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Artificial Neural Networks with various Transfer Functions for Modeling Rainfall Patterns in Sokoto, Nigeria

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ABSTRACT: Accurate rainfall prediction is crucial for agricultural practices and water resource management in semi-arid regions. Hence, the objective of this paper is to employ Artificial Neural Networks (ANNs) with various transfer functions for modeling rainfall patterns in Sokoto, Nigeria. Rainfall data from 1990 to 2019 alongside average temperature, relative humidity, and year were utilized. Three candidate transfer functions (logsig, purelin, tansig) were compared within a multi-layered ANNs architecture. The performance of each model was evaluated using correlation coefficient (R) and root mean square error (RMSE). The results revealed that the ANN with the tansig transfer function achieved the highest R (0.8789) and the lowest RMSE (0.0125), demonstrating a strong positive relationship between predictions and actual data with minimal errors. This performance surpassed previously reported ANNs models for rainfall prediction in some Nigerian northwestern regions. The study concludes that tansig is the most effective transfer function for modeling Sokoto's rainfall patterns using ANNs. This model can be a valuable tool for stakeholders in agriculture and water management to make informed decisions based on predicted rainfall patterns.

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Modelling and prediction of rainfall pattern play a crucial role in enhancing the sustainability of various practices, including agroforestry. Accurate forecasting of rainfall patterns assist farmers or agroforestry practitioners to make informed decisions regarding crop selection, irrigation scheduling, and land management practices, leading to improved productivity and resource conservation (Tuel and Meyers, 2012), thereby ensuring long-term viability of agroforestry systems (Diaz-Uriarte and Alvarez de Andrés, 2006). For instance in crop selection, knowledge of rainfall modelling and prediction will enable the implementation of appropriate measures such as planting drought-resistant crops or establishing water retention structures to minimize crop losses and soil erosion, thereby promoting the resilience of agroforestry practices (Alam *et al.*, 2016). In planning and management of agroforestry landscapes, accurate rainfall forecasting enables farmers to optimize land use and agroforestry system designs based on anticipated rainfall patterns. This includes decisions on tree species selection, spacing, and agroforestry layout to maximize water use efficiency and ecosystem services while minimizing environmental risks (Garrity *et al.*, 2010). A number of methods have been applied to rainfall data

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modelling to understand and predict precipitation patterns. For instance, parametric models such as Generalized Linear Models (GLM), Hidden Markov Models (HMM), Non-parametric Models (NM) models, Machine learning methods (such as Support Vector Regression (SVM), Artificial Neural Networks (ANNs), Adaptive Neuro Fuzzy Inference System (ANFIS) and Gradient Boosting Machine (GBM)), empirical models and dynamic models have been widely reported (Roy *et al.,* 2021) with varied performances. However, ANNs remains popular in use due to its ability to capture complex nonlinear relationships that are inherent to meteorological processes (Allawi *et al.,* 2023). ANNs excel at learning from data patterns and making predictions without relying on explicit programming of rules, making them suitable for handling the intricate and dynamic nature of rainfall patterns. In addition, ANNs can adapt and optimize their internal parameters during training, allowing it to continually improve performance in predicting rainfall patterns over time (Allawi *et al.,* 2023). In addition, ANNs can incorporate various input variables to enhance the accuracy and robustness of rainfall predictions (Assiri and Qureshi, 2022). Utilizing ANNs for rainfall modelling offers several advantages, including their ability to handle large and diverse datasets, adaptability to changing environmental conditions, and potential for integration with other modelling techniques to improve overall forecasting accuracy (Allawi *et al.,* 2023). The performance of ANNs modeling and prediction strongly depends on ANNs simulation parameters such as type utilized (Cascade-forward backpropagation, competitive, elman back propergation, Hopfield, amongst others), training function parameter, adaption learning function, number of layers and number of neurons in the layer and transfer functions. Transfer functions in ANNs are crucial as they introduce nonlinerity, allowing the network to model complex relationships effectively (Gusri *et al.,* 2020), therefore, utilising the right transfer function parameter become important. These transfer functions parameter transform the weighted sum of inputs into an output signal, allowing for the modeling of nonlinear relationships between input and output variables (He and Takase, 2006). Common transfer functions include sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU), each offering different properties suited for various network architectures and tasks (He and Takase, 2006). The choice of transfer function influences the network's ability to learn and generalize patterns from the data. Amongst studies that utilized ANNs to model the rainfall pattern, Abdulkadir *et al.,* (2016) trained ANNs with sixty years (1952 – 2011) monthly historical rainfall data. The performance of the trained network had a correlation coefficient of 0.88 which the author claimed to be fit for subsequent quantitative prediction of rainfall in Ilorin Township of Kwara State Nigeria. In addition, Bączkiewicz *et al.,* (2021) presented the use of a regressive model based on a unidirectional multilayer type of neural network, also called a Multilayer Perceptron (MLP), to predict selected weather indicators for the city of Szczecin in Poland. The author found that the model was effective in determining the daily parameters at 96% compliance with the actual measurements for the prediction of the minimum and maximum temperature for the next day and 83.27% for the prediction of atmospheric pressure. Relying on the past convincing utilization of ANNs to model meteriology data, present authors observed that a study on the effect of the ANNs transfer function which is the main sorce of non-linearity in ANNs modelling is scarce and presently constitutes a gap in study. Therefore, the focus of this study is to bridge these observed gap in study by utilizing a case study of Sokoto State in the North-Western part of Nigeria because of the requirement for adequate water management for agro-forestry related matters in the area. Hence, the objective of this paper is to employ Artificial Neural Networks (ANNs) with various transfer functions for modeling rainfall patterns in Sokoto, Nigeria

MATERIALS AND METHODS

The Study Area: Sokoto State is situated in the northwestern part of Nigeria (approximately between 10°E and 14°E longitude and 11°N and 13°N latitude). It is a semi-arid region that is characterized by a distinct wet and dry season (Ayoade, 1973). Its sub-tropical steppe climate features an average annual rainfall amount ranging between 34 mm and 726 mm depending on the source and time period considered. Modeling Sokoto states's rainfall patterns is a crucial step because it can help predict future trends. With accurate models, stakeholders can gain insights to adapting agro-forestry practices in the area to ensure food security for the continually increasing population. The vulnerability of Sokoto state to both droughts and floods requires effective models that can predict the likelihood and severity of climatic events, enabling proactive measures to mitigate their impact (Atedhor, 2015). Furthermore, Sokoto state's population is growing like every other part of Nigeria, and there is likelihood of putting increasing pressure on its limited water resources, therefore climatic event prediction is important.

ANNs modeling: In a bid to have a simple and accurate ANNs model, the selection of an appropriate topology cannot be overemphasized (Onwude *et al.*, 2016). Therefore, a feed-forward back propagation ANNs type, comprising of either logsig, tansig or purelin transfer function was selected to investigate the best ANNs topology that predict the rainfall data in this study. The training function was kept constant to TRAINBFG (useful for training neural networks effectively, ensuring convergence and generalization while avoiding over-fitting), Adaption learning function was also kept constant to LEARNGDM (to incorporate momentum to accelerate learning and overcome local minima more effectively). MATLAB 2021b software was utilized to implement the ANNs. Data were partitioned into training (60%), validation (15%), and testing (25%) for the entire ANNs modeling runs. A mean of three different simulations is reported for each investigated ANNs topology due to randomness in MATLAB's ANNs number generator for network weights.

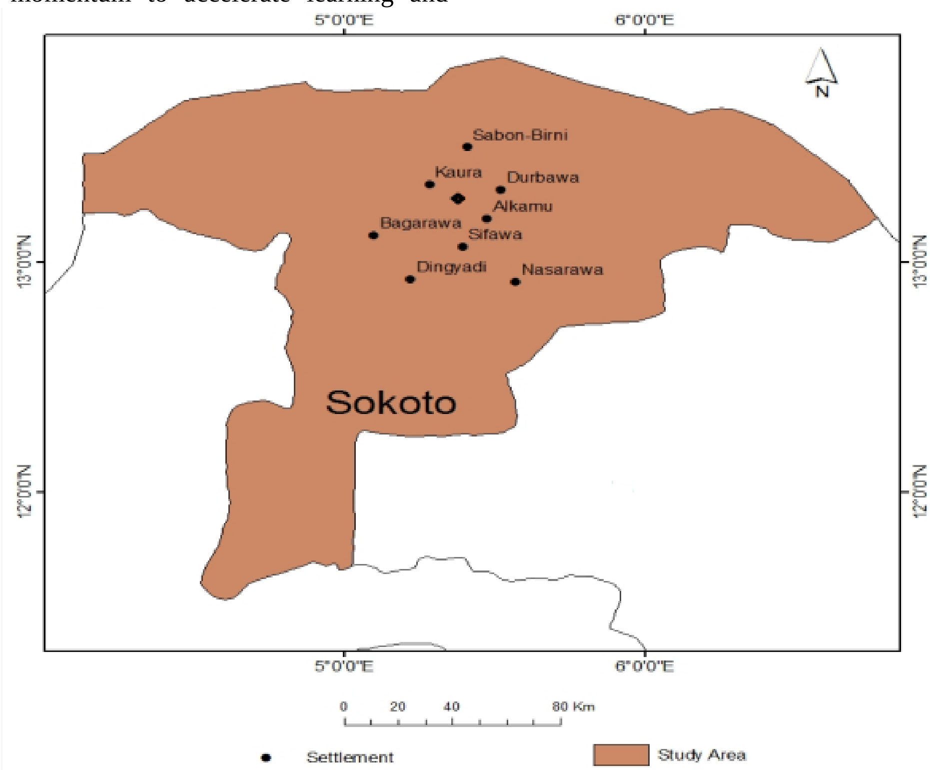

Fig 1: Map of Sokoto
Source: Atedhor, (2015)

Before ANNs simulation, normalization of the data to enhance accuracy and speed was done in accordance with the method of Kaveh *et al.*, (2018) using Microsoft Excel Office Software in accordance with Equation 1.

$$X_n = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where, X_n depicts the normalized value of the specific data point, X_i depicts the value of each data point, X_{max} depicts the maximum value in the whole data under consideration, and X_{min} depicts the minimum value in the whole data under consideration.

ANNs prediction efficiency: The model performance was established by applying statistical metrics (Correlation coefficient (R) and root mean square error (RMSE)) as represented in Equation (2) - (4).

$$\sqrt{R = 1 - \frac{\sum_{i=1}^{n_{Exp.data}}(Data,i - Pred,i)^2}{\sum_{i=1}^{n_{Exp.data}}(X'_e - Data,i)^2}} \quad (2)$$

$$X'_e = \frac{1}{n_{Exp.data}} \sum_{i=1}^{n_{exp.data}} Data,i \quad (3)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(Data,i - Pred,i)^2}{N}} \quad (4)$$

Where *Pred,i* is the ith predicted value, *Data, i* is the ith data value. N is observation number. Furthermore,

$Pred, i$ is the model value, $Data, i$ is the data value, $n_{Exp.data}$ is the number of the experimental point,

RESULTS AND DISCUSSION

The statistical summary of the rainfall data of Sokoto State in the Northwestern part of Nigeria that was utilized for ANNs modeling in this study is represented in Table 1. The summary is for the four input factors (year, month, average temperature and relative humidity) and one output factor (rainfall output). Consistent with the desk, the information covers 30 years, from 1990 to 2019. The website seems to endure notable heat temperatures on average, as indicated by the implied temperature of roughly 29.10 °C. With a minimum temperature of 22.35 °C and a maximum temperature of 35.15 °C, the temperature variety suggests fluctuation. Seasonal variations in climatic patterns are reflected in this variability. The facts show mild humidity levels, with a mean relative humidity of roughly 44.47 percent. However, the variety of 11% to 82% indicates a sizable variation in humidity, which might also affect how relaxed human beings feel and feature consequences for such things as agriculture, the longevity of infrastructure, and health. A slight amount of precipitation is usually recommended through the suggested rainfall of about 57.83 mm.

Table 1: Statistical summary of the Sokoto State rainfall data

Summary	Year	Month	Average Temperature	Relative Humidity	Rainfall
Mean	2004.5	6.5	29.10	44.47	57.82
Standard Error	0.45	0.18	0.14	1.17	4.46
Median	2004.5	6.5	28.65	42	3.35
Mode	1990	1	28	25	0
Standard Deviation	8.66	3.45	2.81	22.27	84.68
Sample Variance	75.12	11.94	7.91	496.24	7172.04
Kurtosis	-1.20	-1.21	-0.60	-1.48	2.29
Skewness	1.99E-17	-2.48E-18	0.21	0.21	1.63
Range	29	11	12.8	71.21	374.90
Minimum	1990	1	22.35	11	0
Maximum	2019	12	35.15	82.21	374.90
Sum	721620	2340	10477.77	16010.71	20818.18
Count	360	360	360	360	360

The huge range of zero mm to 374.9 mm, however, shows considerable variation in the total quantity of rainfall. The place's standard situations can be inferred from the median values. For example, the median relative humidity of 42% and the temperature of 28.65 °C imply the usual circumstances that humans can stumble upon. The mode of zero mm suggests that dry periods are common, but the median rainfall of 3.35 mm indicates that normal rainfall occasions are very rare. Values for skewness and kurtosis reveal information on the symmetry and shape of every variable's distribution. At the same time as skewness numbers display the distribution's asymmetry, negative kurtosis values advocate flatter distributions. Modelling and projecting future weather styles and their feasible consequences can be aided by using information about kurtosis and skewness values. The kurtosis and skewness values in this instance factor into complex non-linear records, necessitating a modelling method capable of coping with them.

ANNs simulation: After series of trial runs with different ANNs structures, the best performed structure is represented in Figure 2. The structure consited of four input layers representing four output factors and one output layer representing one output factor. The three (3) hidden layers were utilized. The hidden layer 1 was composed of twenty (20) neurons, the hidden layer 2 was composed of one (1) neuron, and hidden layer 3 was composed of ten (10) neurons. This represented the best ANNs structure that modeled the complexly non-linear data under consideration. The result of the ANNs simulation (modeling and prediction) showing the effect of selected transfer functions is represented in Table 2. TANSIG (Hyperbolic Tangent Sigmoid) is an activation function that regulates the input values between -1 and 1. LOGSIG (Logistic Sigmoid) is a frequently used activation function that controls the input values between 0 and 1. PURELIN (Pure Linear) is a linear activation function where the output is just a scaled version of the input. According to the table, TANSIG has the lowest root mean square error (RMSE) and the highest correlation coefficient (R). The linear relationship between the expected and actual values is measured by the R, which also indicates its direction and strength. A number nearer 1 in this case denotes a more robust positive linear relationship between the model's predictions and the observed data. The average extent of the discrepancy between the anticipated. The

ANNs training progress for best activation function (TANSIG) is represented in Fig 3. The figure showed that the best training, validation and test performances were achieved at epochs 8, being the point of minimum mean squared error (0.0125) as signified by the small circular demarcation on the figure. After the demarcation, the figure showed that the error increased which is an indication for over-fitting. It therefore means that to prevent over-fitting (that is, memorising the data rather than understanding the pattern in the data), the ANN structure should be trained for not more than 8 epochs. The performance of the ANNs structure with the best activation function (TANSIG) is represented in Figure 4

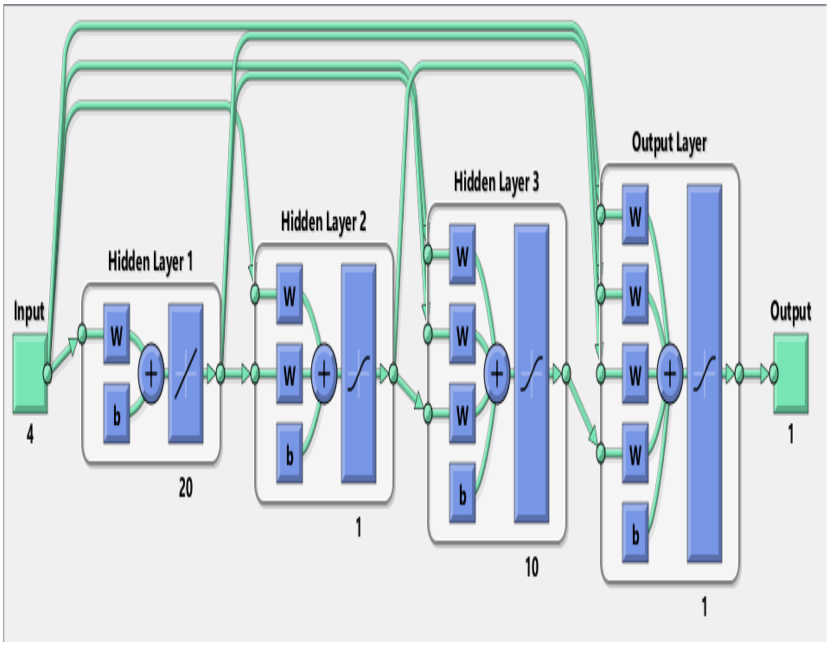

Fig 2: ANNs topology

Table 2 performance of selected transfer functions

Transfer function type	R	RMSE
LOGSIG	0.8163	0.0132
PURELIN	0.7882	0.0188
TANSIG	**0.8789**	**0.0125**

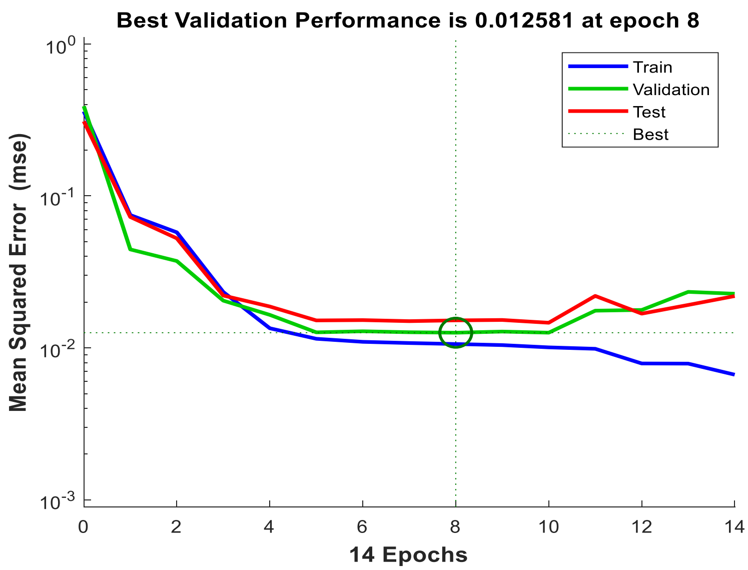

Fig 3: Training progression of the ANNs structure

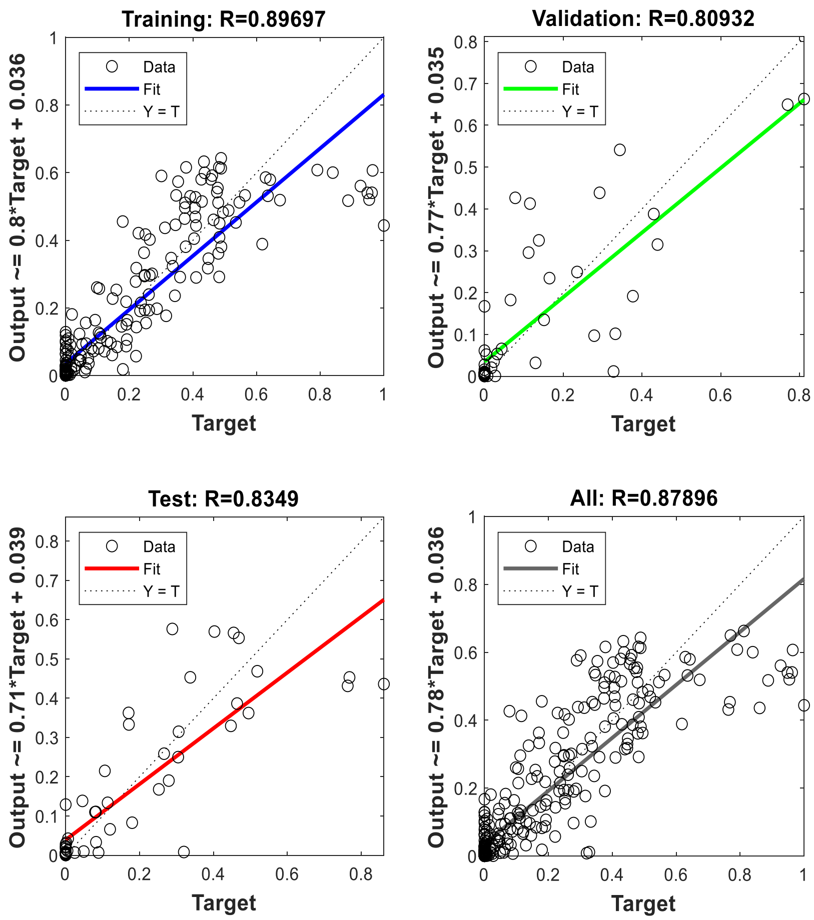

Fig 4: Predictive performance of the ANNs structure

The ANNs structure had 0.8969, 0.8093, and 0.8349 correlation coefficient value for predicting training, validation, and testing data, respectively. On the overall, the structure had a correlation coefficient of 0.8789. In a related study on the utilization of ANNs for predicting rainfall data, Abdulkadir et al., (2017) reported the average correlation coefficient values of 0.80, 0.62, 0.65, 0.67, 0.79, 0.76 and 0.81 with corresponding mean square errors of 2.12, 0.23, 0.26, 0.36, 2.61, 1.18 and 1.03 for Abuja, Makurdi, Ilorin, Lokoja, Lafia, Minna and Jos rainfall pattern, respectively. This showed that the enhancement and choice of the ANNs structure in this study that yielded a correlation coefficient of 0.8789 was more capable in capturing the dynamics of complexly non-linear rainfall data.

Conclusion: This study highlights the effectiveness of Artificial Neural Networks (ANNs), particularly with the Tansig transfer function, in modeling rainfall patterns in Sokoto State, Nigeria. The superior performance of the Tansig function demonstrates its ability to capture non-linear relationships in rainfall data, with high accuracy and minimal errors. The ANN model provides a valuable tool for stakeholders in agriculture and water resource management, enabling better planning for resource allocation and proactive drought mitigation. Future research should explore the inclusion of more climatic variables, larger geographical scopes, and alternative ANN architectures to enhance prediction accuracy further. These efforts will contribute to the sustainable management of water and agricultural resources in the region.

Declaration of Conflict of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper.

Data Availability Statement: Data are available upon request from the authors

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