1997–2002), Ramirez *et al.* (2005) undertook a study about forecasting daily rainfall using MLP in six different sites in the Sao Paulo region during summer and winter and the results indicated that ANN forecasted models for different weather parameters were superior and more accurate than the multiple linear regression and regional ETA models specified for the same. The ANN model was used by Hung *et al.* (2009) to conduct a study on rainfall prediction in Bangkok, Thailand. Comparing the generalized feed-forward ANN model to the MLP neural network model, the results revealed that the generalized feed-forward ANN model demonstrated more accuracy in the prediction of rainfall. Tripathy *et al.* (2011) undertook a study on weather forecasting using ANN and particle swarm optimization (PSO). The basic weather parameters, including rainfall, humidity, and minimum and maximum temperatures, were forecasted using the MLP-NN and PSO methods for understanding and interpreting the future weather conditions. The experimental results concluded that the method used was appropriate and provided meaningful results. Islam *et al.* (2016) conducted a study on monthly weather forecasting of heavy rainfall through an ANN model with a feed-forward MLP network using the monthly rainfall data of Barisal, Bangladesh, and also applied the mean square error (MSE) function to ascertain whether the projected model was validated.

Dash *et al.* (2017) underwent a study about the prediction of rainfall using single-layer feed-forward neural networks (SLFN) and extreme learning machines (ELM) and the results indicated that the mean absolute error for the ELM (3.87%) model was comparatively smaller than the SLFN (6.39%). Deo *et al.* (2017) conducted a study on the wavelet extreme learning machine (W-ELM) model for predicting drought index and the results suggested that the W-ELM model showed better performance compared to ELM, LSSVR (least squares support vector regression), ANN, and their wavelet-equivalent counterparts (W-ANN, W-LSSVR). Cholissodin and Sutrisno (2018) investigated the use of simplified deep learning techniques based on ELM for forecasting rainfall. The forecasting of rainfall is important for planning the agriculture activities of every country in the world. But due to sudden changes in atmospheric processes, the accuracy of predicted results using different models was less than optimal. In this study, an ELM-based simplified machine learning model was used to predict rainfall with maximum accuracy. The results suggested that simplified deep learning techniques based on extreme learning machines produced more accurate results compared to the ELM model. Dash *et al.* (2018) conducted a study about forecasting rainfall in Kerala, India, using K-nearest neighbour (KNN), ANN and ELM and the results advocated that ELM gives more accurate results compared to ANN and KNN models and the best ELM architecture selected for modeling the rainfall was 8-15-1. Yaseen *et al.* (2021) used data intelligence models for projecting a standardized precipitation index in Bangladesh and findings showed that for all four different meteorological stations, the ELM model produced the most precise prediction when compared to other models employed in the study.

Scientists all over the world have developed different methods for forecasting time series data over the years. The forecasting methodologies include both statistical and machine-language approaches. For forecasting, especially weather parameters, stochastic processes such as SARIMA (seasonal autoregressive integrated moving average), ETS (exponential smoothing), GARCH (generalized autoregressive conditional heteroscedasticity), SMA (simple moving average), and MLR (multiple linear regression) have been used in recent years. The machine-language approach using neural networks is the most advanced method developed for forecasting weather parameters. Neural networks have a good ability to model complex data structures. The different types of neural network models employed for forecasting weather parameters are ANN and WNN (wavelet neural networks) (Paul *et al.*, 2013). Hybrid models, including ARIMAX-GARCH (Paul *et al.*, 2014), SARIMA-ANN (Mukaram and Yusof, 2017), ETS-ANN (Panigrahi and Behera, 2017), SARIMA-GARCH (Pandey *et al.* 2019), etc., are also used for forecasting time series data. In this study, a comparison of machine language approaches using ANN, MLP feed-forward neural networks, and ELM neural network methods is employed for modeling and forecasting rainfall in different zones of Kerala.

2. MATERIALS AND METHODS

2.1 Study area and data collection

The present study is mainly focused on modelling and forecasting the monthly rainfall in different parts of Kerala using artificial neural network (both MLP and ELM). R software was the tool used for undertaking analysis of monthly rainfall data (Crone and Kourentzes, 2010; Kourentzes *et al.*, 2014; Ord *et al.*, 2017). The data was taken from three different parts of Kerala, such as the northern, central and southern zones. The monthly rainfall data for the northern zone of Kerala was collected from RARS Pilicode in Kasaragod district, which is the north-most district of Kerala, over a period of 39 (1982–2020) years. The geographical location of Pilicode is latitude and longitude and has a 15-metre elevation. The average total rainfall received in a year at Pilicode is 3379 mm, and most of the rainfall was received in the month of June.

The monthly rainfall data for the central zone of Kerala was collected from RARS Pattambi in Palakkad, which is the centre-most district of Kerala, over a period of 39 years (1982–2020). The location of Pattambi is represented by the coordinates 10.8057 N latitude and 76.1957 E longitude. The Pattambi region within the central zone of Kerala has an average annual rainfall of 1838 mm, and over the month of July, it showed maximum rainfall.

The monthly rainfall data for the southern zone of Kerala was collected from RARS Vellayani in Trivandrum, the southernmost district of Kerala, over a period of 35 years (1985–2020). Trivandrum is also known as the capital city of Kerala. The geographical location of Vellayani is at 8.4316N latitude and 76.986E longitude, with an elevation of 8m above mean sea level. The mean annual rainfall of Vellayani was 1704 mm, and over the years, June received the maximum amount of rainfall. The three different locations from which monthly rainfall data is taken are indicated in Fig. 1.

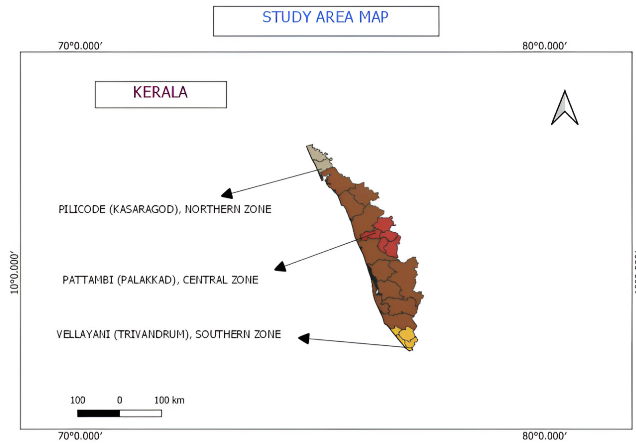


Fig. 1. Study area map for northern, central and southern zones of Kerala

3. METHODOLOGY

3.1 Artificial Neural Network (ANN)

The ANN is one among the highly advanced computation models applied to identify particular patterns that exist among input and output (Shukla *et al.*, 2021). Human brains are used as inspiration while creating ANNs, which are made up of interconnected nodes of input, hidden layer, and output (Lippmann, 1987). Neural networks are employed in different fields like forecasting, speech processing, robotic control, image recognition, machine vision, state estimation, etc. (Rosenblatt, 1962). The patterns of data consisting of complex structures with high dimensions are easily identified with the help of artificial neural networks (Nalcaci *et al.*, 2019). ANN has been successfully used in the forecasting of weather parameters, especially rainfall, over the last two decades (Sahai *et al.*, 2000; Bodri and Cermak, 2000; El-Shafie *et al.*, 2011; Krishnan *et al.*, 2022; Krishnan *et al.*, 2023). The estimation algorithm employed in ANN is a well-known back propagation algorithm (Rumelhart *et al.,* 1986). The ANN is competent to regulate or investigate a specific study and derive facts using analogous dispensation (Venkatesh and Bind, 2022).

3.1.1 Multi-layer Perceptron (MLP) Feed Forward Neural Network

A feed-forward neural network is used for forecasting weather parameters, which can transform real-valued inputs into outputs (Ramirez *et al.,* 2005). Multi-layer perceptron (MLP) is one of the most accepted methods used for modeling and forecasting different weather parameters using ANN. A multi-layer perceptron is a feed-forward, back-propagation neural network consisting of all the properties of a neural network such that all the input values depend on the output values (Özmen and Weber, 2014).

The MLP feed-forward neural network model with a single hidden layer is mathematically expressed as (Haykin, 1999):

$$\hat{z}_t = \beta_0 + \sum_{j=1}^{q} \beta_j f\left(\gamma_{0j} + \sum_{i=1}^{p} \gamma_{ij} z_{t-i}\right) + \varepsilon_t, \quad (1)$$

where, $z_{t-i}\ (i=1,2,...,p)$ represents the p inputs, $\hat{z}_t$ denotes the output, $\beta_j\ (j=0,1,2,...,q)$ and γ_{ij} $(i=0,1,2,...,p;\ j=0,1,2,...,q)$ indicates connection weights and ε_t is the error term. The letters p and q indicate number of inputs and hidden nodes, respectively, β_0 and γ_{tj} are constant terms and f is the activation function (Waciko and Ismail, 2020). An architecture of multi-layer perceptron feed forward neural network is depicted in Fig. 2.

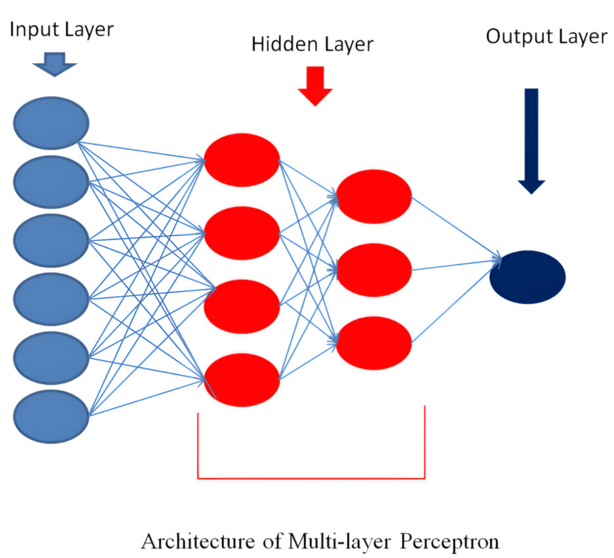


Fig. 2. Architecture of MLP feed forward neural network

3.1.2 Extreme Learning Machine (ELM) Neural Network

Huang *et al.* (2006) created another sort of neural network called ELM consisting of a single hidden layer and a feed-forward neural network such that it does not demand tuning of the hidden layers and retains extremely high learning speed (Wang *et al.* 2015). The specialty of ELM is that there is a random selection of input weights and hidden biases (Dash *et al.,* 2017). The usage of ELM in forecasting showed much better performance compared to MLP since it has time-saving and tuning-tree benefits and also extracts non-linear information from the data.

The mathematical formula for the ELM-NN model for output is expressed as:

$$f(x) = h(x)\beta, \quad (2)$$

where $f(x)$ indicates an output vector and $h(x)$ is the hidden layer of the output vector $[h_1(x), h_2(x), ..., h_n(x)]^T$ and $h(x)$ is playing a crucial role by mapping the input set with n. -dimension into the space of the hidden layer with L-dimension. The coefficient $\beta = [\beta_1, \beta_2, ..., \beta_L]^T$ expresses the weight vector, which connects the hidden layer with the output layer. The architecture of an extreme learning machine neural network is presented in Fig. 3.

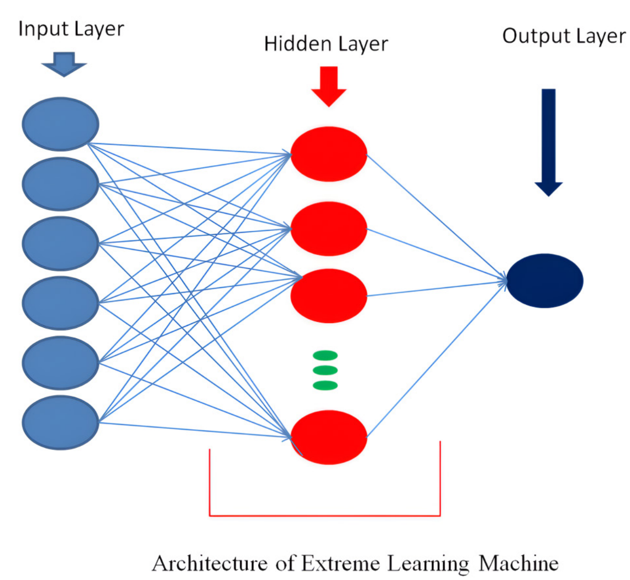


Fig. 3. Architecture of ELM feed forward neural network

3.2 Comparison and Evaluation of the predicted model

The efficacy of the model is validated using different methods like mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE).

3.2.1 Mean square error

The MSE can be defined as the mean of the square of the disparity among actual y_i and predicted $\hat{y}_i$ values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \qquad (3)$$

3.2.2 Root mean square error

The RMSE is defined as the square root of the MSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \qquad (4)$$

3.2.3 Mean absolute error

The MSE can be easily defined as the mean of the absolute disparity among actual y_i and predicted $\hat{y}_i$ values.

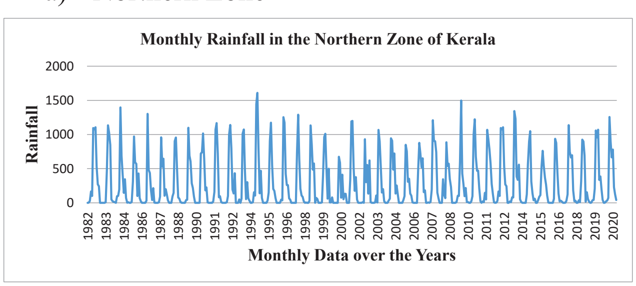
$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \qquad (5)$$

The model with least value for MSE, RMSE and MAE is selected as the best performing model.

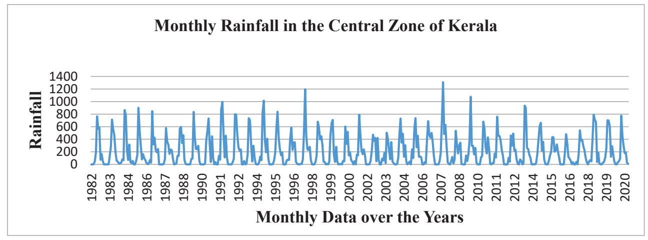
4. RESULTS AND DISCUSSION

The current research work focuses on modelling and forecasting rainfall in the northern, central and southern zones of Kerala, ANN with multi-layer perceptron feed-forward networks and extreme learning machine neural networks are employed, and results are compared to determine which model performs better in the respective zones. The rainfall data is split into two parts: training and testing data sets. The testing data for northern and central Kerala consists of data from 1982 to 2015 (34 years), whereas for southern Kerala, the testing data is from 1985 to 2015 (31 years). The testing set consists of data from 2016 to 2020. The time series plots of rainfall for three different zones of Kerala are given in Fig. 4.

a) Northern Zone



b) Central Zone



c) Southern Zone

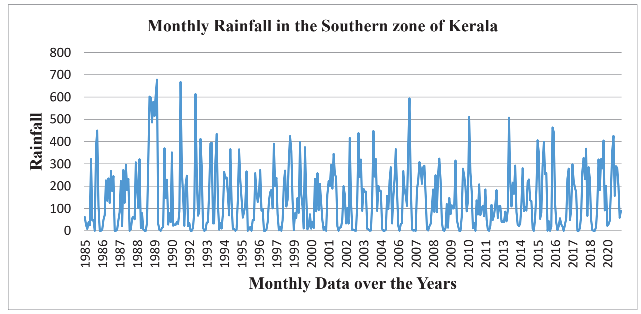


Fig. 4. Time series plot for monthly rainfall for northern, central and southern zones of Kerala

The time series plots for rainfall clearly depict that the northern zone of Kerala is receiving the maximum amount of rainfall compared to the central and southern zones of Kerala. The rainfall in the southern zone is the least, and it shows a different seasonal pattern throughout the year, whereas the seasonal patterns in the northern and central zones are slightly similar. The neural network models MLP and ELM are applied to the testing data using R software. The best model architecture selected for the rainfall using MLP and ELM in the northern, central and southern zones is described in Table 1.

Table 1. Best selected architecture for MLP and ELM in each zones of Kerala

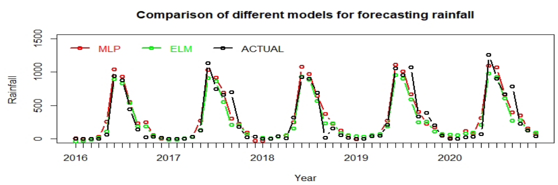
Zone	Model	Architecture*
Northern	MLP	22-5-1
	ELM	22-100-1
Central	MLP	23-5-1
	ELM	23-100-1
Southern	MLP	23-5-1
	ELM	23-100-1

*No. of Input nodes-No. of Hidden Layers-No. of Output Nodes

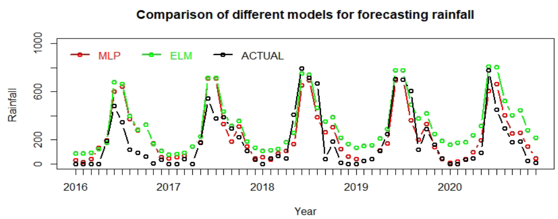
The next step is the determination of the best method for modeling the rainfall. The rainfall for the following five years is projected using both MLP and ELM models and compared with the testing data to ascertain the most effective way of modeling the precipitation.

The comparison between actual rainfall and predicted rainfall using MLP and ELM is illustrated in Fig. 5.

a) Northern Zone



b) Central Zone



c) Southern Zone

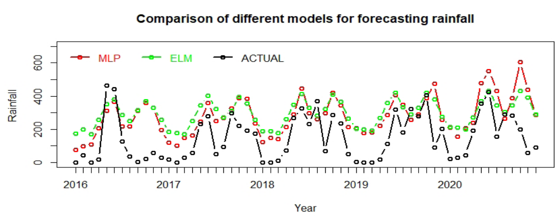


Fig. 5. Comparison of forecasted monthly rainfall using MLP and ELM models with actual observations

The comparison of rainfall predictions between MLP and ELM is displayed in Fig. 5. But in order to confirm which model performs better in forecasting rainfall in the respective zones of Kerala, the error values MSE, RMSE and MAE are calculated using observed and predicted values, which are presented in Table 2.

Table 2. Validation and Evaluation of MPL and ELM for each zones of Kerala

Zone	Model	MSE	RMSE	MAE
Northern	**MLP**	**17004.85**	**130.40**	**84.76**
	ELM	18692.03	136.71	79.81
Central	**MLP**	**15910.49**	**126.13**	**90.92**
	ELM	28039.67	167.45	145.10
Southern	**MLP**	**29273.07**	**171.09**	**145.58**
	ELM	31734.40	178.14	158.50

The results shown in Table 2 clearly suggest that the MLP method is outperforming the ELM method in modeling and forecasting rainfall in the northern, central and southern zones of Kerala. It is noted that for the central and southern zones, the MSE, RMSE and MAE values of the MLP model showed the least error values, whereas for the northern zone, MAE showed the least value for the ELM method, but MSE and RMSE were the lowest for the MLP method. This clearly indicated that the MLP method is showing the best performance in three different zones of Kerala. It is to be noted that the forecasting of rainfall using MLP and ELM is not very accurate in the southern zone because the fluctuations in the seasonal pattern of rainfall over the years are higher compared to the northern and central zones of Kerala. Using the MLP model, the predicted rainfall for Kerala's various zones for the subsequent five years is displayed and validated in Fig. 6.

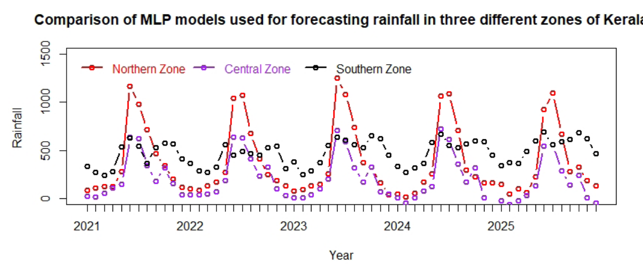


Fig. 6. Comparison of monthly rainfall forecasted for next 5 years using MLP for northern, central and southern zones of Kerala

Fig. 6 clearly shows that for the next 5 years, the highest rainfall will be received in the northern zone of Kerala, whereas the least rainfall will occur in the central zone of Kerala. Fig. 6 also claims that the southern zone will get constant rainfall throughout the months for the next 5 years (2021-2025). The results of forecasting the rainfall also suggested there will be an increase in rainfall in the northern zone of Kerala, and maximum rainfall will be observed in June and July. The study also indicated that for the central zone of Kerala, there will be almost similar rainfall compared to previous years. The southern zone also showed an increasing tendency for rainfall, with the maximum amount of rainfall predicted in June and October. The study urges farmers to take the necessary precautionary measures to cope with increasing amounts of rainfall in different zones of Kerala so that crop loss can be avoided. The study also suggested that necessary measures should be taken to avoid water stagnation in heavy rainfall-predicted zones and to maintain the availability of water throughout the year in each zone of Kerala.

5. CONCLUSION

The modeling and forecasting of rainfall with maximum precision is one of the most important problems faced by researchers, even though there has been much development in strategies related to the forecasting of weather parameters. Rainfall is an important weather parameter that directly and indirectly affects agriculture and allied sectors. Sudden changes and uneven rainfall can adversely affect crop yield and may result in crop loss, such that prediction of rainfall with maximum accuracy is needed to take control measures to avoid such problems. In this study, for modeling and forecasting rainfall with maximum precision, ANN with MLP feed forward neural networks and ELM neural networks were used in three different zones of Kerala. The monthly rainfall data was collected for a period of 39 years (1982–2020) from regional agricultural research stations (RARS), Pilicode and Pattambi, for the northern and central zones of Kerala, whereas for the southern zone of Kerala, data was collected from RARS, Vellayani, for a period of 36 years (1985–2020).

The models for rainfall are fitted using MLP and ELM, and in order to validate the model, forecasting of rainfall was carried out. Based on MSE, RMSE, and MAE values, the model's validity was determined. In terms of predicting rainfall, the results showed that the MLP model performed better than the ELM model. The MLP and ELM models showed much accuracy in forecasting rainfall in the northern and central zones, whereas in the southern zone the error values are comparatively higher, which indicates the fluctuations in seasonal patterns are higher. However, an outperforming MLP model was employed to project future rainfall in different zones of Kerala. The predicted rainfall showed maximum rainfall in the northern zone and minimum rainfall in the central zone, whereas steady rainfall throughout the months was predicted in the southern zone of Kerala for the next 5 years (2021-2025). The study also suggested that there will be an increase in rainfall in the northern and southern zones of Kerala, whereas almost similar rainfall is predicted in the central zone of Kerala compared to earlier periods. Necessary measures should be taken to avoid problems of water stagnation in high rainfall zones and also to maintain the availability of water throughout the year in each zone of Kerala.

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REFERENCES

Anctil, F., Perrin, C. and Andréassian, V. (2004). Impact of the length of observed records on the performance of ANN and of conceptual parsimonious rainfall-runoff forecasting models. *Environmental Modelling & Software*, **19(4),** 357-368. https://pdf.sciencedirectassets.com/271872/1-s2.0-S1364815200X00485/1-s2.0-S136481520300135X/main.pdf

Bodri, L. and Cermak, V. (2000). Prediction of Extreme Precipitation Using a Neural Network: Application to Summer Flood Occurrence in Moravia. *Advances in Engineering Software*, **31(5),** 311–321. https://pdf.sciencedirectassets.com/271418/1-s2.0-S0965997800X00439/1-s2.0-S0965997899000630/main.pdf

Cholissodin, I. and S. Sutrisno (2018). Prediction of rainfall using simplified deep learning based extreme learning machines. *Journal of Information Technology and Computer Science*, **3(2)**, 120-131. https://jitecs.ub.ac.id/index.php/jitecs/article/view/58

Crone, S.F. and Kourentzes, N. (2010). Feature selection for time series prediction – A combined filter and wrapper approach for neural networks. *Neurocomputing,* **73(10-12)**, 1923-1936. https://pdf.sciencedirectassets.com/271597/1-s2.0-S0925231210X00042/1-s2.0-S0925231210000974/main.pdf

Dash ,Y., Mishra, S.K. and Panigrahi, B.K. (2017). Rainfall prediction of a maritime state (Kerala), India using SLFN and ELM techniques. In 2017 International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT). IEEE. 1714-1718. https://ieeexplore.ieee.org/abstract/document/8342829

Dash, Y., Mishra, S.K. and Panigrahi, B.K. (2018). Rainfall prediction for the Kerala state of India using artificial intelligence approaches. *Computers & Electrical Engineering*, **70**, 66-73. https://pdf.sciencedirectassets.com/271419/1-s2.0-S0045790618X00068/1-s2.0-S004579061732791X/main.pdf

Deo, R.C., Tiwari, M.K., Adamowski, J.F. and Quilty, J.M. (2017). Forecasting effective drought index using a wavelet extreme learning machine (W-ELM) model. *Stochastic environmental research and risk assessment*, **31,**1211-1240. https://link.springer.com/content/pdf/10.1007/s00477-016-1265-z.pdf

El-Shafie, A.H., El-Shafie, A., El Mazoghi, H.G., Shehata, A. and Taha, M.R. (2011). Artificial neural network technique for rainfall forecasting applied to Alexandria, Egypt. *International Journal of Physical Sciences*, **6(6)**, 1306-1316. https://academicjournals.org/journal/IJPS/article-full-text-pdf/A8043DC28734.pdf

Haykin, S. (1999). Neural Networks: A Comprehensive Foundation. 2ed Prentice-Hall, New Jersey. https://cdn.preterhuman.net/texts/science_and_technology/artificial_intelligence/Neural%20Networks%20-%20A%20Comprehensive%20Foundation%20-%20Simon%20Haykin.pdf

Huang, G.B., Zhu, Q.Y. and Siew, C.K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, **70 (1-3)**, 489-501. https://www.sciencedirect.com/science/article/abs/pii/S0925231206000385

Hung, N.Q., Babel, M.S., Weesakul, S. and Tripathi, N.K. (2009). An artificial neural network model for rainfall forecasting in Bangkok, Thailand. Hydrology and Earth System Sciences, 13 (8), 1413-1425. https://hess.copernicus.org/articles/13/1413/2009/

Islam, T., Saha, S., Evan, A.A., Halder, N. and Dey, S.C. (2016). Monthly Weather Forecasting through ANN Model: A Case Study in Barisal, Bangladesh. *International Journal of Advanced Research in Computer and Communication Engineering*, **5(6)**, 1-6. https://ijarcce.com/upload/2016/june-16/IJARCCE%201.pdf

Kourentzes, N., Barrow, B.K. and Crone, S.F. (2014). Neural network ensemble operators for time series forecasting. *Expert Systems with Applications*, **41(9)**, 4235-4244. https://www.sciencedirect.com/science/article/abs/pii/S0957417413009834

Krishnan, G.K.B., Mehta, V. and Yadav, R.S. 2022. Assessment of future pattern of rainfall in different zones of Kerala using incorporation of SARIMA, ANN and Hybrid SARIMA-ANN models. *Economics Affairs*, **67(05)**, 823-832. https://ndpublisher.in/admin/issues/EAv67n5q.pdf

Krishnan, G. K.B., Mehta, V. and Rai, V. N. **2023**. Stochastic modelling and forecasting of relative humidity and wind speed for different zones of Kerala. *MAUSAM,* **74(4)** (October 2023), 1053-1064. https://mausamjournal.imd.gov.in/index.php/MAUSAM/article/view/5603

Lippmann, R. (1987). An introduction to computing with neural nets. IEEE ASSP Mag, **4(2)**,4-22. https://ieeexplore.ieee.org/abstract/document/1165576

Mukaram, M.Z. and Yusof, F., 2017. Solar radiation forecast using hybrid SARIMA and ANN model: A case study at several locations in Peninsular Malaysia. *Malaysian Journal of Fundamental and Applied Sciences Special Issue on Some Advances in Industrial and Applied Mathematics*, 346-350. https://mjfas.utm.my/index.php/mjfas/article/view/895/pdf

Nalcaci, G., Özmen, A. and Weber, G.W. (2019). Long-term load forecasting: models based on MARS, ANN and LR methods. *Central European Journal of Operations Research*, **27**, 1033-1049. https://link.springer.com/content/pdf/10.1007/s10100-018-0531-1.pdf.

Ord, K., Fildes, R. and Kourentzes, N. (2017). Principles of Business Forecasting 2e. Wessex Press Publishing Co., Chapter 10. https://wessexlearning.com/products/principles-of-business-forecasting-2nd-ed

Özmen, A. and Weber, G.W. (2014). RMARS: robustification of multivariate adaptive regression spline under polyhedral uncertainty. *Journal of Computer and Applied Mathematics*, **259(B),** 914–924. https://www.sciencedirect.com/science/article/pii/S0377042713005104

Pandey, P.K., Tripura, H. and Pandey, V. (2019). Improving prediction accuracy of rainfall time series By Hybrid SARIMA–GARCH modeling. *Natural Resources Research*, **28,** 1125-1138. https://link.springer.com/article/10.1007/s11053-018-9442-z

Panigrahi, S. and Behera, H.S. (2017). A hybrid ETS–ANN model for time series forecasting. *Engineering Applications of Artificial Intelligence*, **66**, 49-59. https://www.sciencedirect.com/science/article/abs/pii/S0952197617301550

Paul, R.K., Prajneshu and Ghosh, H. (2013). Wavelet Frequency Domain Approach for Modelling and Forecasting of Indian Monsoon Rainfall Time-Series Data. *Journal of The Indian Society of Agricultural Statistics*, **67(3)**, 319-327. http://www.isas.org.in/jisas/volume/vol67/issue3/4-RanjitKumar.pdf

Paul, R.K., Ghosh, H. and Prajneshu. (2014). Development of out-of-sample forecast formulae for ARIMAX-GARCH model and their application. *Journal of The Indian Society of Agricultural Statistics*, **68(1)**, 85-92. http://www.isas.org.in/jisas/volume/vol68/issue1/08-RanjitKumar.pdf

Ramirez, M.C.V., de Campos Velho, H.F. and Ferreira, N.J. (2005). Artificial neural network technique for rainfall forecasting applied to the Sao Paulo region. *Journal of hydrology*, **301(1-4)**, 146-162. https://www.sciencedirect.com/science/article/abs/pii/S0022169404003191

Rosenblatt, F. (1962). Principles of neurodynamics: perceptrons and the theory of brain mechanisms. Spartan Books, pp 666. https://safari.ethz.ch/digitaltechnik/spring2018/lib/exe/fetch.php?media=neurodynamics1962rosenblatt.pdf

Rumelhart, D.E., Hinton, G.E. and Williams, R.J. (1986). Learning representations by back-propagating errors. *Nature*, **323**, 533–536. https://www.nature.com/articles/323533a0

Sahai, A.K., Somann, M.K. and Satyan, V. (2000). All India Summer Monsoon Rainfall Prediction Using an Artificial Neural Network. *Climate Dynamics*, **16**, 291- 302. https://link.springer.com/content/pdf/10.1007/s003820050328.pdf

Shukla, A., Kumar, S. and Singh, H. (2021). MLP-ANN-Based execution time prediction model and assessment of input parameters through structural modeling. *Proceedings of the National Academy of Sciences, India Section A: Physical Science*, **91**, 577-585. https://link.springer.com/article/10.1007/s40010-020-00695-9

Tripathy, A.K., Mohapatra, S., Beura, S. and Pradhan, G. (2011). Weather forecasting using ANN and PSO. *International Journal of Scientific Engineering and Research*, **2(7)**, 1-5. https://www.ijser.org/viewPaperDetail.aspx?JUL1116

Venkatesh, K. and Bind, Y.K. (2022). ANN and neuro-fuzzy modeling for shear strength characterization of soils. *Proceedings of the National Academy of Sciences, India Section A: Physical Science*, **92**, 243-249. https://link.springer.com/article/10.1007/s40010-020-00709-6

Waciko, K.J. and Ismail, B. (2020). SARIMA-ELM hybrid model versus SARIMA-MLP hybrid model. *International Journal of Statistics and Applied Mathematics*, **5(2)**, 01-08. https://www.mathsjournal.com/pdf/2020/vol5issue2/PartA/5-1-13-832.pdf

Wang, J., Hu, J., Ma, K. and Zhang, Y. (2015). A self-adaptive hybrid approach for wind speed forecasting. *Renewable Energy*, **78**, 374-385. https://www.sciencedirect.com/science/article/abs/pii/S0960148115000336

Yaseen, Z.M., Ali, M., Sharafati, A., Al-Ansari, N. and Shahid, S. (2021). Forecasting standardized precipitation index using data intelligence models: regional investigation of Bangladesh. *Scientific reports*, ***11*****,** 3435. https://www.nature.com/articles/s41598-021-82977-9.pdf.