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Hybrid predictive based control of precipitation in a water-scarce region: A focus on the application of intelligent learning for green irrigation in agriculture sector

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A B S T R A C T

A growing need for irrigation in agriculture results from recent climatic parameter uncertainties brought on by climate change, global warming, and other factors. The present-day tumultuous, unpredictable, ever-changing, and ambiguous nature of the onset, cessation, and duration of adverse weather conditions poses a formidable obstacle for farmers in formulating informed judgments pertaining to agricultural practices. In this study, the metrological simulation was carried out based on different input variables, including wind speed, wind direction, relative humidity, and minimum and maximum temperature, to predict the rainfall in the arid agricultural area of Kano, Nigeria. For this purpose, an adaptive neuro-fuzzy inference system (ANFIS), feed-forward neural network (FFNN), and multi-linear regression (MLR) were utilized. Five evaluation criteria for predictive control, including determination coefficient (R^2), Nash–Sutcliffe efficiency (NSE), mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE), were used to figure out how accurate the models were based on how the features were chosen. The output proved the reliable accuracy of intelligent regression learning. The results depicted that MLR-M1 with R^2 = 0.9989, NSE = 0.9872, and RMSE = 0.0016 performs the best at predicting rainfall, even though all three computational models (ANFIS, FFNN, and MLR) produced good results. The predictive models justified reliable tools for the management of water resources, especially in the agricultural sector.

1. Introduction

The world population is adding up rapidly, which necessitates more demand for food and water than what we have now; demand for water increases with agriculture taking the lion's share of about 70% (Abioye, Abidin, Aman, Mahmud, & Buyamin, 2021; Yahaya et al., 2022). Because traditional cultivation methods are insufficient to meet food demand, the world's population explosion and climate change pose a threat to food security. Due to the desertification brought on by climate change and global warming, agricultural water is becoming more and more scarce. During the agricultural revolution, irrigation was used to make up for the difference in crop production between rainfed agriculture and irrigation. Since then, issues of dam construction and other technical issues have been the bottleneck, especially in areas where technical know-how is inadequate. This problem is exacerbated in areas with low rainfall or in desert areas of the world (Bwambale, Abagale, & Anornu, 2022).

Irrigation and seasonal rainfall are the main sources of water for cultivation activities. Climate change and global warming are causing problems with the starting, ending, duration, and shift in seasonal rainfall, causing it to be difficult to be predicted, because it is chaotic, and fluctuating, which is not favorable to cultivation (Abioye et al., 2020). The main function of irrigation is to meet the water demand of a crop; its success depends on how well it is scheduled and executed. Irrigation scheduling is the act of pro-

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viding the exact amount of water demand at the right time and location (Saleem et al., 2013). Irrigation serves as a method of applying water artificially for agricultural purposes to maintain soil moisture, prevent desert encroachment, and maintain the cooling effect of the soil surface (Oborkhale, Abioye, Egonwa, & Olalekan, 2015). (Ma, Shi, Chen, Hsu, & Chuang, 2019) developed a system that received environmental data from sensors and images, then processed it using artificial intelligence to predict the moisture level of the soil. It is profitable and beneficial to apply the exact amount of water needed by a specific plant at the right time to check over- and under irrigation (Adeyemi, Grove, Peets, Domun, & Norton, 2018). Precision irrigation is achieved by finding the exact volume needed by a plant at a particular time at a precise location (Smith & Baillie, 2009). Sometimes, precision irrigation is regarded as "drip irrigation". The main aims that could be achieved by drip irrigation include saving water and costs, reducing adverse environmental effects, and maximizing agricultural yield (Smith & Baillie, 2009).

Similarly, Chen et al. (2021) created a data-driven predictive control model that predicts dynamic stem water potential using stem, soil, and root statistics as well as weather forecasted data, saving more than 7% of irrigation water when compared to the commonly used on–off system and eliminating the problem of over- or under-irrigation. Yazdi, et al. proposed an improvement of the traditional method of water allocation for irrigation by using real time weather data and employing neural network techniques. The method requires recent weather data from the previous ten days. To achieve precision irrigation, there is a need to predict plants' future behavior and use that prediction to plan for that predicted demand. Model prediction control has been used in irrigation in many aspects, which include irrigation scheduling, soil moisture regulation, canal control, precipitation and evapotranspiration predictions, and water potential regulation (Bwambale et al., 2022).

Progress in the Internet of things (IoT) and advancements in computation made it easier to generate big data from agricultural facilities (Bwambale et al., 2022). The IoT allows for the low-cost setup of data collection systems as well as mechanisms for monitoring and irrigation control (Cáceres, Millán, Pereira, & Lozano, 2021). Chen et al. (2020) designed and proposed a system that controls irrigation based on tree trunk water instead of soil moisture. When it was compared to on–off and certainty equivalent MPC, it outperformed both. Table 1 shows a brief related review of the recent developments in the field. Other researchers that employed the application of soft computing in hydro-environmental engineering and modelling are presented in the following (Adnan, Dai, et al., 2023; Adnan, Mostafa, et al., 2023; Mostafa et al., 2023). The study aimed to use metrological simulation to predict rainfall in the arid agricultural area of Kano, Nigeria, based on different input variables as follows wind speed, wind direction, relative humidity, and minimum and maximum temperature. The motivation for using machine learning control in irrigation in Kano, Nigeria is to improve the efficiency and effectiveness of water usage in agriculture. With the use of machine learning algorithms, it is possible to optimize irrigation schedules, reduce water waste, and increase crop yields. This technology can also help farmers adapt to changing climate conditions and improve the sustainability of agriculture in Nigeria. Besides the contribution mentioned above, this study explored the comprehensive decades' bibliographic review as visualized in Fig. 1. The survey was based on obtained 1,170 documents from Scopus database with the keywords coverage of machine learning control, and irrigation. Fig. 1a presented more than 800 keywords that were above the threshold showing the global interest in the field. Similarly, Fig. 1b among the 109 countries, more than 50 countries meet the threshold with China, United State of America (USA), India on top across the globe. It is clearly seen that there is limited research in Nigeria hence this indicated a virgin area in Kano, Nigeria.

The research gap in the context of predictive-based control of precipitation in Kano, Nigeria refers to the lack of existing studies or comprehensive research on utilizing predictive methods to manage and regulate rainfall patterns in the region. Currently, there is limited knowledge and understanding of how predictive-based control mechanisms can be applied to influence or manipulate precipitation events in specific geographic locations like Kano. However, conducting this work is necessary for several reasons. Firstly, Kano, Nigeria, like many other regions, is vulnerable to the impacts of erratic and insufficient rainfall, which can have

Table 1
Review comparison of the related literature.

Ref	Type	Parameter	Methods
(Ma et al., 2019)	Predict soil moisture	Weather parameters, image	AI (fuzzy) and Image processing
(Adeyemi et al., 2018)	Predict one-day-ahead soil volumetric moisture	Soil moisture, precipitation climatic parameters	Dynamic neural network
(Shang, Chen, Stroock, & You, 2019)	Predictions of evapotranspiration, precipitation, soil moisture level, and water usage	Past data (evapotranspiration and precipitation), Soil moisture level, and water usage	Support vector cluster
(Chen et al., 2021)	Predict dynamic state of stem water level	Forecasted weather data stem, root, and soil water content	Linearization and discretization of nonlinear model
(Saleem et al., 2013)	Realtime Irrigation scheduling	Desired soil moisture. Evapotranspiration and precipitation	Model predictive control
(Yazdi et al., 2013)	Estimating irrigation requirement	Real time climatic data	Neural networks
(Balbis & Jassim, 2018)	Irrigation scheduling	Evapotranspiration Climate condition	System identification (MATLAB)
(Bwambale et al., 2022)	Soil moisture	Evapotranspiration, Rainfall, Irrigation	MPC
(Gomez, Capraro, Soria, & Peña, 2018)	Irrigation scheduling	Evapotranspiration, Rainfall, Irrigation	MPC
	Irrigation scheduling	Precipitation, Evapotranspiration	Robust MPC
(Abioye et al., 2021)	Irrigation scheduling	Soil moisture, Actual evapotranspiration	Discrete time MPC
(Cáceres et al., 2021)	Irrigation scheduling	Soil moistures at different level	Real time optimizer + MPC
(Guo & You, 2018)	Precipitation, and evapotranspiration prediction	Precipitation, Evapotranspiration	Robust MPC
(Chen et al., 2020)	Soil water potential regulation	Weather forecast data. Precipitation, Evapotranspiration	Robust MPC

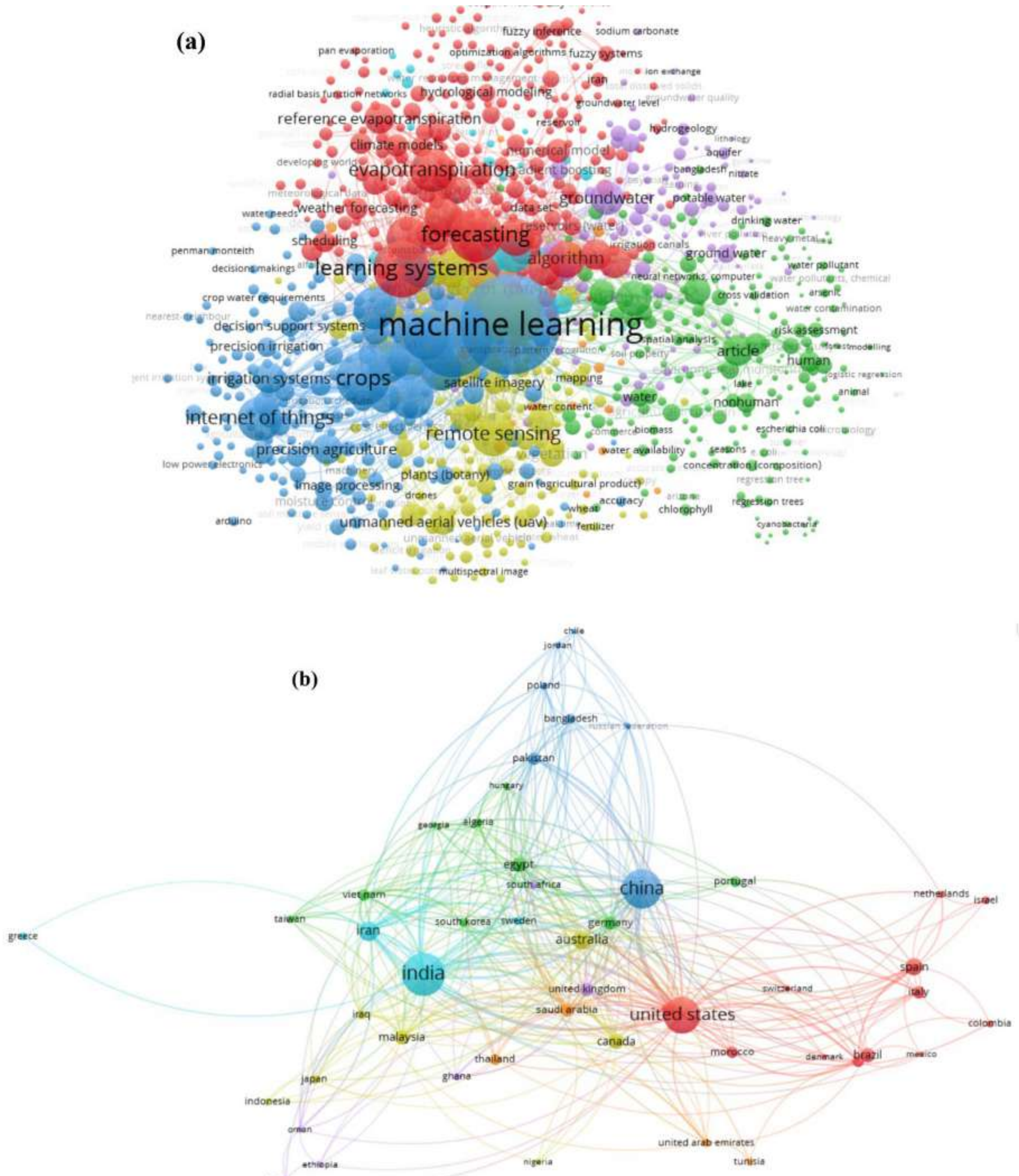

Fig. 1. a) major keywords used over the literature on ml and irrigation b) investigated research region for ml and irrigation control.

severe consequences for agricultural productivity, water resource management, and overall socio-economic stability. By developing a predictive-based control system for precipitation, it is possible to enhance the resilience of the region's agricultural sector, optimize water allocation strategies, and mitigate the negative effects of water scarcity. Secondly, the advancement of predictive-based control techniques for precipitation in Kano could contribute to a more sustainable and efficient use of water resources. By accurate forecasting and influencing rainfall patterns, it becomes feasible to optimize irrigation scheduling, reduce water waste, and promote responsible water management practices. Furthermore, this research can potentially bridge the existing gap between meteorological forecasting and actionable interventions. By establishing a predictive-based control system tailored to Kano's unique climatic conditions, policymakers and stakeholders can make informed decisions on when and how to intervene to maximize the benefits of rainfall while minimizing the risks associated with extreme weather events.

2. Proposed artificial intelligent models

One major limitation of AI-based methodology is its susceptibility to bias and discrimination. AI-based algorithms learn patterns and make predictions based on the data they are trained on, which can reflect societal biases present in the data. If the training data is biased or contains discriminatory patterns, the resulting model can perpetuate and amplify these biases when making decisions or predictions. Additionally, AI-based models can struggle with interpreting causal relationships or understanding context, leading to potential errors or misinterpretations. Ensuring fairness, interpretability, and addressing bias are critical challenges in AI-based models that require careful consideration and mitigation strategies. AI models are an effective tool used for predicting and forecasting rainfall due to their effectiveness and accuracy, as revealed by many research studies when solving nonlinear sets of variables (Jibril et al., 2022). Therefore, in order to predict the rainfall, the study used three AI-based models (ANFIS, FFNN, and MLR). Using the conventional feature extraction method, the suggested modeling technique replicates R (mm) based on the correlation coefficient between the parameters. Based on sensitivity analysis, Eq. (1) tells us how to group the input features that will be used to calibrate the ANFIS, FFNN, and MLR models (see Fig. 2). The prediction was based on the current scenario of rainfall.

$$R\,(\mathrm{mm}) = \begin{cases} M1 = Rh + Wd \\ M2 = Rh + Wd + Tmin \\ M3 = Rh + Wd + Tmin + Ws + Tmax \end{cases} \tag{1}$$

The different input combinations used for the models' training are denoted by M1, M2, and M3. where Rh is the relative humidity, Wd is the wind direction, Tmin and Tmax depict the minimum and maximum temperature, and WS is the wind speed (Fig. 2). A methodology for external validation was applied throughout the analysis of the dataset, dataset used is received from Nigeria metrological agency (NiMet) for the Kano city, Nigeria, which comprises of daily weather indicators, for the duration of eight years, starting from 1st January 2015 to August 2022. It is then divided into calibration (80%) and verification (20%) sets. Prior to modeling, the model performances were validated using the k-fold cross-validation method. Despite the fact that different validation techniques can be utilized, the k-fold cross-validation technique is frequently employed (for a small dataset) to produce unbiased model performance predictions (Abba et al., 2020) (Pham et al., 2019). In order to boost the dataset's consistency and model accuracy, the dataset was normalized to have a range between zero and one, and Eq. (2) was used to reduce data redundancy.

$$X_i = \frac{x_{u-}x_{min}}{x_{\max-}x_{min}} \tag{2}$$

"X_i" represents the dataset's normalized quantity, "X_u" is the un-normalized quantity, "X_{min}" is the minimum quantity, and "X_{max}" is the maximum quantity.

2.1. Theory of models

2.1.1. Adaptive neuro-fuzzy inference system (ANFIS)

Jang established ANFIS in 1990 (Jang, 1993), It uses both a fuzzy inference system and neural networks as part of a hybrid modeling approach (FIS) and possesses the ability to resolve interactions that are complex in nature (Armaghani & Asteris, 2021) (Malami et al., 2021). FIS is well-liked overall because it can translate foreknowledge into some limitation sets. By combining FL algorithms and neural networks with the ANFIS, a multi-layer feed-forward neural network (MFFNN), also known as a backpropagation neural network, can store the mapping (BPNN) (Malami et al., 2021) (see Fig. 3). The Takagi Sugeno IF-THEN fuzzy rules used in the ANFIS are used to describe the knowledge between an engineering system's input and output variables. In this method, fuzzy logic and neural network learning functionality are combined to provide a system model that is more accurate (Golafshani, Behnood, & Arashpour, 2020) (Okeke et al., 2022). The Sugeno fuzzy inference system, where all inputs and outputs are membership functions assigned to input values, estimates output values for new input values by formulating rules based on known data (Cho et al., 2016). This membership function includes gaussian (gaussm), bell-shaped (gbellmf), sigmoidal (sigmf), triangular (Trimf), and triangular-triangular (tramf). The ANFIS structure consists of five main layers shown in Fig. 1, which are fuzzification (fuzzy clusters are generated from input values), rules, Eq. (6), normalization

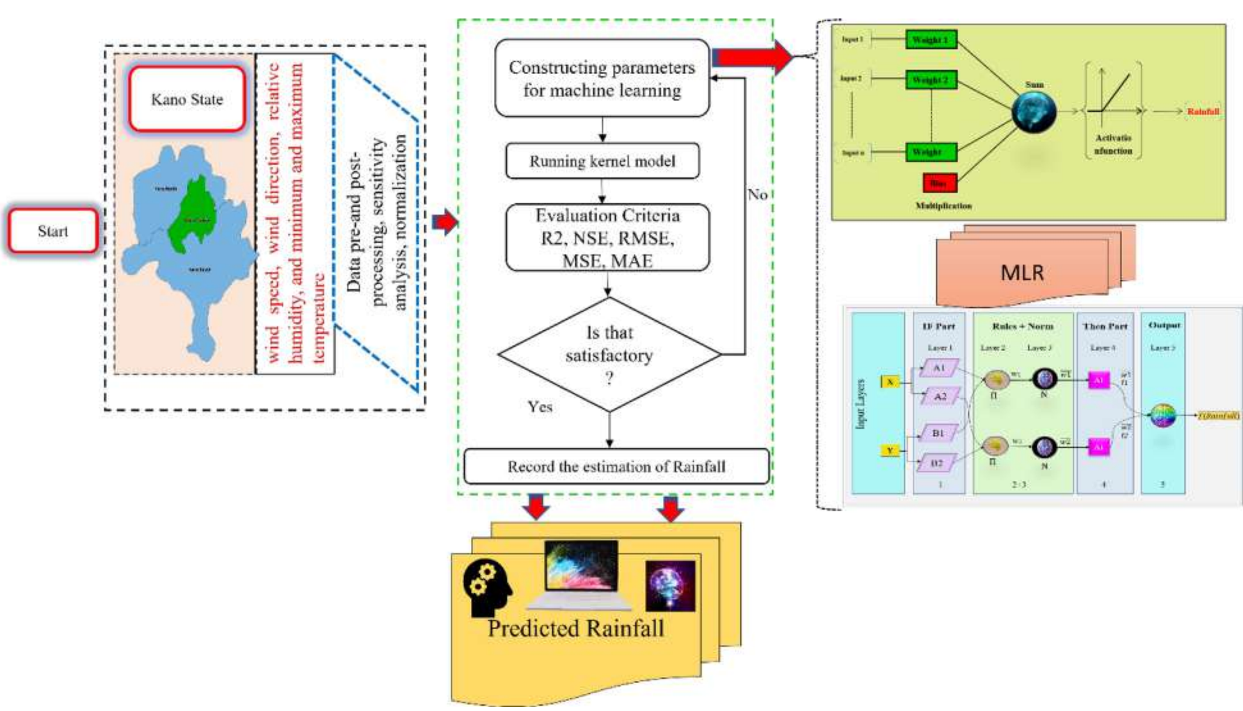

Fig. 2. Proposed modelling schema used in this study.

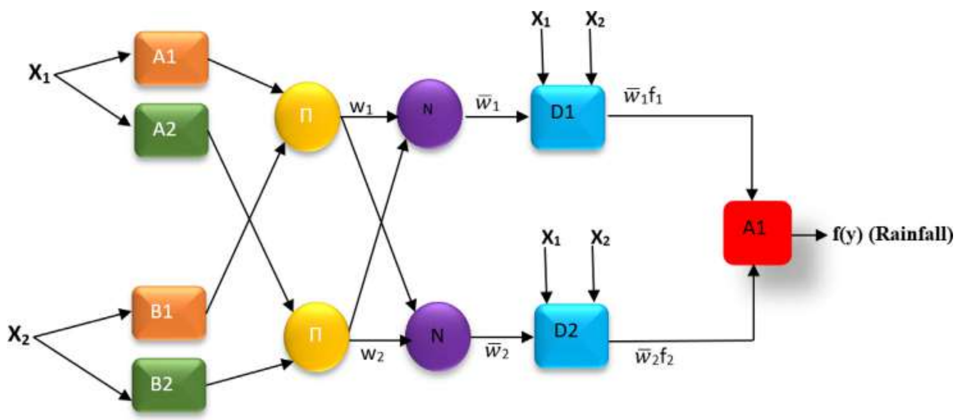

Fig. 3. The two inputs and one output ANFIS structure (Karaboga & Kaya, 2019).

(which determines the normalized firing strengths for each rule), Eq. (7), defuzzification (where each node calculates the weighted values of the rules), Eq. (8), and aggregation (by adding the results obtained for each rule in the defuzzification layer, the actual output of ANFIS is obtained), and Eq. (9) (Golafshani et al., 2020) (Karaboga & Kaya, 2019) (Ly et al., 2019) (Malami et al., 2021). Once the parameters of the model have been determined, the outcome of the model is determined for each batch of training data and compared with the experimental measurements to determine the discrepancy between the real and accepted values. When the halting condition is satisfied, the model is complete.

Assume the FIS has one output, "f," and two inputs, "x" and "y." A first order Sugeno fuzzy has the following rules:

$$Rule(1): if\, \mu(x) is A_1 and \mu(y) is B_1; then f_1 = p_1x + q_1y + r_1 \tag{3}$$

$$Rule(2): if\, \mu(x) is A_2 and \mu(y) is B_2; then f_2 = p_2x + q_2y + r_2 \tag{4}$$

The membership function for the supplied inputs × and y is represented as A_1, B_1,A_2,B_2, and the parameters for the outlet functions are p_1,q_1,r_1, and p_2,q_2,r_2,. The structural formula and of the 5-layer ANFIS are as follows.

Layer 1

$$Q_i^1 = \mu_{Ai}(x)\text{ for } i = 1,2 \text{ or } Q_i^1 = \mu_{Bi}(x) \text{ for } i = 3,4 \tag{5}$$

The term Q_i^1 refers to the grade of membership for the × and y inputs, and the Gaussian membership function was chosen as the membership function since it minimizes prediction error.

Layer 2

$$Q^2{}_i = w_i = \mu_{Ai}(x).\, \mu_{Bi}(y) \text{ for } i = 1,2 \tag{6}$$

Layer 3

$$Q_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \qquad i = 1,2 \tag{7}$$

Layer 4

$$Q_i^4 = \bar{w}_i(p_ix + q_iy + r_i) = \bar{w}_i f_i \tag{8}$$

The consequent parameters p_1, q_1, r_1, are irregular parameters.

Layer 5

$$Q_i^5 = \bar{w}_i(p_ix + q_iy + r_i) = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{9}$$

2.1.2. Feedforward neural network (FFNN)

The most popular and effective forward type of ANN algorithm in the literature is the FFNN (Haruna et al., 2021). FFNN is also referred to as a neural network or a multilayer perceptron (MLP). FFNN is frequently employed when the variables are neither sequential nor time-dependent. Among other ML algorithms, the FFNN mathematical model looks at the correlations between the input and output sets of nonlinear data sets. Neurons were previously used by ANN to mimic a biological brain's nervous system. It is common practice to employ FFNN with backpropagation (BP) computations to address a range of design problems (Meshram, Ghorbani, Shamshirband, Karimi, & Meshram, 2019). The eight-layer FFNN diagram for the top model in this investigation is shown in Fig. 4. The whole number of features in the dataset, or the number of neurons, is present in the input layer. The input layer receives data about the inputs and transmits it to the second layer. A hidden layer that contains several neurons that transmit changes from the input layer to the output layer exists between the input and output layers. Depending on how closely two neurons are related to one another, each neuron in the hidden layer has a different weight. The characteristic or objective of the issue that we are attempting to predict is the output layer (Nguyen, Ly, Mai, & Tran, 2020).

2.1.3. Multilinear regression analysis (MLR)

Regression models are used to examine various types of relationships between the predictors and the dependent variable as well as to assess the degree of correlation between them. Simple linear regression (SLR) and multiple linear regression are the two subcategories of linear regression models (MLR). Multiple linear regression (MLR) is a model that predicts the linear correlation of two or more predictor variables using only one criterion, whereas simple linear regression (SLR) is a model that predicts the correlation of variables from a single predictor using only one criterion. A summary of the data, an analysis of the relationship between the variables, and a straight line that best fits the target and output data are all produced by multiple linear regression (Khademi, Akbari, Jamal, & Nikoo, 2017). Eq (10) represents the MLR in its general form.

$$Y = a_o + \Sigma_{j=1}^{m} a_j X_j \tag{10}$$

Where y is the output in the model, X_j is the input data of the model, which is independent and a0, a_1, a_2, ..., a_m are partial regression coefficients.

2.2. Performance evaluation criteria

In this study, the performance of the ANFIS, FFNN, and MLR models given by Equations 11–15 was judged by five statistical measures: the determinacy coefficient (R2), the Nash coefficient

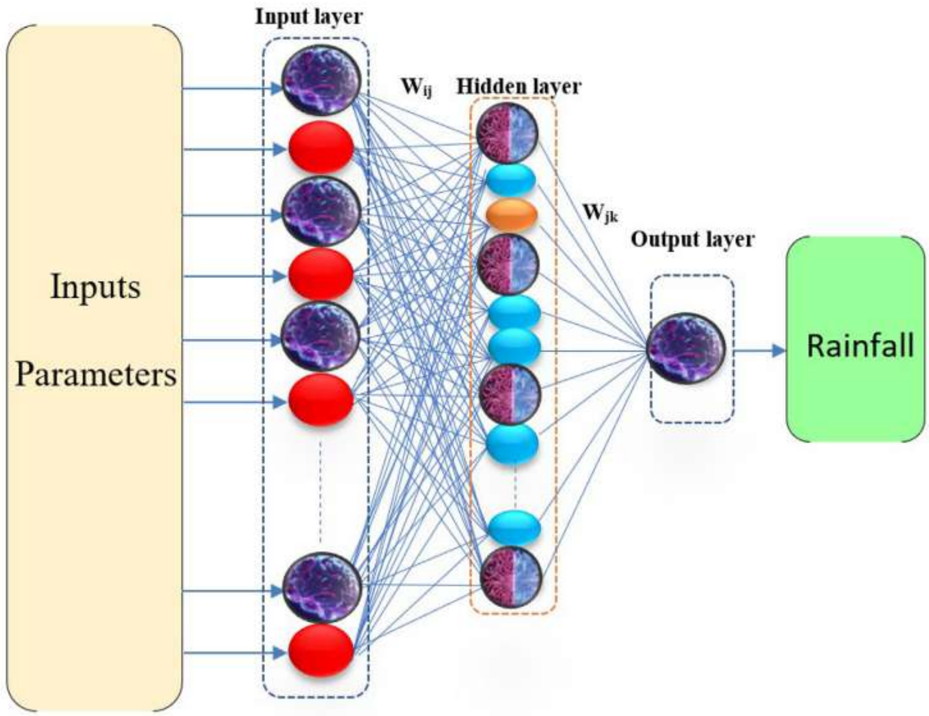

Fig. 4. Structure of FFNN.

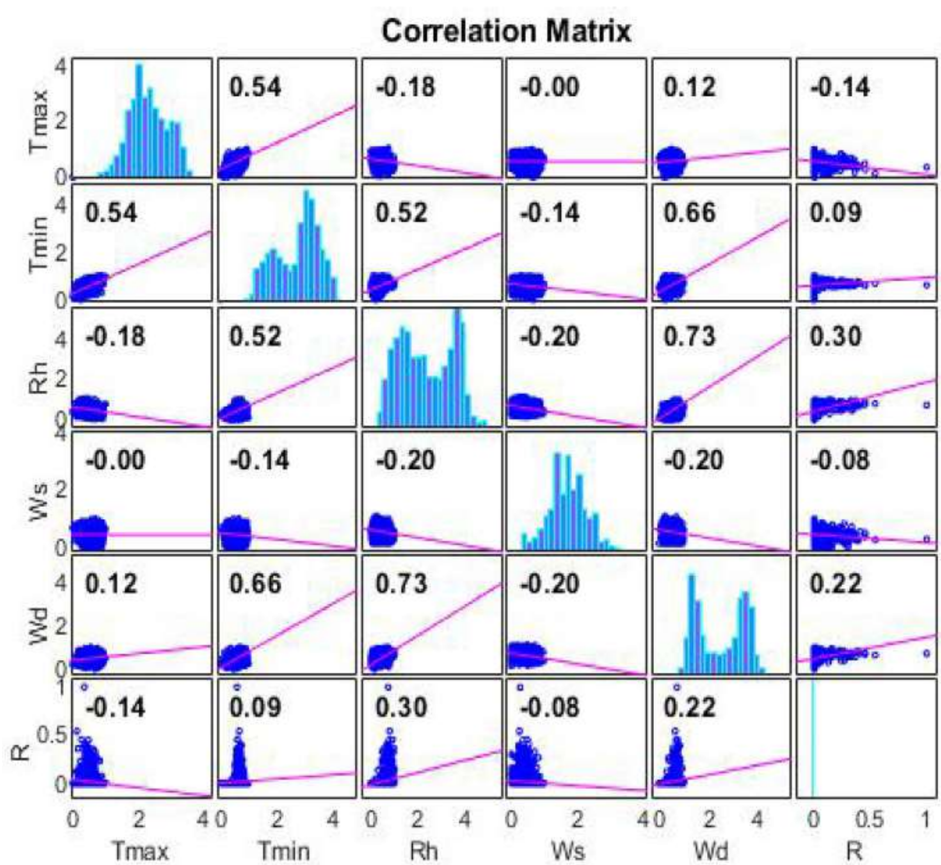

Fig. 5. Matrix of correlations for the parameters used to model rainfall.

(NSE), the mean square error (MSE), the mean absolute error (MAE), and the root mean square error (RMSE).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_R - P_R)^2}{\sum_{i=1}^{n}(O_R - O_{Rm})^2} \quad (11)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(P_R - O_R)^2}{\sum_{i=1}^{n}(P_R - O_{Rm})^2} \quad (12)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_R - P_R)^2 \quad (13)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{\mathrm{i=1}}^{\mathrm{N}}|\mathrm{P_R} - \mathrm{O_R}| \quad (14)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_R - P_R)^2} \quad (15)$$

where O_R stands for observed Rainfall in mm, P_R for predicted Rainfall in mm, O_{Rm} for observed mean Rainfall in mm, and N for the number of data points for each dataset.

3. Result of AI-based model

3.1. Results

Modelling rainfall in arid regions such as Northern Nigeria can be challenging due to the scarcity of rainfall data and the complex nature of rainfall processes in these regions. However, there are some essential parameters that can be used to model rainfall in arid regions to serve the irrigation and agricultural demand. The ML-based models (ANFIS, FFNN, and MLR) used in the study were constructed using rainfall data collected at various temperatures. The following sections contain the results and a discussion of them. Both the input and the target were normalized prior to the modeling activity. The descriptive statistics of the datasets and critical data used in model development are shown in Table 1 (Abba, Hadi, & Abdullahi, 2017) (Nourani, Elkiran, & Abba, 2018). The most frequent and efficient input combinations with the target variable were examined using a correlation matrix in a conservative statistical method, as illustrated in Fig. 5. The matrix is capable of establishing what kind of linear relationship exists between the variables and looking at the primary signs of any potential correlation between sets of variables. Direct relationships between two variables are indicated by positive correlation values, whereas negative correlation values indicate stationary and significant variables with a probability of less than 0.05 (P 0.05).

This statistical table presents summary statistics for six different parameters related to metrological input variable conditions. Tmax (maximum temperature) is 34.059, with a standard deviation of 4.240. The maximum and minimum temperatures observed are 44.8 and 20.4, respectively. The distribution of Tmax appears to be slightly positively skewed, with a skewness of 0.001. Similarly, Tmin (minimum temperature) was 19.783, with a standard deviation of 4.959. The maximum and minimum temperatures observed are 29.8 and 5.0, respectively. The distribution of Tmin appears to be slightly negatively skewed, with a skewness of −0.406. The R (rainfall) was observed to be 2.360 mm, with a standard deviation of 9.244 mm. The maximum amount of rainfall observed is 182.4 mm, with a minimum of 0.0 mm. The distribution of R is highly skewed, with skewness of 6.838. Also, WS was found to be 9.692 m/s, with a standard deviation of 3.953 m/s. The maximum and minimum wind speeds observed are 2.5 and 0.0 m/s, respectively. The distribution of WS appears to be slightly negatively skewed, with skewness of −0.074. However, the WD was observed to be 160.10 degrees, with a standard deviation of

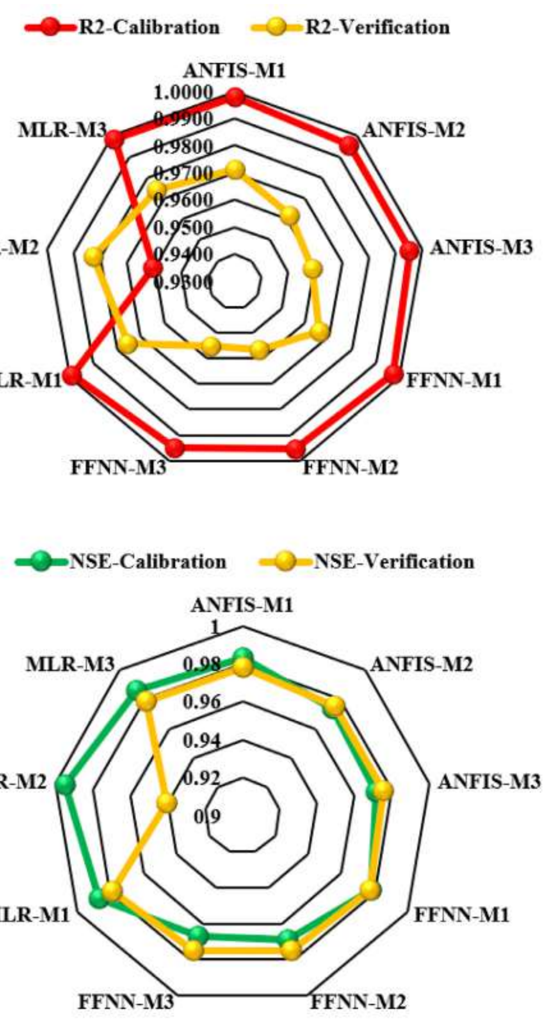

Fig. 6. Overall comparison using radar plots for R^2 and NSE criteria.

Table 2
Statistical between the input and output parameters.

Parameters	Tmax	Tmin	R	WS	WD	RH
Mean	34.059	19.783	2.360	9.692	160.10	48.26
Median	33.800	21.100	0.000	10.000	1675.0	46.0
Standard Deviation	4.240	4.959	9.244	3.953	73.088	22.815
Kurtosis	2.460	2.104	77.791	3.051	1.462	1.719
Skewness	0.001	−0.406	6.838	−0.074	−0.042	0.097
Minimum	20.40	5.00	0.000	0.0	0.000	6.000
Maximum	44.80	29.80	182.400	2.500	322.5	100.0

73.088 degrees. The maximum and minimum wind directions observed are 322.5 and 0.0 degrees, respectively. The distribution of WD appears to be slightly positively skewed, with skewness of −0.042. Lastly, RH was 48.26%, with a standard deviation of 22.815%. The maximum and minimum relative humidity observed is 100.0% and 6.0%, respectively. The distribution of RH appears to be slightly positively skewed, with skewness of 0.097. In addition, Kurtosis measures the degree of peakedness of distribution, with higher kurtosis indicating a more peaked distribution. Most of the parameters appear to have a relatively low kurtosis, except for R, which has a very high kurtosis of 77.791. This indicates that the distribution of rainfall is highly peaked and has heavy tails.

3.2. Evaluation and comparative analysis

It is worth mentioning that rainfall modelling plays a critical role in agriculture and irrigation as it helps farmers and water resource managers to predict and plan for potential changes in rainfall patterns. This information can aid in making informed decisions about crop management and water allocation, improving yields, and conserving resources. The performance assessment analysis results for prediction models are presented in Table 2. While taking into consideration errors and goodness of fit standards, the statistical indices (R^2, NSE, MSE, MAE, and RMSE) are used to evaluate the models' estimated efficiency and propensity for making predictions. According to Table 2′s findings, almost all the combinations satisfied the models' accuracy level in terms of the statistical requirements (M1, M2, and M3). These approaches are acknowledged to be able to manage models with multiple uncontrolled parameters, reduce the error function, and address data fitting issues based on the acquired results. They have proven to be an average response to extremely complex, nonlinear circumstances. The statistical criterion for precision was met by more than half of the models (R2 values up to 0.95). ANFIS, and FFNN

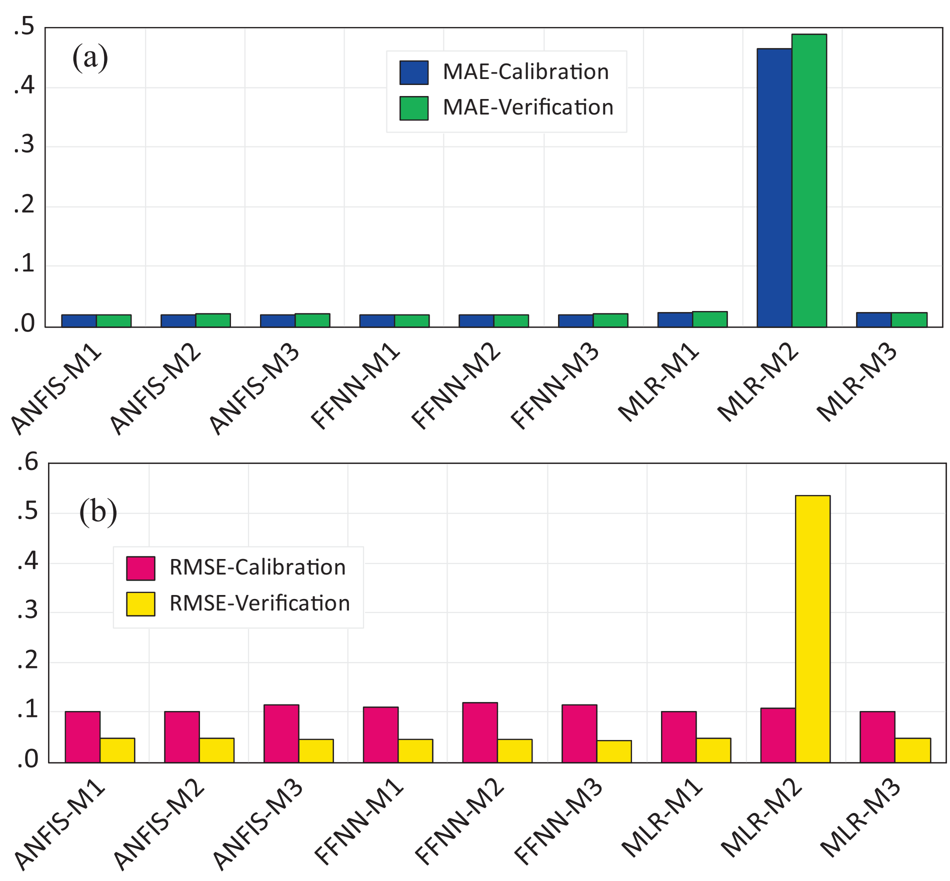

Fig. 7. Comparison of error plot for the all the models.

Table 3
Five separate data-driven models' outcomes.

Models	Calibration phase		MSE	MAE	RMSE	Verification Phase		MSE	MAE	RMSE
	R2	NSE				R2	NSE			
ANFIS-M1	0.9980	0.9833	0.0100	0.0181	0.1000	0.9713	0.9780	0.0020	0.0184	0.0452
ANFIS-M2	0.9955	0.9736	0.0100	0.0173	0.1000	0.9616	0.9755	0.0020	0.0198	0.0452
ANFIS-M3	0.9954	0.9711	0.0130	0.0170	0.1141	0.9591	0.9754	0.0018	0.0189	0.0429
FFNN-M1	0.9974	0.9782	0.0120	0.0180	0.1096	0.9662	0.9774	0.0020	0.0183	0.0448
FFNN-M2	0.9952	0.9688	0.0140	0.0170	0.1184	0.9568	0.9752	0.0019	0.0186	0.0431
FFNN-M3	0.9950	0.9670	0.0130	0.0179	0.1141	0.9550	0.9750	0.0017	0.0196	0.0415
MLR-M1	0.9989	0.9872	0.0100	0.0216	0.1000	0.9752	0.9789	0.0022	0.0231	0.0466
MLR-M2	0.9603	0.9948	0.0114	0.4646	0.1068	0.9828	0.9403	0.2873	0.4891	0.5360
MLR-M3	0.9987	0.9863	0.0100	0.0218	0.1000	0.9743	0.9787	0.0021	0.0222	0.0461

model combinations attained satisfy with criteria. In the MLR model, only MLR-M1 and MLR-M3 achieved the required criteria. It is highlighted that the MLR-M1 model performs the best for predicting the rainfall (R) mm, with R^2 = 0.998907, NSE = 0.987205, and the lowest RMSE of 0.001685 in the calibration phase (Fig. 6). These approaches have been found to be successful at min-

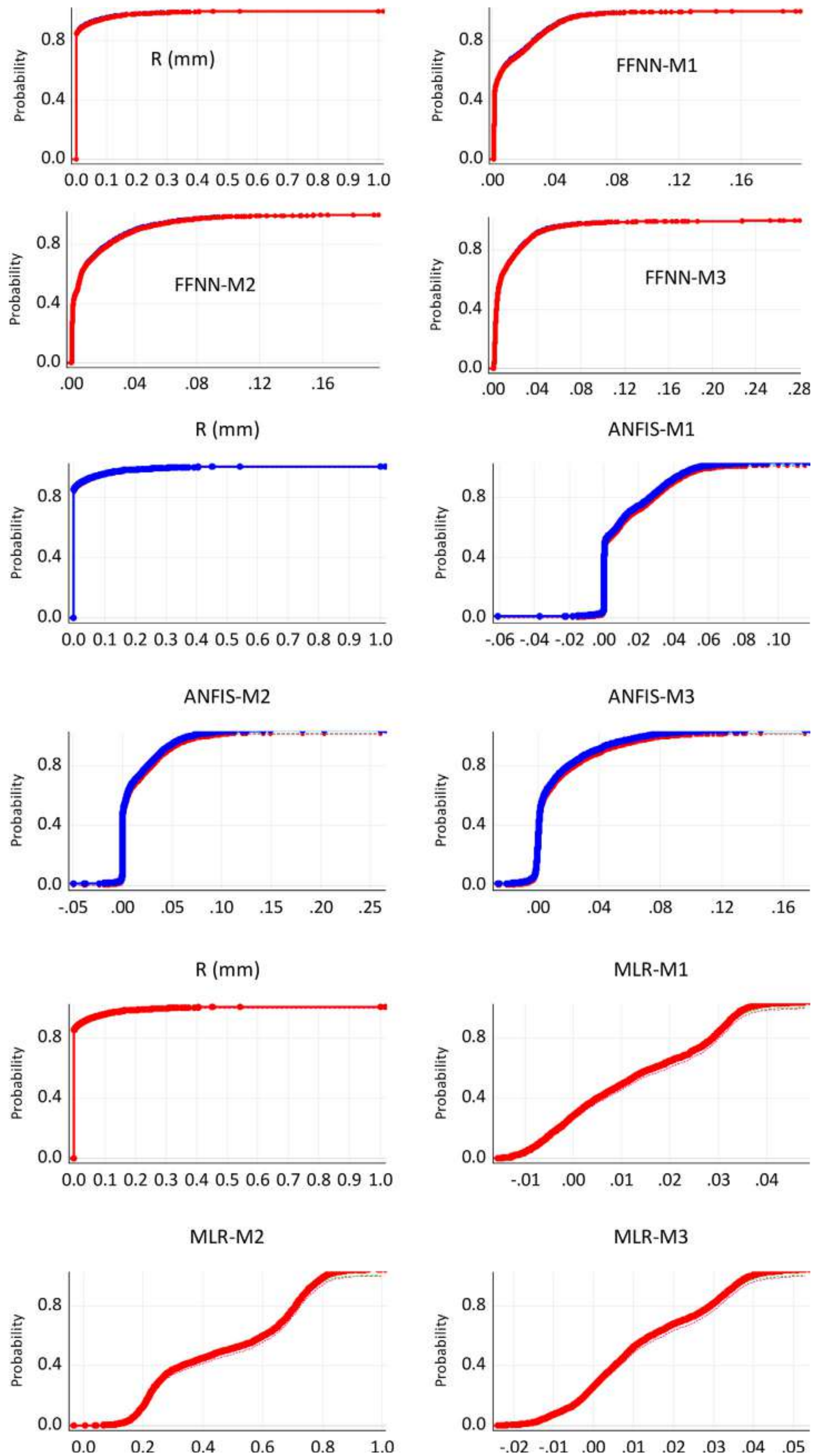

Fig. 8. CDF between the predicted models and observed data.

imizing the error function, controlling models with multiple uncontrolled parameters, and addressing issues with fitting data. They've evolved into a common strategy for dealing with extremely complex, nonlinear situations.(See Fig. 7 Table 3).

During the modeling phase, the R^2 performance evaluation criterion was utilized to compare all the models using the radar diagram. Fig. 4 displays the ANFIS, FFNN, and MLR-M. These models produce predictions more accurately when compared to other models. The suitability of AI-based modeling for engineering and scientific research is discussed in this article. The numerical comparison showed that, in the calibration phase, ANFIS-M1 and MLR-M1 performed the best with R^2 values of 0.9980 and 0.9989, respectively. However, in the verification phase, ANFIS-M1 and MLR-M1 had lower R^2 values than other models, indicating overfitting. On the other hand, ANFIS-M3 and FFNN-M3 had the highest R^2 values in the verification phase, indicating better generalization ability. In terms of NSE, MLR-M2 had the highest value in the calibration phase, but it had a much lower value in the verification phase, indicating poor generalization ability. In contrast, ANFIS-M1 had a relatively consistent NSE value between calibration and verification phases.

However, MSE and RMSE are two other commonly used evaluation metrics that measure the average squared and root-mean-squared errors, respectively. ANFIS-M1 and MLR-M1 had the lowest values for both metrics in the calibration phase, but their performance deteriorated in the verification phase. In general, ANFIS-M3 and FFNN-M3 had the lowest values for these metrics in the verification phase. To conclude, MAE measures the average absolute difference between the predicted and actual values. ANFIS-M1 and MLR-M1 had the lowest MAE values in the calibration phase, while ANFIS-M3 and FFNN-M3 had the lowest values in the verification phase. Generally, ANFIS-M3 and FFNN-M3 seem to be the most promising models, as they had consistently high performance across different evaluation metrics in the verification phase. However, it's worth noting that different metrics may have different levels of importance depending on the specific application.

During the model, an error plot was also employed to depict the overall error of the model and to reveal the model with the least error, as shown in Fig. 6, which shows how accurate and effective an AI based model is when dealing with a nonlinear set of variables. In comparison, MLR-M1 has the lowest overall error with a RMSE of 0.00168, which reduces the error of ANFIS-M1 by 35.77% and FFNN by 25.73%. Fig. 8 shows how the data values are uniformly distributed using the cumulative distribution function (CDF) model. The distribution of sizable datasets can be compared using this information. As a result, although the variation is independent of the models' quantitative reliability, it resembles the data dispersion.

4. Conclusion

AI-based models are getting more and more popular due to their accuracy and effectiveness when dealing with non-linear sets of variables. Three models ANFIS, FFNN, and MLR were used in this study to create models to forecast the rainfall R (mm) in the arid agricultural area of Kano, Nigeria. Although all of the computational models (ANFIS, FFNN, and MLR) produced good results, the MLR-M1 model performed the best for forecasting the rainfall (R) mm, with R^2 = 0.998907, NSE = 0.987215, and the lowest RMSE of 0.001685 in the calibration phase the findings in this research will help to make knowledge-based plans for irrigation and effective management. The proposed model can serve as a background and could be part of the tools used by farmers and researchers in decision making in sub-Saharan Africa, where it is highly needed. In conclusion, the application of MLs models, namely ANFIS, FFNN, and MLR, has shown promise in predicting rainfall patterns. The models were trained using various input variables such as temperature, humidity, and wind speed to accurately forecast rainfall. The ANFIS and FFNN models outperformed the MLR model in terms of accuracy and precision in some scenarios. Additionally, the models' ability to handle non-linear relationships and complex data sets make them suitable for rainfall prediction. However, the accuracy of these models can be affected by the quality and quantity of the input data. Generally, the application of MLs models in rainfall prediction provides a promising avenue for advancing our understanding of climate patterns and enhancing weather forecasting capabilities. The outcomes of this paper suggested that other feasible alternatives should be used to improved the accuracy of the approach.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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