Original Research Article

Evapotranspiration Estimation Using Artificial Neural Network Over South-Western Nigeria.

ABSTRACT

In this study, Artificial Neural Network was used for the estimation of Evapotranspiration over South-Western Nigeria. Using a 36 years meteorological data of South-Western Nigeria obtained from NASA (National Aeronautics and Space Administration) Power data, the Multilayer Perceptron Neural Network and Radial Basis Function Neural Network under several Neural Network Architecture was used, training, testing and validation operations also were performed for estimating evapotranspiration closely to the target calculated value. The performance of each neural network under several NN Architecture was evaluated using statistical indicator such as R (Correlation of Coefficient), R^2 (Coefficient of Determination), MAE (Mean Absolute Error) and RMSE (Root Mean Square Error). Results present Multilayer Perceptron Neural Network the best neural network with about 70% of its R-values (0.70) because ETo varies in the same pattern as the four of the input parameters used (minimum and maximum air temperature, solar radiation, and wind speed) compare to Radial Basis Network that has 50% of its R-values below (0.70) under several NN Architecture because of the inverse relationship and poor correlation of the ETo and relative humidity. Also, LAGOS and OYO dataset produced the highest performance with an R-value of (0.999998) as a result of uniformity in the climatic trend over 36years while OGUN dataset produced the lowest performance of (0.467169) as a result of significant variation in the climatic trend over the past 36years. The study presented here has profound implications for future studies of estimating evapotranspiration and one day help solve the problem of water scarcity and food insecurity.

Keywords: Evapotranspiration, Architecture, Artificial Neural Network, Performance, Multilayer Perceptron Network, Radial Basis Function.

1. INTRODUCTION

Water Usage in the field of agriculture is at the peak of any discussion of food security [1]. Globally, water application, usage and management has been a key factor in the increasing fruitfulness of agriculture and also in ensuring foreseeable output. Water can be considered as one of the crucial and most essential natural renewable resources on the planet earth for the continuous existence of man and living organisms. Water is well known as the most abundant resources on the earth surface, but just about 1% is available for human use or consumption [2]. It can be used for several purposes ranging from agricultural activities such as planting, aquatic farming, livestock rearing, and irrigation, to commercial or industrial uses which include Hydro-electric power generation, firefighting, industrial or production processes etc to domestic or household usage for drinking, cooking, laundry, bathing, etc. According Food and Agriculture Organization (FAO), from the 1960s, food per capital has generally been provided at reducing prices, but at the expense of water resources considering the fact that global food supply and production has at least kept pace with rapid growth in the world's population. Future increase in the competition of available water resources has been projected with particular reference to agriculture. Agricultural production will need to expand 70% as a result of projected increase in population growth to about 10billon in both cities and rural settlements by

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2050, thereby causing proportionate increase in the demand for food for survival. By 2050, Agriculture constitutes about 70% of the total water withdrawals [3]. The above food security and water estimations appears controversial, because from the perspective of increase in population there is need to reduce the amount of water used for agriculture, but also from view of food security, adequate water usage and management is a key component of sustainable food production. Thorough consideration of proper usage, and management of considering crop's water requirement for agriculture and better crop yield led to the study of evapotranspiration [3]. Evapotranspiration involves the combination of two different processes by which water is removed on one hand from the surface of the soil by direct evaporation to the atmosphere and on the other hand from plant tissues and pores of leaves by transpiration [4]. Transpiration and Evaporation occurs concurrently, and it is quite difficult to differentiate or distinguish between the two [5]. In hydrologic cycle, one of the major elements is evapotranspiration, its precise and accurate estimations are of significant importance for several research studies such as simulation of crop yields, planning and management of water resources, hydrologic water balance and system design and management of irrigation system [6]. Artificial neural network is a branch of artificial intelligence. An Artificial Neural Network is a massively parallel distributed system and processor comprising of simple processing units, and possesses the natural propensity and capability of storing knowledge for further applications [7]. In the past years, there have been a number of researches and developments in the applications of ANNs to solve problems relating to agriculture [8,9] used Artificial Neural Networks (ANNs) for rainfall-runoff modelling, river-stage forecasting using ANN [10,11]. Ariapour and Zavareh, (2011) using feed-forward multiple-layer network with a sigmoid function and a hidden layer developed an ANN model for estimating daily evaporation (Case-study; Borujerd Meteorological Station). Estimation of daily standard evapotranspiration for wheat and maize using ANN, each crop was designed with different structures of ten models of ANN [12], the research led to a conclusion that locally calibrated Equation-based calculated ETo produces an accurate estimated ETo of wheat and maize unlike measured values of ETo. Of wheat and maize. Evaluation of the performance of alternative Equations except FAO Penam for evaluating evapotranspiration using artificial neural network (ANN) and support vector machine (SVM) [13]. The aim of the study is to estimate or predict evapotranspiration using artificial neural network and the objectives are i) evaluation of evapotranspiration using statistical performance tests. ii) Determination of the most suitable neural network architecture for estimating evapotranspiration iii) Comparison of the performance Multilayer perceptron neural network and Radial Basis Neural Network for evapotranspiration estimation.

2. METHODOLOGY

2.1 Study locations

South-Western Nigeria is one among the six geopolitical zones of Nigeria consisting of six states as presented in the Figure 1.

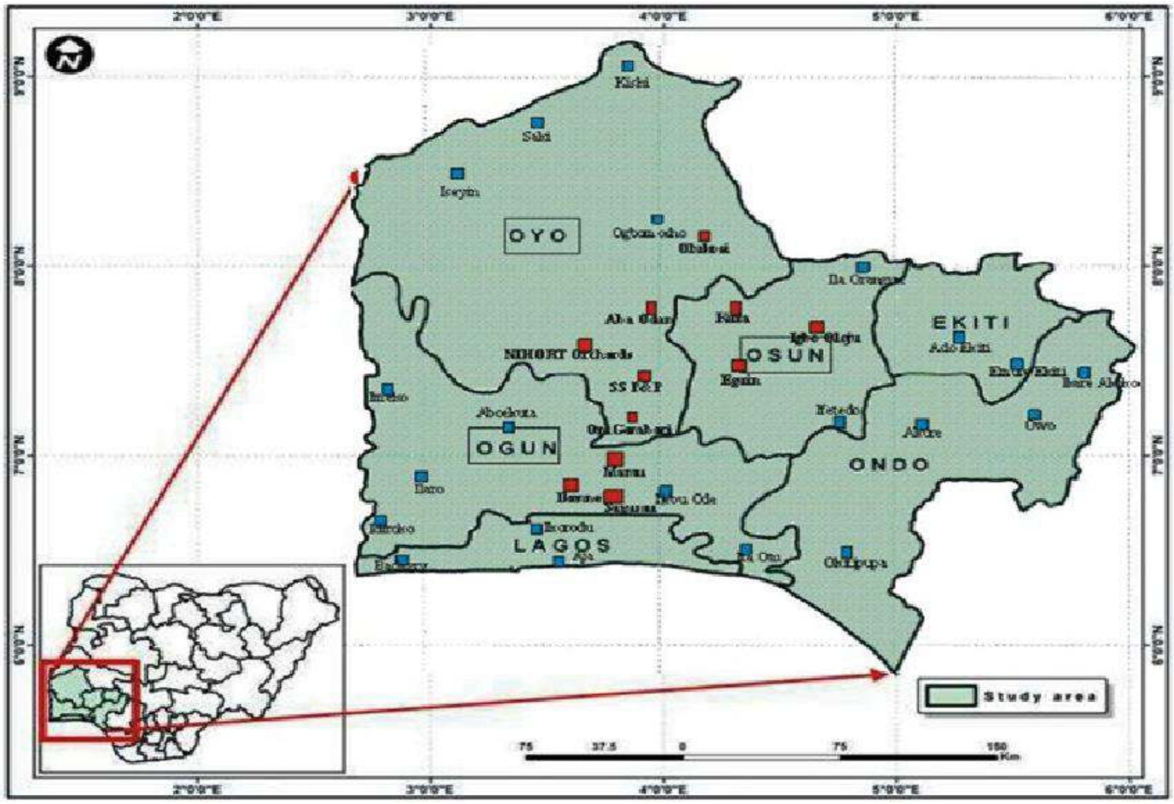


Fig. 1: A Map showing the South-Western Nigeria geopolitical zone (Adedapo, 2015).

Table 1: Geographical information of the locations under study.

Geographical Location	Latitude	Longitude	GPS Coordinates	Elevation (meters)
Lagos	6.45	3.40	$6^{0}\ 27^{I}\ 14.65^{II}$ N, $3^{0}\ 23^{I}\ 40.81^{II}$ E	39
Ogun	7.00	3.58	$7^{0}\ 0^{I}\ 0^{11}$ N, $3^{0}\ 34^{I}\ 60^{II}$ E	77
Ondo	7.17	5.08	$7^{0}\ 10^{1}\ 0.01^{II}$N, $5^{0}\ 04^{I}\ 59.99^{II}$ E	264
Ekiti	7.67	5.25	$7^{0}\ 40^{I}\ 0^{11}$ N, $5^{0}\ 15^{I}\ 0^{11}$ E	458
Osun	7.50	4.50	$7^{0}\ 30^{I}\ 0^{11}$N, $4^{0}\ 30^{I}\ 0^{II}$ E	246
Oyo	8.00	4.00	$8^{0}\ 0^{I}\ 0^{11}$ N, $4^{0}\ 0^{I}\ 0^{11}$ E	304

The GPS Coordinates and the elevation of the geographical locations are presented in Table 1 The elevation above the sea level is required for the calculation of the atmospheric pressure.

2.2 Data collection

The first and preliminary step in designing an Artificial Neural Network (ANN) model is collection and preparation of data. For this project, meteorological data were obtained and mined from National Aeronautics and Space Administration (NASA). Universal Meteorological data can be accessed from the strong track record of NASA. NASA has publicly archived all of its data received from spacecraft projects, including over 4TB of new Earth Science data each day. Meteorological and Solar parameters were accessed in the POWER web site via the Data Access Viewer (DAV) at https://power.larc.nasa.gov/data-access-viewer/. The procedures of obtaining the archived data are as follows:

Step 1: Selection of the user communities (geographical locations): Access to the database of NASA Surface meteorology and Solar Energy for a particular grid (South-Western Nigeria). The specific geographical locations (Osun state, Ondo State, Ogun State, Lagos State, Ekiti State, Oyo State) for data were selected on the global map using the “Power single point solar access” as presented in Figure 3.2.

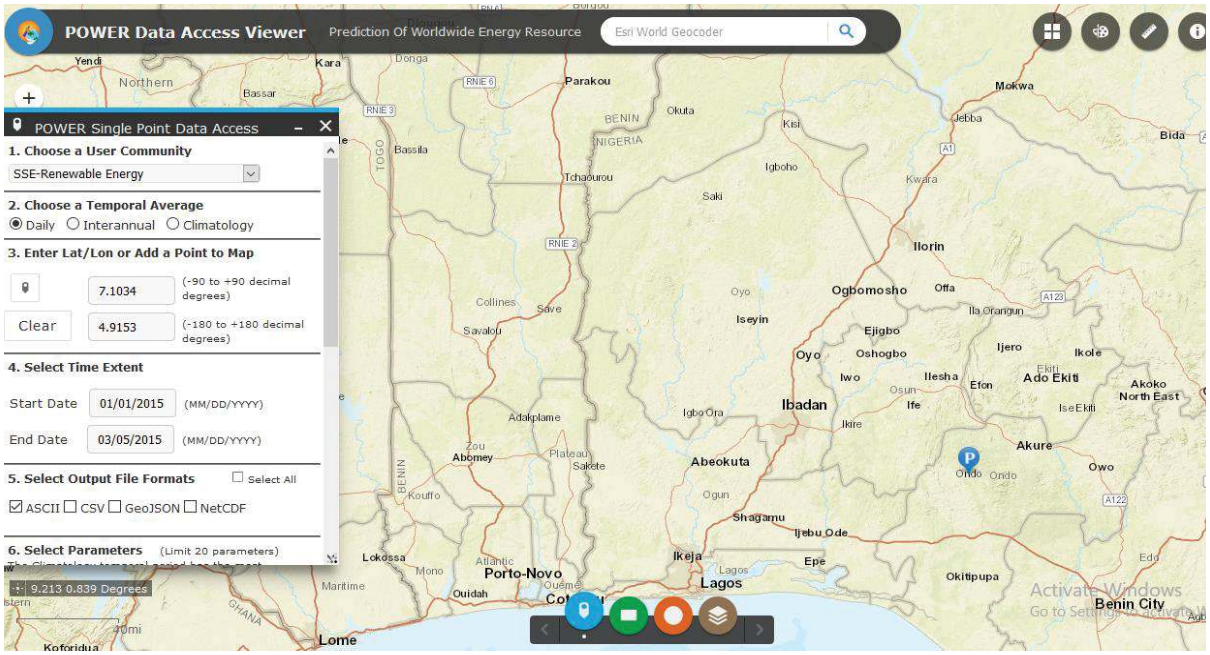


Fig. 2: NASA power data access viewer for point location (https://power.larc.nasa.gov/data-access-viewer)

Step 2: Choosing a temporal average: A temporal average was chosen, which can be daily, monthly (to obtain monthly averaged radiation), or climatology (to obtain an average of monthly and annual data over 22 years). The daily temporal average was chosen for this project to have a time-series meteorological dataset on daily basis between 1984 and 2019 (35years interval). This is presented in Figure 3.

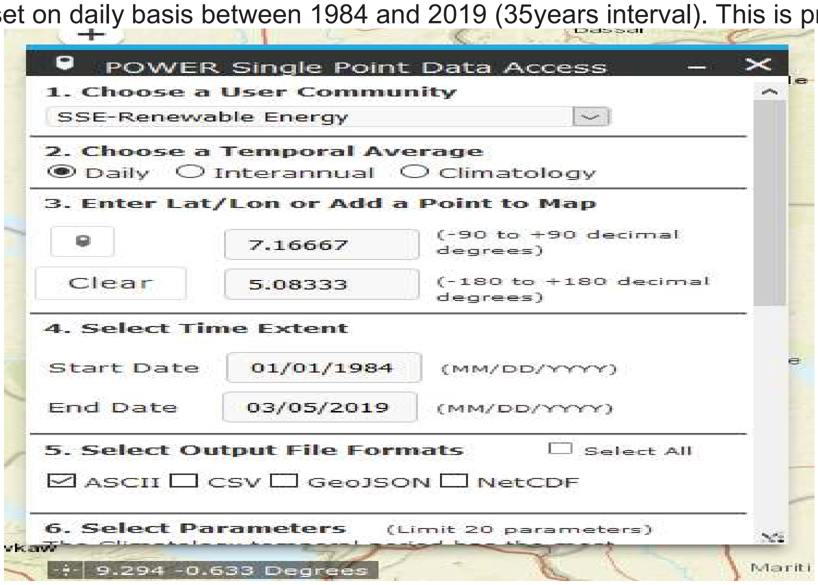


Fig. 3: NASA Power Single Point Data Access (https://power.larc.nasa.gov)

Step 3: Selection of meteorological parameters**:** Meteorological parameters required for the monthly or daily values were selected as presented in Figure 4. The meteorological parameters include; Temperature (Min. and Max.) in ^{0}C, Relative Humidity in %, Extra-terrestrial Radiation, Rainfall Intensity, Solar Radiation in MJm-2per day, Wind speed (Min. and Max.) in ms-1

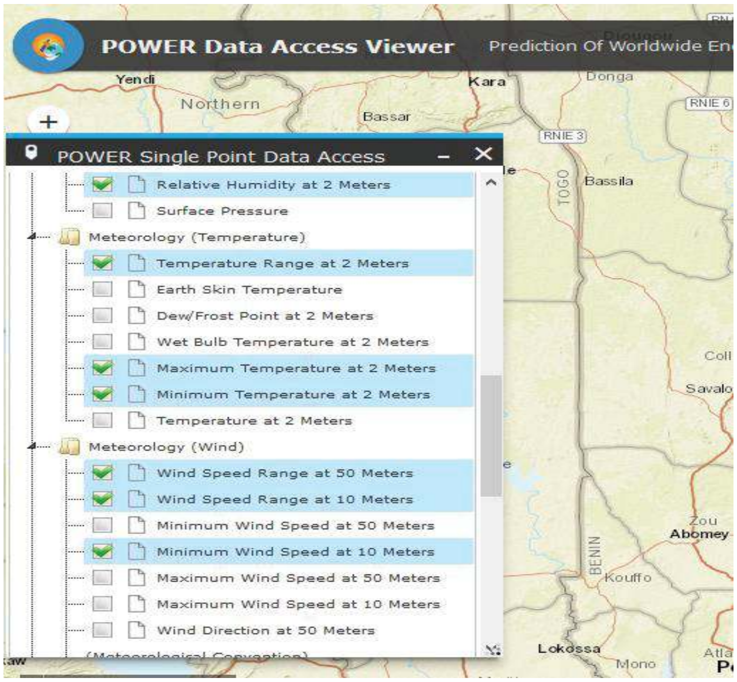


Fig. 3: Meteorological Parameters available on NASA Power Data Access (https://power.larc.nasa.gov/data-access-viewer)

2.3 Data Pre-Processing

The conduction of Data Pre-Processing is of high significance in the development of Artificial neural network model for effective and efficient training [14]. The procedures required for the pre-processing of the meteorological data are as follows:

i) Solving the problem of missing data: The average of neighbouring values is used as a replacement for missing data [14].

ii) Randomization of data**:** Randomization is used in optimization to alleviate the computational burden associated to robust control techniques: a sample of values of the uncertainty parameters is randomly drawn and robustness is enforced for these values only.

2.4 Statistica 64 (Statistica Automated Neural Networks SANN)

Neural networks are able to perform several major tasks, including regression and classification, like most statistical models. Regression tasks connect a number of input variable (x) to a set of continuous outcomes (t) target variables. In comparison, classification activities, given a set of input values, assign category memberships to a categorical target variable. Regression will be considered in more detail in the next section. It is possible to define networks that are partially connected to only some units in the preceding layer.

2.5 MATLAB R2018a

The training, validation and testing of the Neural Network would be done on the Matlab R2018a, Version 8.1.0.604, the neural network would use 70% of the data for training, 30% for testing and validation. The regression fit, and MSE (mean square error), R^2(coefficient of determination) and Root mean square error, would be generated from the Matlab Neural Network Automatically

2.5.1 Training of the multilayer perceptron network

Training of the network involves the modification of weights so as to make both the actual output (predicted) and the target (measured) of close values. Dataset of periods from 1984- 2010 is used for training the network [15]. Built-in-transfer functions are provided by MATLAB which are used for this project. STATISTICA Automated Neural Networks provides several options for training MLP neural networks. These include BFGS (Broyden-Fletcher-Goldfarb-Shanno), Scaled Conjugate, and Gradient Descent. The several layers in Multilayer Perceptron Neural Network can be presented in Figure 5:

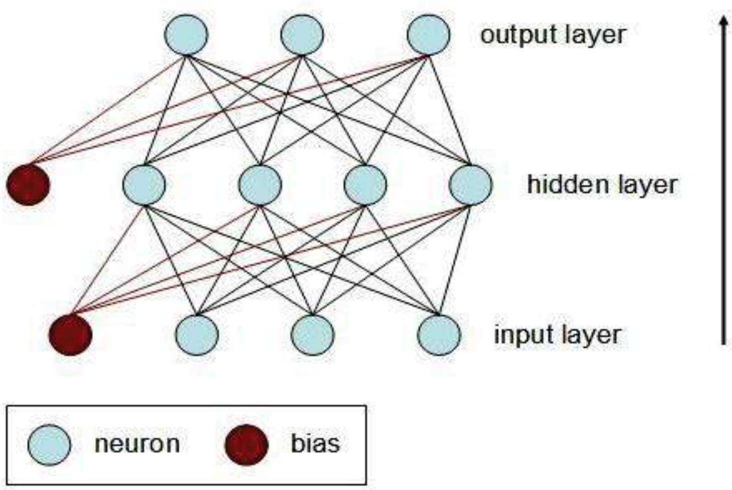


Fig. 5: A schematic diagram of a fully connected MLP2 neural network with three inputs, four hidden units (neurons), and three outputs (Bishop,1995)

2.5.2 Training Radial Basis Function Neural Networks

The methods used to train radial basis function networks is fundamentally different from those employed for MLPs. This mainly is due to the nature of the RBF networks with their hidden neurons (basis functions) forming a Gaussian mixture model that estimates the probability density of the input data [15]. For RBF with linear activation functions, the training process involves two stages.

1. In the first stage, we fix the location and radial spread of the basic functions using the input data (no targets are considered at this stage).
2. In the second stage, we fix the weights connecting the radial functions to the output neurons. For identity output activation functions, this second stage of training involves a simple matrix inversion. Thus, it is exact and does not require an iterative process.

The linear training, however, holds only when the error function is sum-of-squares and the output activation functions are the identity. If these requires are not met, i.e., in the case of cross-entropy error function and output activation functions other than the identity, we have to resort to an iterative algorithm, e.g., BFGS (Broyden-Fletcher-Goldfarb-Shanno), to fix the hidden-output layer weights in order to complete the training of the RBF neural network. The several layers in Radial Basis Function Neural Network can be presented in Figure 6

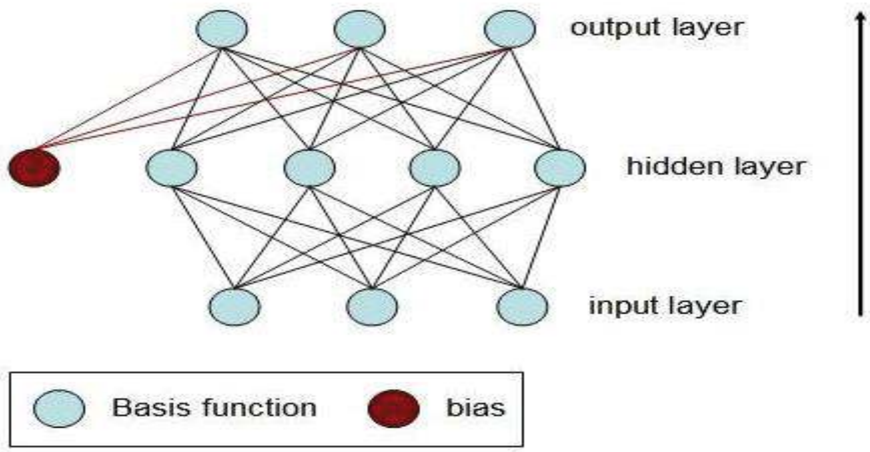


Fig. 6: A schematic diagram of an RBF neural network with three inputs, four radial basis functions and 3 outputs (Bishop, 1995).

2.6 Testing of the network

Meteorological datasets within the period 2010 -2019 was being used for the testing of the network. Testing of the neural network helps to unveil unseen data to the model and also to evaluate the performance of the developed ANN model.

2.6.1 Statistical indicator for error analysis and comparison

In order to evaluate the performance of the developed ANN models quantitatively and verify whether there is any underlying trend in performance of ANN models, statistical analysis involving the root mean square error (RMSE), coefficient of determination (R^2), and the mean bias error (MBE) were conducted. The expressions for the aforementioned statistical parameters are expressed in Equation 1-6:

$$\text{MSE (Mean Square Error)} = \frac{\sum_{i=1}^{N}(Y_i - Y_i^1)^2}{N} \tag{1}$$

$$\text{RMSE (Root Mean Square Error)} = \sqrt{\frac{\sum_{i=0}^{N}(Y_i - Y_i^1)^2}{N}} \tag{2}$$

$$\text{R Correlation Coefficient} = \frac{\sum_{i=1}^{N}(Y_i - \overline{Y_i})\left(Y_i^1 - \overline{Y_i^1}\right)}{\sqrt{\sum_{i=1}^{N}(Y_i - \overline{Y_i})^2 \sum_{i=1}^{N}\left(Y_i^1 - \overline{Y_i^1}\right)^2}} \tag{3}$$

$$\text{Coefficient of Determination R2} = \left(\frac{\sum_{i=1}^{N}(Y_i - \overline{Y_i})\left(Y_i^1 - \overline{Y_i^1}\right)}{\sqrt{\sum_{i=1}^{N}(Y_i - \overline{Y_i})^2 \sum_{i=1}^{N}\left(Y_i^1 - \overline{Y_i^1}\right)^2}}\right)^2 \tag{4}$$

Ranking of all the GRNN training set, would also be carried out based on the following ranking points:

1. Number of Variables: 1(High) - 4 (low)

2. R (correlation coefficient): Closest to 1.0 (High), Farthest from 1.0 (Low)

3. R^2 (coefficient of determination): Closest to 1.0 (High), Farthest from 1.0 (Low)

4. MSE (Mean square error): Closest to 0.0 (High), Farthest from 0.0 (low)

5. RMSE (Root Mean square error): Closest to 0.0 (High), Farthest from 0.0 (low)

3. RESULTS AND DISCUSSION

3.1 Performance Evaluation of Individual Station in South-Western Nigeria

3.1.1 Ondo Station:

As presented in Table 2, MLP 5-7-1 NN Architecture is the highest ranked network with performance of 0.999970, RMSE of 0.010526 while RBF 5-5-1 NN Architecture is the lowest ranked network with a performance of 0.398519, RMSE of 1.258855. Figures 7-8 present the regression plots for Ondo.

1. According to the Ondo Climatic Data Trend Analysis for the past 36 years as presented in Table 2, constant or uniform climate distribution was observed.
2. There was little or no changes in the climatic conditions of the location. [16] observed similar trend, on the assessment of the meteorological condition in Akure, Ondo state, the data gathered in this study showed high temperature and solar radiation, humidity, and low rainfall which is of a great impact on the evapotranspiration.
3. The use of the most preferable and significant input parameters which include: wind speed (most significant), solar radiation, maximum and minimum temperature and relative humidity (least significant)
4. The MLP network performed excellently well as a result of the BFGS (Broyden-Fletcher-Goldfarb-Shanno), training or learning function used. [17] stated that, MLP network does not make any assumption regarding the underlying probability density functions.
5. The gaussian learning function used for training the RBF network influenced the poor performance obtained.

Table 3: MLP Validation and Calibration performance for Ondo

Index	Network Architecture Name		Correlation R	Correlation of Determination R^2	Mean Square Error (MAE)	Root Mean Square Error (RMSE)
ONDO STATION						
1	MLP 5-3-1	**Cal.**	0.999871	0.999741	0.000476	0.021806
		Val.	0.999873	0.999746	0.021897	0.000479
2	MLP 5-5-1	**Cal.**	0.999946	0.999892	0.000198	0.014080
		Val.	0.999951	0.999902	0.000187	0.013661
3	MLP 5-7-1	**Cal.**	0.999970	0.999940	0.000111	0.010526
		Val.	0.999959	0.999917	0.000156	0.012509
4	MLP 5-9-1	**Cal.**	0.999964	0.999928	0.000132	0.011505
		Val.	0.999960	0.999920	0.000151	0.012287
5	MLP 5-11-1	**Cal.**	0.999954	0.999907	0.000171	0.013062
		Val.	0.999957	0.999914	0.000163	0.012766
6	RBF 5-5-1	**Cal.**	0.593860	0.352670	1.188030	1.089968

		Val.	0.615250	0.378530	1.178304	1.085497
7	RBF 5-5-1	**Cal.**	0.380345	0.144660	1.569782	1.252909
		Val.	0.404641	0.163730	1.584716	1.258855
8	RBF 5-5-1	**Cal.**	0.398519	0.158820	1.543805	1.242499
		Val.	0.421748	0.177870	1.557487	1.247993
9	RBF 5-7-1	**Cal.**	0.725097	0.525770	0.870351	0.932926
		Val.	0.727894	0.529830	0.889874	0.943331

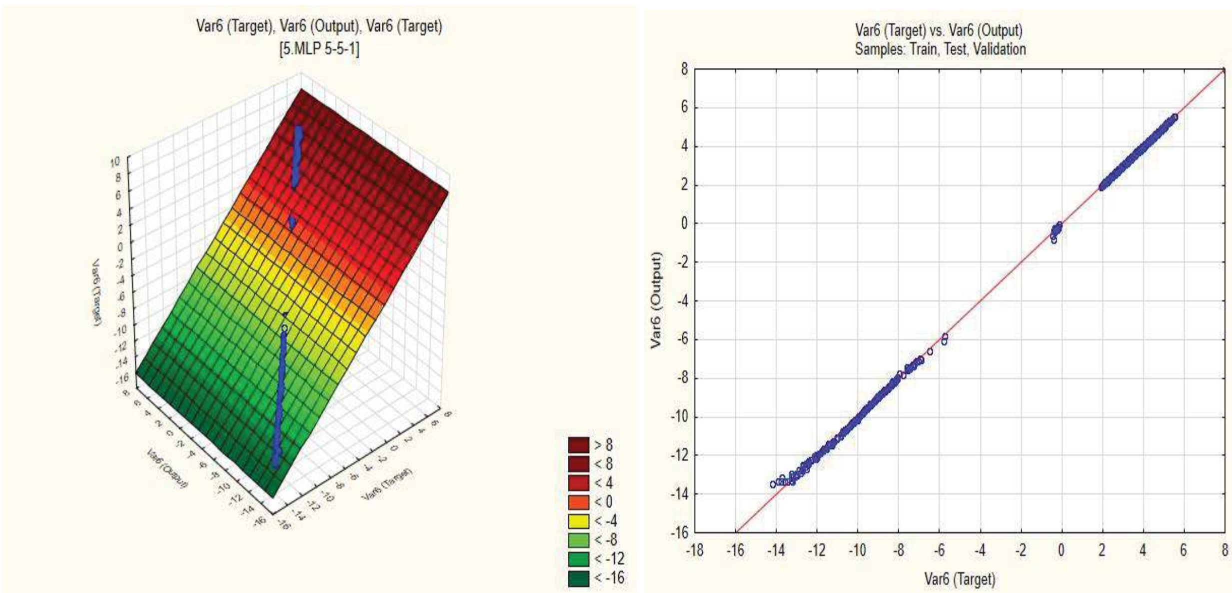


Fig. 7: a) 3D Regression plot of Target Dataset and MLP Network 5-75-1 Output (ONDO) b) 2D Regression plot

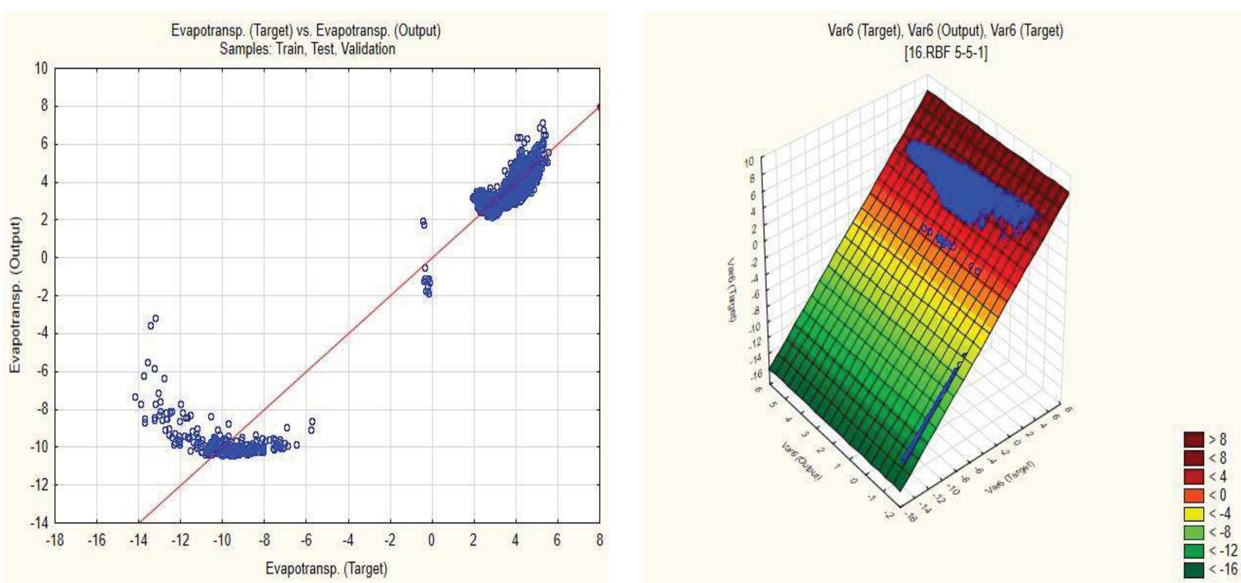


Fig. 8: a) 3D Regression plot of Target Dataset and RBF Network 5-5-1 Output (ONDO) b) 2D Regression plot.

3.1.2 Ogun Station

Ogun station is an exception to the general excellent performance obtained for all the Multilayer Perceptron network developed. MLP 5-9-1 NN Architecture is the highest ranked network with performance of 0.467169, while RBF 5-5-1 NN Architecture is the lowest ranked network with a performance of 0.330425, RMSE of 1.441640. Table 4 present the statistical indicator for error analysis and comparison, and also Figure 9 presents the regression plot for some of the NN Architecture. The poor performance of both MLP and RBF network is due to the following reasons:

1. Cessation-date of rainy season - Cessation date is determined when the available water content at the root zone has dropped to 50% as a result of high temperature and high humidity [18].
2. Presence of heavy Industrial plants such as Lafarge Ewekoro Cement, Dangote Cement and other industries has led to the presence of high CO_2 (Carbon dioxide) and other harmful gases in the atmosphere resulting in greenhouse effect and climate change in Ogun state [19].
3. Variation in the annual average value of the meteorological parameters used for the Artificial Neural Network. Irregularities in the Data Trend Analysis for location under study.
4. Poor training performance due to the learning functions (Gaussian) used and the training epoch for Radial Basis Function.
5. Presence of outliers in the Input data used for training purpose
6. Poor correlation between input data (relative humidity, solar radiation, mean temperature) and also between input and output data.

Table 4: MLP and RBF Validation and Calibration performance for Ogun

Index	Network Architecture Name		Correlation R	Correlation of Determination R^2	Mean Square Error (MAE)	Root Mean Square Error (RMSE)
OGUN STATION						
1	MLP 5-3-1	**Cal.**	0.451963	0.204270	2.875810	1.683067
		Val.	0.465528	0.216716	2.887143	1.699160
2	MLP 5-5-1	**Cal.**	0.464916	0.216147	2.832715	1.69582r1
		Val.	0.466587	0.217704	2.880848	1.697306
3	MLP 5-8-1	**Cal.**	0.466377	0.217507	2.827810	1.681609
		Val.	0.463809	0.215119	2.890438	1.700129
4	MLP 5-7-1	**Cal.**	0.463614	0.214938	2.837157	1.684386
		Val.	0.466475	0.215119	2.890438	1.700129
5	MLP 5-9-1	**Cal.**	0.467169	0.218247	3.000000	1.732050
		Val.	0.485270	0.235487	3.000000	1.732050
6	RBF 5-5-1	**Cal.**	0.330425	0.10918	2.078326	1.441640
		Val.	0.330088	0.10896	1.939788	1.392763
7	RBF 5-5-1	**Cal.**	0.346516	0.12007	2.052913	1.432799
		Val.	0.334550	0.11192	1.934257	1.390776
8	RBF 5-5-1	**Cal.**	0.352726	0.12442	2.042783	1.429259
		Val.	0.360759	0.13015	1.894166	1.376287

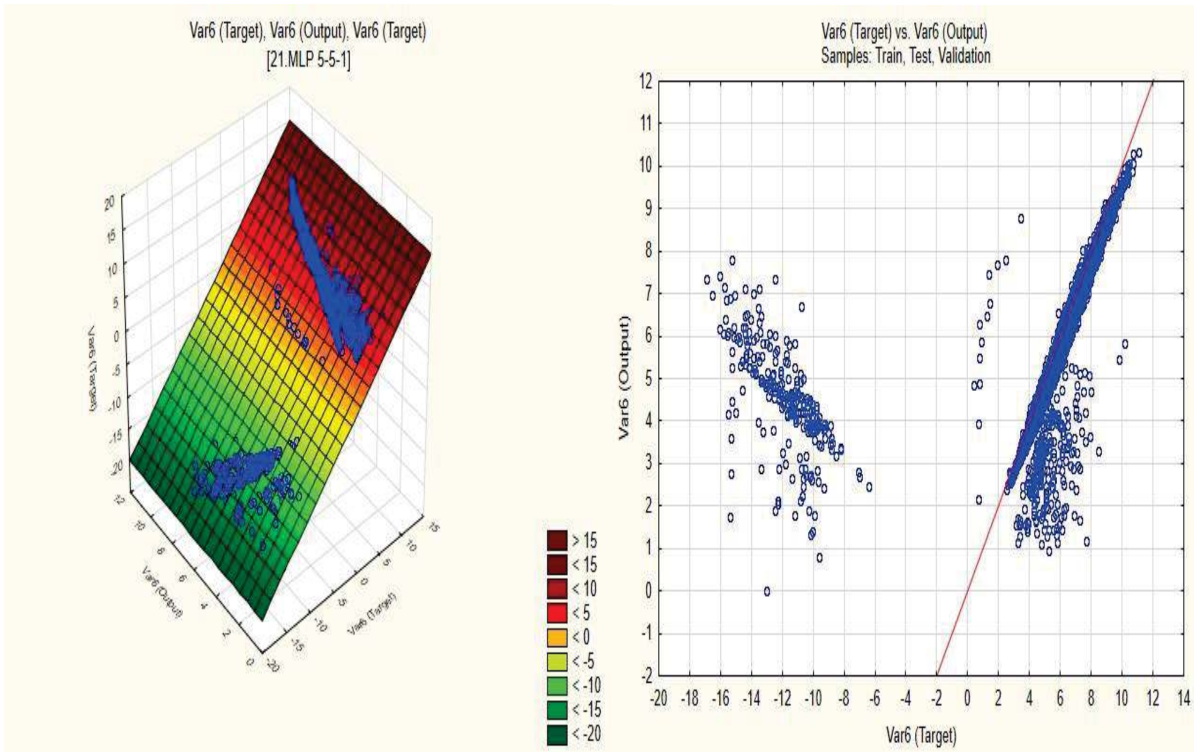


Fig. 9: Regression plot of Target Dataset and MLP Network 5-8-1 Output (OGUN)

3.1.3 Lagos Station

As presented in Table 5, MLP 5-9-1 NN Architecture is the highest ranked network with performance of 0.999998, and RMSE of 0.010526 while RBF 5-5-1 NN Architecture is the lowest ranked network with a performance of 0.492501, and RMSE of 1.762307. Figures 4.16- 4.27 present the regression plot of the target dataset and the MLP output. For Lagos Station 70% of the ANN performed excellently good, due to the following reasons:

1. The correlation between input data (Relative humidity, wind speed and mean temperature) fell between the acceptable range for excellence performance of the MLP Neural Network.
2. The availability of 36years dataset for the MLP neural network provided the network with wide range of dataset for effective and efficient performance
3. Uniformity in the climatic condition of Lagos over the past 36years with just a little variation or changes as result of environmental pollution causing the ozone layer gradual depletion.
4. Poor performance of the radial basis function neural network was due to the low number of neurons used in the hidden layer.
5. The use of Gaussian learning/training function instead of Sigmoid functions resulted in the poor performance obtained for RBF network.

Table 5: MLP and RBF Validation and Calibration performance for Lagos

Index	Network Architecture Name		Correlation R	Correlation of Determination R^2	Mean Square Error (MAE)	Root Mean Square Error (RMSE)
LAGOS STATION						
1	MLP 5-3-1	**Cal.**	0.998982	0.997965	0.007992	0.089403
		Val.	0.998988	0.947244	0.000000	0.000000
2	MLP 5-4-1	**Cal.**	0.967716	0.936474	0.250244	0.500243
		Val.	0.966145	0.945460	0.000000	0.000000
3	MLP 5-5-1	**Cal.**	0.999889	0.999777	0.000913	0.030220
		Val.	0.999896	0.999792	0.000811	0.028480
4	MLP 5-6-1	**Cal.**	0.998982	0.999856	0.000591	0.024303
		Val.	0.999926	0.999852	0.000578	0.024039
5	MLP 5-7-1	**Cal.**	0.999835	0.999669	0.001359	0.036861
		Val.	0.999848	0.999695	0.001209	0.034764
6	MLP 5-9-1	**Cal.**	0.999998	0.999996	0.000017	0.004106
		Val.	0.999996	0.999993	0.000010	0.003162
7	RBF 5-7-1	Cal.	0.784669	0.61571	1.575713	1.255274
		Val.	0.792501	0.62806	1.451243	1.204675
8	RBF 5-7-1	Cal.	0.707466	0.50051	2.048059	1.431104
		Val.	0.703850	0.49541	1.968112	1.402894
9	RBF 5-5-1	Cal.	0.492501	0.24256	3.105726	1.762307
		Val.	0.507551	0.25761	2.894502	1.701324
10	RBF 5-6-1	Cal.	0.562948	0.31691	2.800859	1.673577
		Val.	0.565940	0.32029	2.650844	1.628141

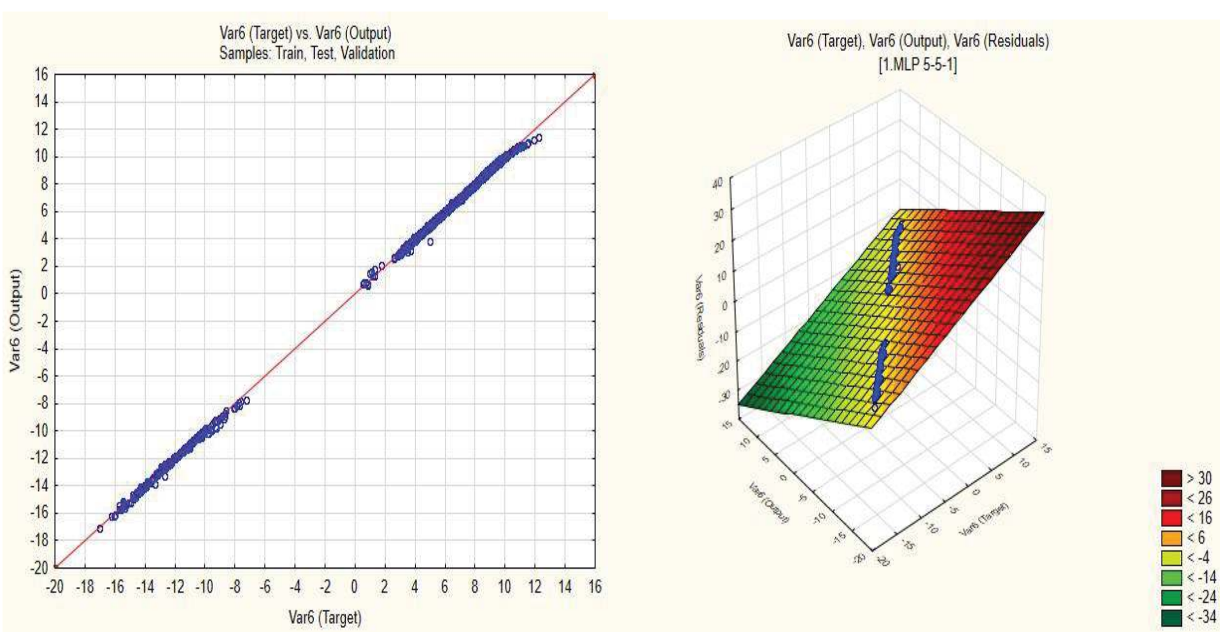


Fig. 10: **3D Regression plot of Target Dataset and MLP 5-5-1 Network (LAGOS).**

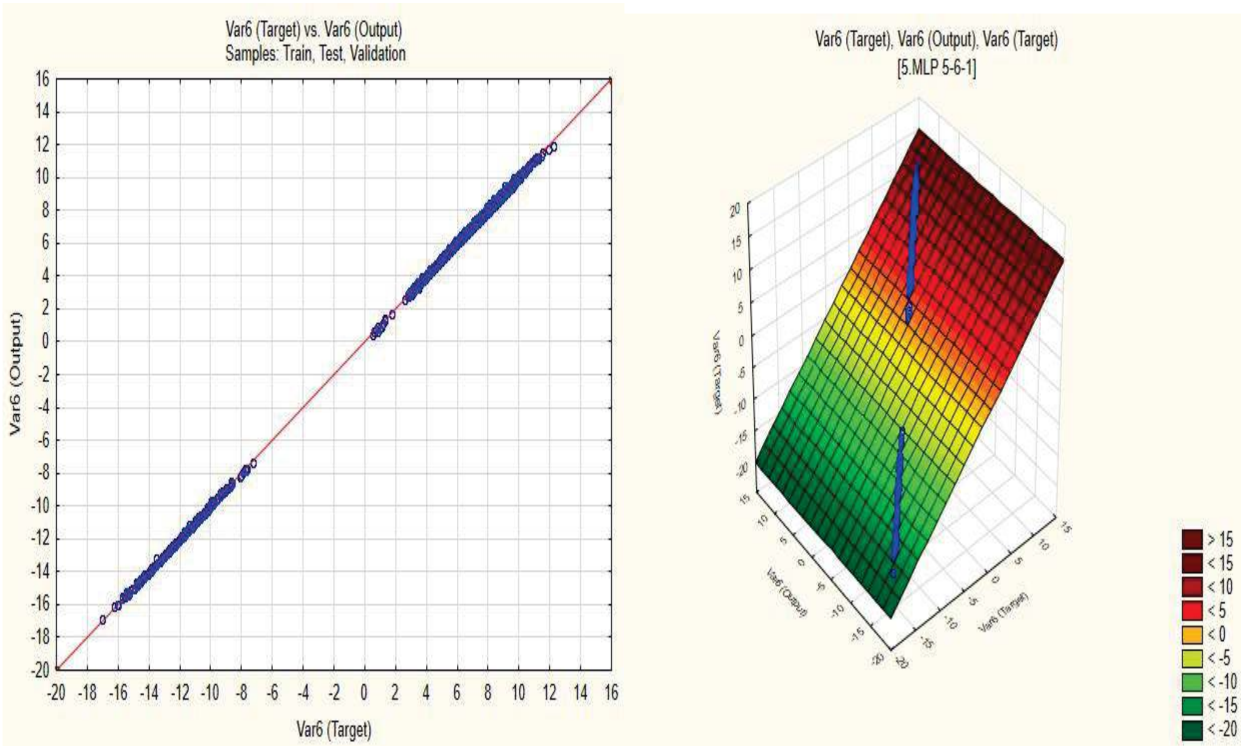


Fig. 11: 3D Regression plot of Target Dataset and MLP Network 5-6-1 Output (LAGOS STATE)

3.1.4 Ekiti Station

As presented in Table 6, MLP 5-9-1 NN Architecture is the highest ranked network with performance of 0.999986, and RMSE of 0.005502 while RBF 5-6-1 NN Architecture is the lowest ranked network with a performance of 0.487091, and RMSE of 0.881861. Figure 12-14 present the regression plot for the target dataset and the Neural Network output. For Ekiti Station 80% of the ANN performed excellently good, due to the following reasons:

1. From the Climatic Data Trend Analysis of Ekiti, negligible changes in the meteorological dataset was noted from 1984 -2008, but for subsequent years from (2008 - Present) variation in solar radiation and net radiation was observed.
2. High correlation between Input data (Wind speed and Mean Temperature).
3. The use of the built-in functions of STATISTICA 64 and MATLAB R2018a such as (Automated Network Search) influenced the performance
4. The low number of neurons used in the hidden layer of the Radial basis functions neural network is responsible for the low performance of RBF network.

Table 6: Summary of the Performance of the Radial Basis Function Neural Network for Ekiti

Index	Network Architecture Name		Correlation R	Correlation of Determination R^2	Mean Square Error (MSE)	Root Mean Square Error (RMSE)
			EKITI STATION			
1	MLP 5-3-1	Cal.	0.994210	0.988454	0.013122	0.018155
		Val.	0.996290	0.992593	0.010914	0.104470
2	MLP 5-6-1	Cal.	0.989680	0.979466	0.023323	0.152915

		Val.	0.992606	0.985268	0.022002	0.148331
3	MLP 5-7-1	Cal.	0.999986	0.999971	0.000030	0.005502
		Val.	0.999990	0.999980	0.000038	0.006146
4	MLP 5-8-1	Cal.	0.999903	0.999763	0.000199	0.014102
		Val.	0.999922	0.999844	0.000277	0.015812
5	MLP 5-9-1	**Cal.**	0.999942	0.999883	0.000119	0.014102
		Val.	0.999960	0.999920	0.000141	0.011869
6	RBF 5-5-1	Cal.	0.774541	0.59991	0.407921	0.638687
		Val.	0.996290	0.992593	0.010914	0.104470
7	RBF 5-6-1	Cal.	0.487091	0.23726	0.777679	0.881861
		Val.	0.478080	0.22856	1.360703	1.166492
8	RBF 5-4-1	Cal.	0.707451	0.50049	0.509295	0.713649
		Val.	0.761760	0.58028	0.787948	0.887664
9.	RBF 5-3-1	Cal.	0.582884	0.33975	0.673176	0.820473
		Val.	0.531909	0.28293	1.261898	1.123342

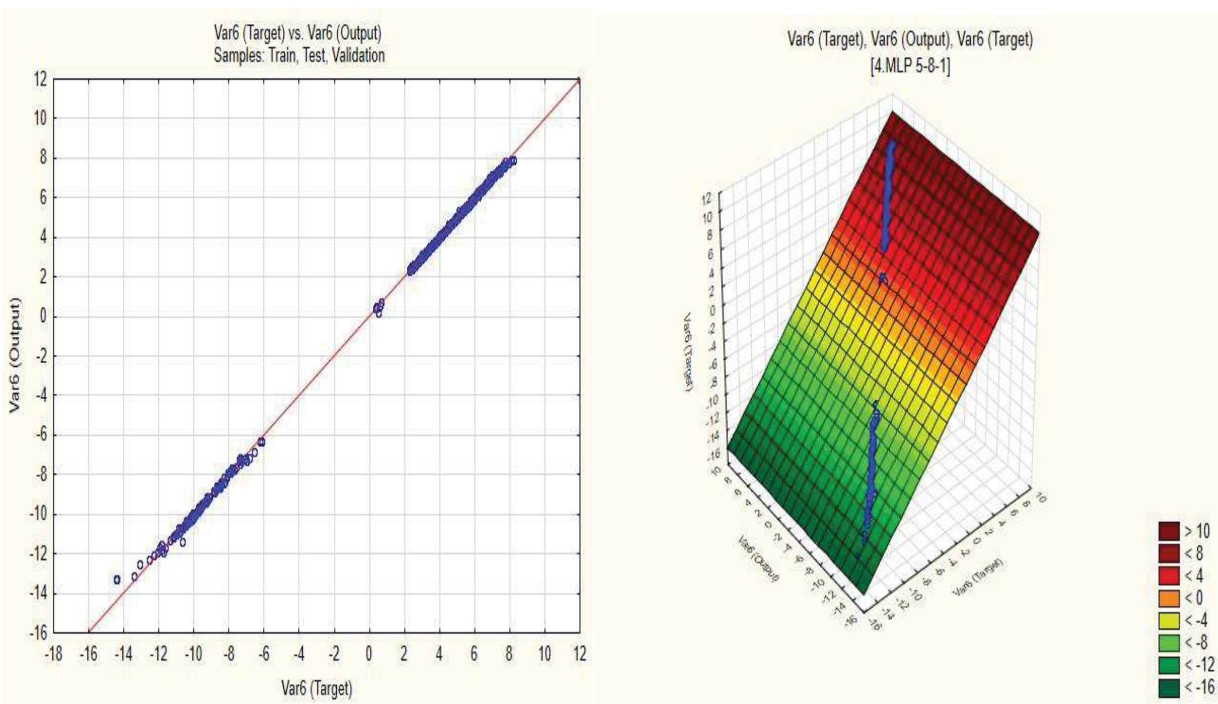


Fig. 12: 3D Regression plot of Target Dataset and MLP Network 5-8-1 Output (EKITI)

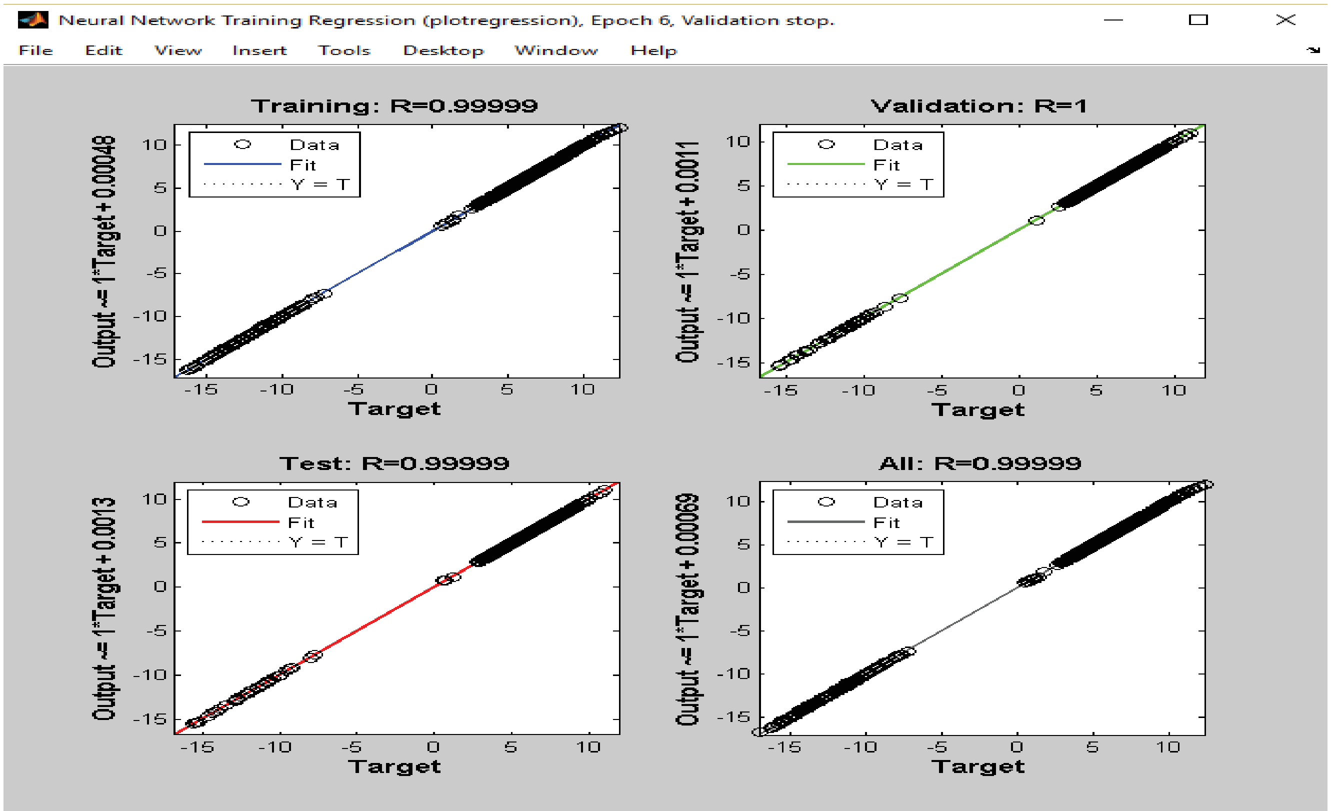


Fig. 13: MATLAB Overall Regression plot of Target Dataset and MLP Network Output (EKITI)

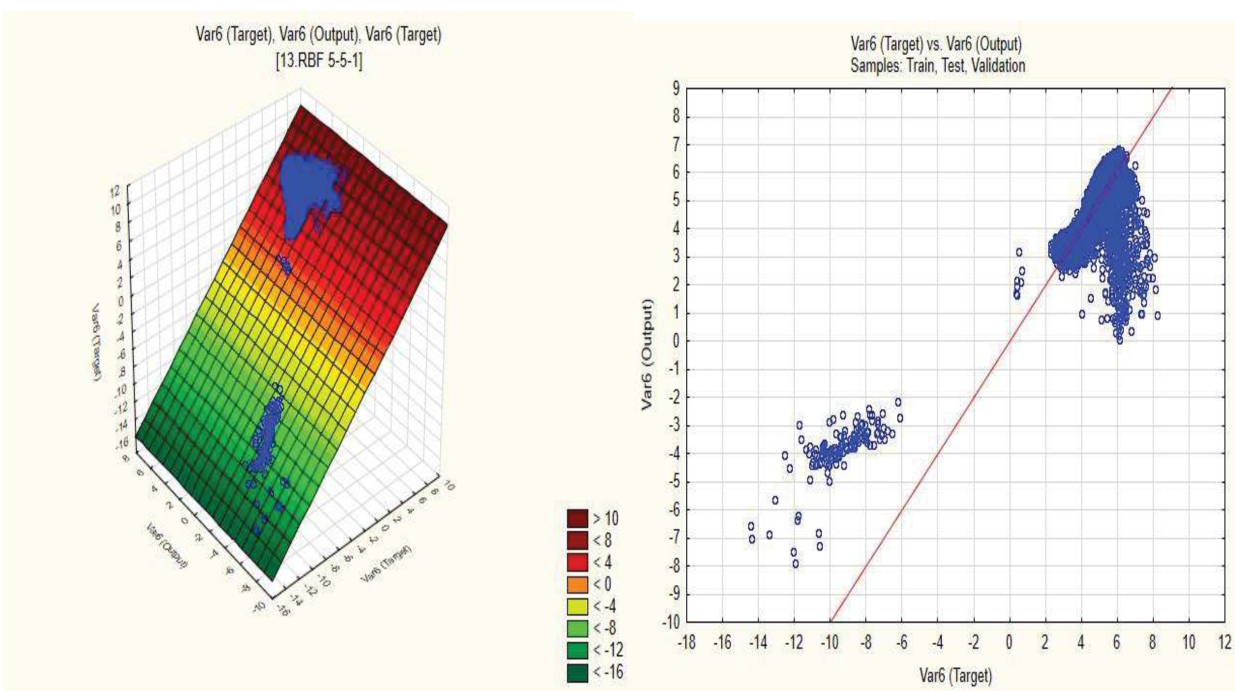


Fig. 14: Regression plot of Target Dataset and RBF Network 5-5-1 Output (EKITI)

3.1.5 Osun Station

As presented in Table 7, MLP 5-8-1 NN Architecture is the highest ranked network with performance of 0.999995, and RMSE of 0.006209 while RBF 5-6-1 NN Architecture is the lowest ranked network with a performance of 0.787379, and RMSE of 1.171910 For Osun Station 95% of the ANN performed excellently good, due to the following reasons:

1. High correlation value between the Input data (Relative humidity, wind speed, mean temperature, and precipitation).
2. The Climatic Data Trend of Osun state reveals uniformity in the climatic condition of the region within the past 30years.

Figures 15-17 present the regression plot for the target dataset and the Neural Network output for Osun.

Table 7: Validation and Calibration performance of MLP and RBF Network for Osun

Index	Network Architecture Name		Correlation R	Correlation of Determination R^2	Mean Square Error (MAE)	Root Mean Square Error (RMSE)
OSUN STATION						
1	MLP 5-6-1	**Cal.**	0.999917	0.999833	0.000603	0.024554
		Val.	0.999939	0.999879	0.000449	0.021180
2	MLP 5-7-1	**Cal.**	0.999917	0.999833	0.000604	0.024570
		Val.	0.999933	0.999867	0.000493	0.022199
3	MLP 5-8-1	**Cal.**	0.999995	1.000000	0.000039	0.006209
		Val.	0.999985	1.000000	0.000108	0.010373
4	MLP 5-9-1	**Cal.**	0.999991	0.999982	0.000065	0.008057
		Val.	0.999991	0.999982	0.000066	0.008096
5	MLP5-11-1	**Cal.**	0.999917	0.999833	0.000604	0.024570
		Val.	0.999933	0.999866	0.000497	0.022293
6	RBF 5-5-1	**Cal.**	0.973630	0.94796	0.188078	0.433680
		Val	0.981300	0.96295	0.136613	0.369612
7	RBF 5-6-1	**Cal.**	0.787379	0.61997	1.373373	1.171910
		Val	0.804285	0.64687	1.303184	1.141571

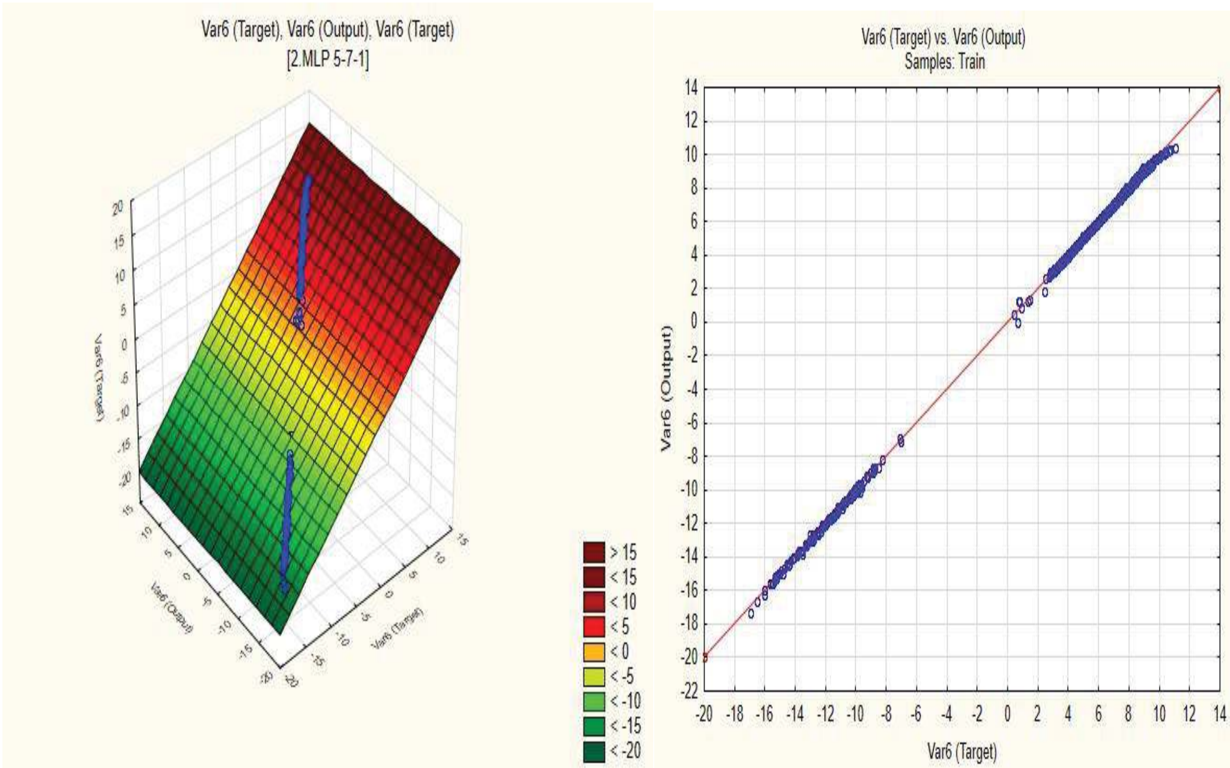


Fig. 15: 3D Regression plot of Target Dataset and MLP Network 5-7-1 Output (OSUN)

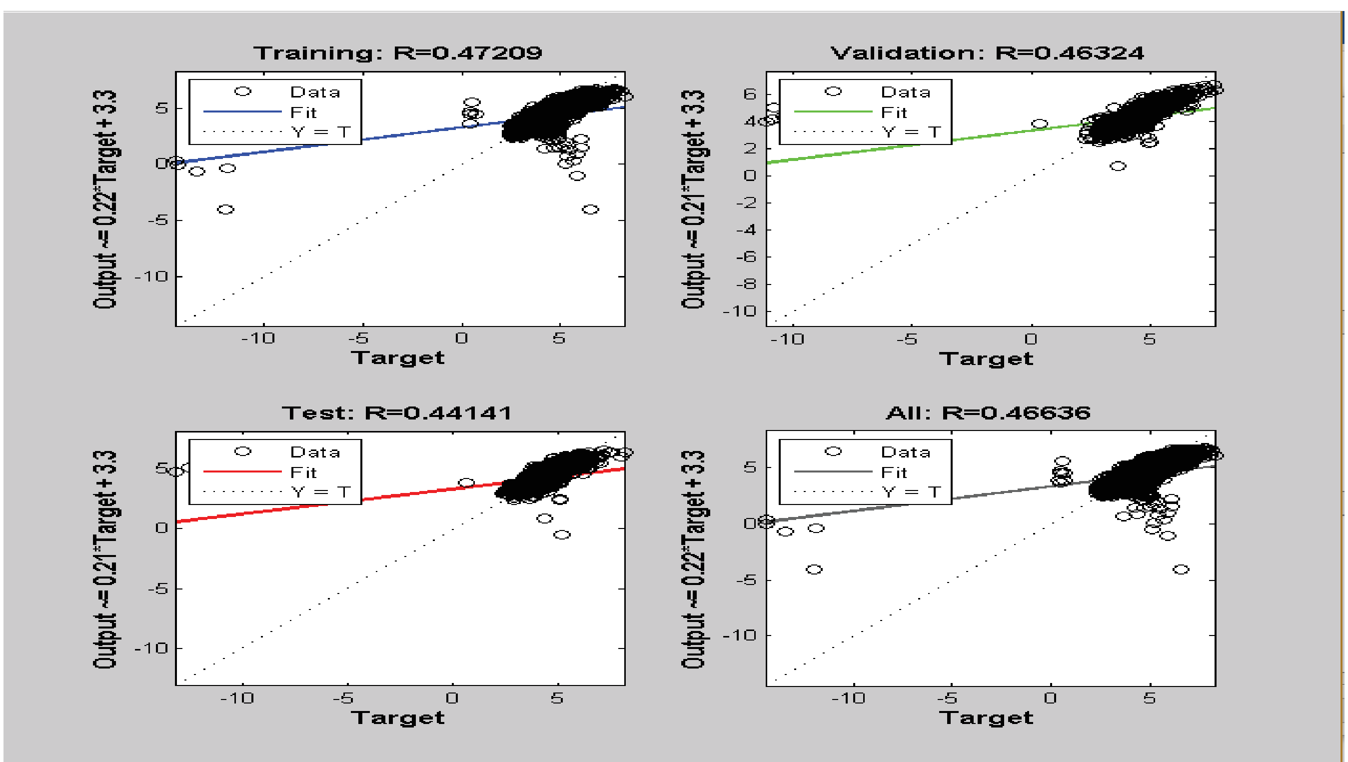


Fig. 16: Overall Regression plot of Target Dataset and MLP Network (OSUN)

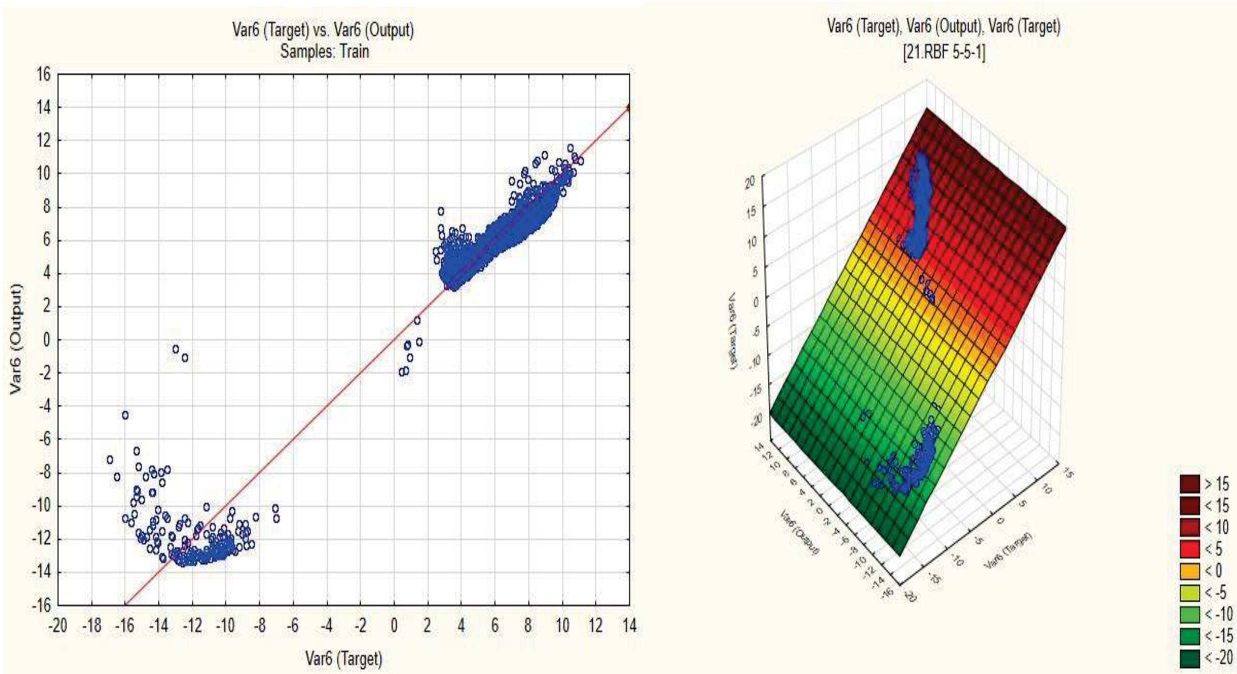


Fig. 17: Regression plot of Target Dataset and RBF Network 5-5-1 Output (OSUN)

3.1.6 Oyo Station

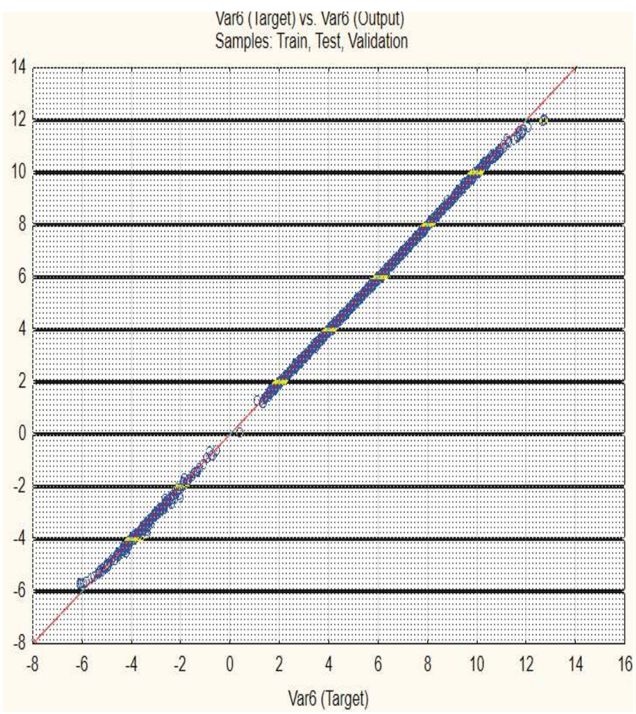
As presented in Table 8 MLP 5-10-1 NN Architecture is the highest ranked network with performance of 0.999998, and RMSE of 0.002513 while RBF 5-5-1 NN Architecture is the lowest ranked network with a performance of 0.645939, and RMSE of 1.023834. For Oyo Station 85% of the ANN performed brilliantly due to the following reasons:

1. The monthly mean ETo varies in the same pattern with the input parameters used which are solar radiation, wind speed, mean air temperature, but varies inversely with relative humidity [20].
2. High correlation between the Input datasets for each year over the last 36years. Also, the correlation obtained for the input and output dataset is far above average and closer to 1.
3. Multilayer perceptron network performance was due to the hidden activation used BFGS unlike poor performance of the Radial basis function network due to a poor learning ability of the gaussian hidden activation used.
4. The weight and biases used for multilayer perceptron network also contributed to the significantly high performed obtained. The STATISTICA software was responsible for the automatic generation of suitable weights and biases used for the training process through a close observation of the input dataset.
5. The negative or inverse relationship between relative humidity and evapotranspiration in OYO State resulted also in the poor performance of the radial basis function network.

Figures 18-20 present the regression plot for the target dataset and the Neural Network output

Table 8: Validation and Calibration performance of MLP and RBF Network for OYO

Index	Network Architecture Name		Correlation R	Correlation of Determination R^2	Mean Square Error (MAE)	Root Mean Square Error (RMSE)
OYO STATION						
1	MLP 5-10-1	**Cal.**	0.999998	1.00000	0.000006	0.002513
		Val.	0.999999	0.00231	0.000005	0.002305
2	MLP 5-11-1	**Cal.**	0.999971	0.99994	0.000106	0.010305
		Val.	0.999977	0.00934	0.000087	0.010305
3	MLP 5-5-1	**Cal.**	0.999735	0.99947	0.000955	0.030897
		Val.	0.999812	0.02641	0.000697	0.030897
4	MLP 5-7-1	**Cal.**	0.999898	0.99980	0.000367	0.019144
		Val.	0.999904	0.01885	0.000355	0.018853
5	MLP 5-9-1	**Cal.**	0.999995	0.99999	0.000018	0.004290
		Val.	0.999996	0.00409	0.000017	0.004091
6	RBF 5-10-1	**Cal.**	0.691406	0.47804	0.938864	0.968950
		Val	0.703951	0.96763	0.936313	0.967633
7	RBF 5-5-1	**Cal.**	0.687579	0.47277	0.948355	0.973835
		Val	0.699725	0.90777	0.947630	0.973463
8	RBF 5-7-1	**Cal**	0.724238	0.52452	0.855261	0.924803
		Val	0.746035	0.55657	0.855261	0.924803



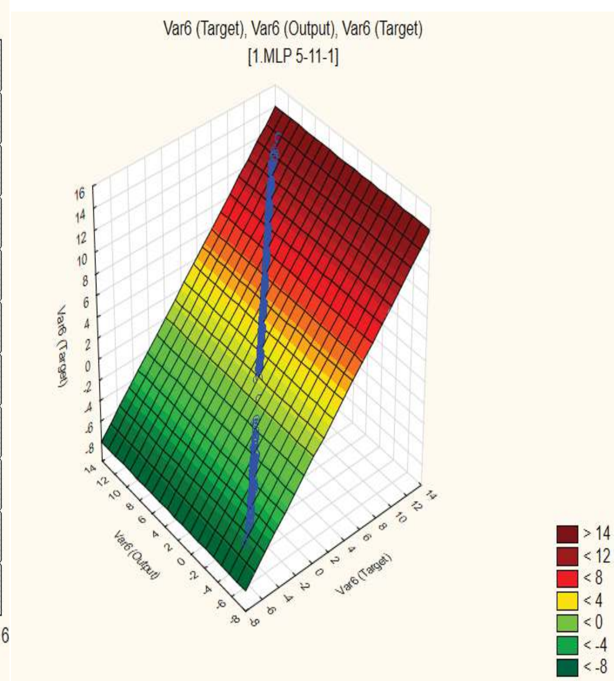


Fig. 18: 3D Regression plot of Target Dataset and MLP Network 5-11-1 Output (OYO)

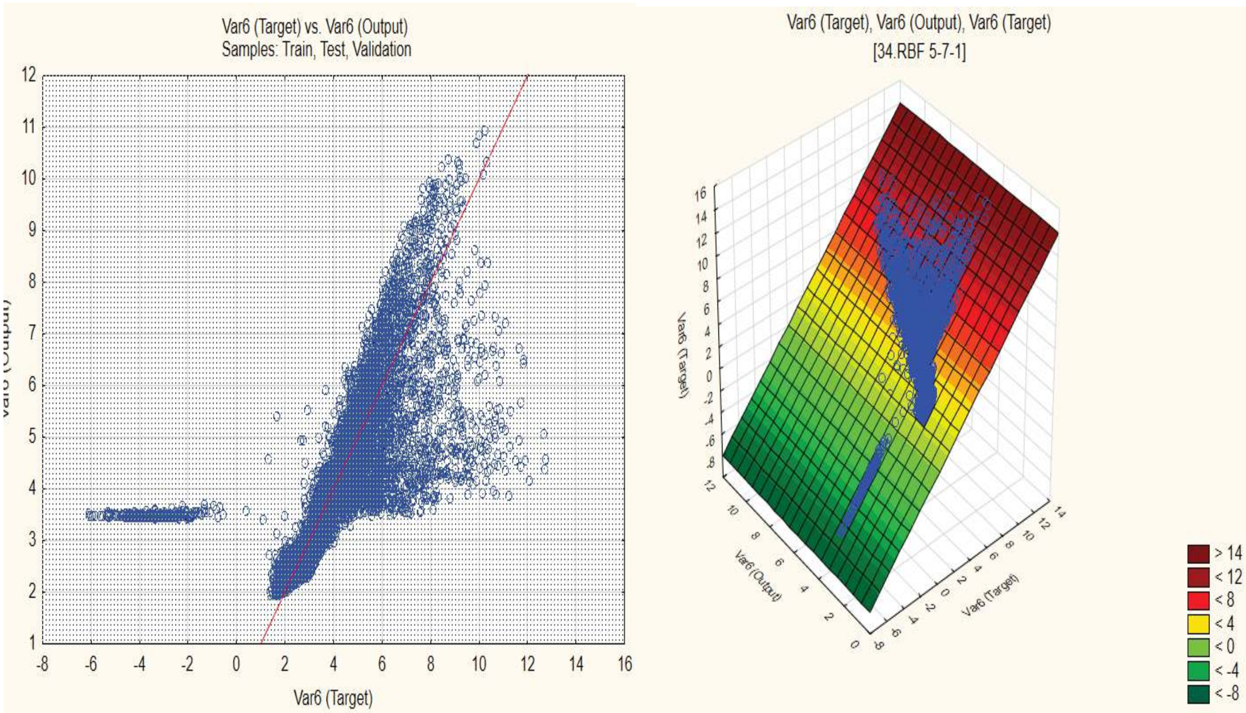


Fig. 19: 3D Regression plot of Target Dataset and RBF Network 5-11-1 Output (OY0)

4. DISCUSSION

4.1 Summary of the Performance of Multilayer Perceptron Network

Table 3 presents the five different architectures of the Multilayer Perceptron Neural Network model showed significant variations based on the four performance criteria. The highest ranked performance with the lowest value of RMSE of forecasting models is 0.010526 (in MLP 5-7-1), and the highest value of the Coefficient of Correlation (CC) is 0.999970 (in MLP 5-7-1). In addition, the lowest value of MAE is also 0.000111 (in MLP 5-7-1) for **Ondo Meteorological data**, while the lowest ranked performance for Ondo with the highest value of RMSE 0.021806 (in MLP 5-3-1), lowest Correlation value of 0.999871 and MAE value of 0.000476. The Multilayer perceptron neural network using different NN Architecture was able to achieve an excellent performance for Ondo. Figure 6 presents the well correlated 2D and 3D Regression plot of the different MLP NN Architectures for Ondo. Table 4 presents the lowest value of the RMSE of forecasting models is 1.681609 (in MLP 5-8-1), and the highest value of the Coefficient of Correlation (CC) is 0.466377 (in MLP 5-8-1). In addition, the lowest value of MAE is also 2.827810 (in MLP 5-8-1) for the **Ogun Meteorological data**, while the lowest ranked performance for Ogun with the highest value of RMSE 1.683067 (in MLP 5-3-1), lowest Correlation value of 0.451963 and MAE value of 2.875810. The Multilayer perceptron neural network using different NN Architecture produced a poor performance for Ogun.

Table 5 present the lowest value of the RMSE of forecasting models is 0.004106 (in MLP 5-9-1), and the highest value of the Coefficient of Correlation (CC) is 0.999998 (in MLP 5-9-1). In addition, the lowest value of MAE is also 0.000017 (in MLP 5-9-1) for the **Lagos Station Meteorological data**, while the lowest ranked performance for Lagos with the highest value of RMSE 0.500243 (in MLP 5-4-1), lowest Correlation value of 0.967716 and MAE value of 0.250244. The Multilayer perceptron neural network using different NN Architectures produced an excellent performance in estimating values close to the target for Lagos.

For Ekiti Station Meteorological data, Tables 6 presents the lowest value of the RMSE of forecasting models is 0.005502 (in MLP 5-7-1), and the highest value of the Coefficient of Correlation (CC) is 0.999986 (in MLP 5-7-1). In addition, the lowest value of MAE is also 0.000030 (in MLP 5-7-1). while the lowest ranked performance for **Ekiti** with the highest value of RMSE 0.153790 (in MLP 5-11-1), lowest Correlation value of 0.989561 and MAE value of 0.023651. The Multilayer perceptron neural network using different NN Architecture produced an excellent performance

Table 7 presents the lowest value of the RMSE of forecasting models is 0.006209 (in MLP 5-8-1), and the highest value of the Coefficient of Correlation (CC) is 0.999995 (in MLP 5-8-1). In addition, the lowest value of MAE is also 0.000039 (in MLP 5-8-1) for the Osun Meteorological data, while the lowest ranked performance for **Osun** with the highest value of RMSE 0.024554 (in MLP 5-6-1), lowest Correlation value of 0.999917 and MAE value of 0.000603. The Multilayer perceptron neural network using different NN Architecture produced an excellent performance considering the highest and lowest ranked correlation values.

4.2 Summary of the Performance of the Radial Basis Function Neural Network

Tables 4 present the five different Radial Basis Function Neural Network (RBFNN) Architecture models which demonstrated significant variations based on the four performance criteria. The lowest value of the RMSE of forecasting models is 0.932926 (in RBF 5-7-1), and the highest value of the Coefficient of Correlation (CC) is 0.725097 (in RBF 5-7-1). In addition, the lowest value of MAE is also 0.870351 (in RBF 5-7-1) for Ondo, while the lowest ranked performance (RBF 5-5-1) with RMSE of 1.252909, Correlation value of 0.380345, and MAE value (1.569782).

Tables 4.4 -4.6 present the lowest value of the RMSE of forecasting models is 1.429259 (in RBF 5-5-1), and the highest value of the Coefficient of Correlation (CC) is 0.352726 (in RBF 5-5-1). In addition, the lowest value of MAE is also 2.042783 (in MLP 5-5-1) for the Ogun, while the lowest ranked performance (RBF 5-5-1) with RMSE of 1.441640, Correlation value of 0.330425, and MAE value (2.078326).

Tables 4.7-4.9 present the lowest value of RMSE of the forecasting models is 1.255274 (in RBF 5-7-1), and the highest value of Coefficient of Correlation (CC) is 0.784669 (in RBF 5-7-1). In addition, the lowest value of MAE is also 1.575713 (in RBF 5-7-1) for the Lagos, while the lowest ranked performance (RBF 5-5-1) with RMSE of 1.762307, Correlation value of 0.492501, and MAE value (3.105726).

For Ekiti Station Meteorological data Tables 4.10-4.12 present the lowest value of the RMSE of forecasting models is 0.638687 (in RBF 5-5-1), and the highest value of the Coefficient of Correlation (CC) is 0.774541 (in RBF 5-5-1). In addition, the lowest value of MAE is also 0.407921 (in RBF 5-5-1), while the lowest ranked performance (RBF 5-6-1) with RMSE of 0.881861, Correlation value of 0.487091, and MAE value (0.777679).

Tables 4.13-4.14 present the lowest value of the RMSE of forecasting models is 0.433680 (in RBF 5-5-1), and the highest value of the Coefficient of Correlation (CC) is 0.973630 (in RBF 5-5-1). In addition, the lowest value of MAE is also 0.188078 (in MLP 5-8-1) for the Osun, while the lowest ranked performance (RBF 5-6-1) with RMSE of 1.171910, Correlation value of 0.787379, and MAE value (1.373373).

4.3 Comparison of Multilayer Perceptron Neural Network and Radial Basis Functions

During training, the MLP 5-9-1 for Lagos Station Meteorological Data performs much better than the others with a correlation value of 0.999998. Also, in the validation and testing phases, the MLP 5-9-1 outperforms all other models in terms of various performance criteria. Table 4.4 indicates that the MLP 5-9-1 has the smallest MAE (0.000010) and RMSE (0.003162), and the highest Correlation value (0.999996) in the validation phase; in the testing phase. In order to show the potential of the MLP Neural Network models, the forecast results of the radial basis function neural network (RBFNN) models are also presented. The radial basis function neural network model was developed and tested with the same data sets used for the MLP models. Table 4.3 indicates that the RBFNN 5-5-1 has the smallest MAE (0.010914) and RMSE (0.104470), and the highest CC (0.996290) in the validation phase. Overall, the performance of the two MLP 5-9-1 is very good. The results demonstrated that the MLP (Multilayer Perceptron Neural Network) can be successfully applied to establish forecasting models that can provide accurate and reliable reference evapotranspiration (ET0) prediction compare to the Radial Basis Function Neural Network. The potential of MLP (Multilayer Perceptron Neural Network) in the estimation of evapotranspiration with 70% of the R-values above 0.7, this is remarkable compared to Radial Basis Neural Network (RBF) which has above 50% of the R-values below 0.7 over the tropical rainforest region of Nigeria. The Multilayer Perceptron Neural Network had a very high performance for Four locations because of the following reasons:

1. The data were well overfitted, that is the network performed excellent learning operation during training, unlike some other networks (such as Generalized Neural Network and Radial Basis Neural Network) that perform poor learning operation resulting in a poor performance well as it encounters new set of data for testing.
2. The datasets of corresponding locations have little or low variation with the average the region which resulted to closely related values from the neural network.
3. MLP/Neural networks do not make any assumption regarding the underlying probability density functions or other probabilistic information about the pattern classes under consideration in comparison to other probability-based models [17].
4. The most preferable and most significant Inputs parameters were used which includes wind speed (most significant), solar radiation, maximum and minimum temperature, and relative humidity (least significant)
5. According to Kolmogorov's Theorem a MLP with one hidden layer of sufficient size can approximate any continuous function to any desired accuracy.
6. Despite the problem of random initialization associated with Multilayer Perceptron Neural Network, a high performance was still achieved.

The Radial Basis Function Neural Network from Table 4.1-4.4 recorded a poor performance of less than 0.7 for about 50% of NN Architecture used, unlike Multilayer Perceptron Neural Network due to the following observations:

1. The MLP has greater generalization for each training example and is a good candidate for extrapolation. The extension of a localized RBF to its neighbourhood is, however, determined by its variance. This localized property prevents the RBF network from extrapolation beyond the training data.
2. The higher the numbers of neurons in the hidden layers of the RBF network the lower the performance for a time-series dataset, while the lower the numbers of neurons in the hidden layer the better the performance of the neural network
3. Lack of the Gaussian function used for the training, testing and validation of the time-series dataset to perform an excellent learning process for a good performance
4. The localized RBF network suffers from the curse of dimensionality. To achieve a specified accuracy, it needs much more data and more hidden units than the MLP. In order to approximate a wide class of smooth functions, the number of hidden units required for the three-layer MLP is polynomial with respect to the input dimensions, while the counterpart for the localized RBF network is exponential [21].
5. The error surface of the MLP has many local minima or large flat regions called plateaus, which lead to slow convergence of the training process for gradient search. For the localized RBF network, only a few hidden units have significant activations for a given input; thus, the network modifies the weights only in the vicinity of the sample point and retains constant weights in the other regions. The RBF network requires orders of magnitude less training time for convergence than the MLP trained with the BP rule for comparable performance [22-24]. For equivalent generalization performance, a trained

MLP typically has much less hidden units than a trained localized RBF network and thus is much faster in performing

5. CONCLUSION.

Multilayer Perceptron Neural Network (MLP) proved more effective and excellent in the estimation of evapotranspiration than Radial Basis Function (RBF) Neural Network (Gaussian training Algorithm), the performance of each of the Neural Network was ranked, and it is observed that ANN will predict ETo better than most models for the South-Western States under study, MLP- NN performed better than the RBF for all input combination, The Input combination of Temperature, Relative Humidity Windspeed and Solar radiation for LAGOS and OYO performed best overall due to little or no changes in the pattern of variation of the input dataset with evapotranspiration over 36 years.

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