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A long-term prediction of global solar radiation over Nigeria using the nonlinear autoregressive neural network

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ABSTRACT

In this study, surface data of minimum and maximum temperature, relative humidity, and wind speed were used as input variables to create, trainand validate the network in which global solar radiation serves as a target. These surface data were obtained from the archives of the Era-interim database of the European center for Medium-Range weather forecast (ECMWF) ata resolution of 0.25o x 0.25o. The dataspan36 years (1980-2015) for the four climatic regions of Nigeria the viz Sahel, Guinea Savannah, Derived Savannah, and Coastal regions. The research aims to evaluate the predictive ability of the Nonlinear Autoregressive Neural Network with Exogenous Input (NARX) model compared with the Multivariate Linear Regression (MLR) model. The efficiency of the two models was compared using the statistical metrics such as correlation coefficient (CC), coefficient of determination (CD), index of agreement (IA), mean bias errors (MBE), root mean square errors (RMSE) and t-statistics (T-test). Analyses showthat in the Sahel region, for instance, the NARX and MLR model have values of 0.876 and 0.450 for CC, 0.767 and 0.240 for CD, 0.813 and 0.763 for IA, 0.081 and 0.846 for MBE, 14.192 and 17.234 for RMSE and 0.4230 and 2.135 for t-test respectively. The statistical metrics for other regions followed similar patterns. Therefore, it can be inferred from these metrics thatthe NARX model gives a better prediction of global solar radiation than the traditional common MLR models in all the zones in Nigeria.

INTRODUCTION

Solar radiation as the radiant energy from the sun is a crucial component of the global energy balance that drives different earth surface systems such as the climatic and hydrologic systems[1]. It passes through the atmosphere to the ground surface and it can be modified through scattering, reflection, and absorption by the atmospheric constituents like air molecules, aerosols, water vapour, ozone, and the clouds[2]. Global solar radiation includes both the direct solar radiation and the diffuse radiation resulting from reflected or scattered sunlight. It is needed to build a reliable solar energy system in a location. The cost of installing actual measuring equipment is high which may make it impossible to have it in many locations. Therefore, there is a need for thedevelopment of alternative techniques for precise modeling, forecasting, and prediction of global solar irradiance due to the increasing interest in renewable energy system implementation in Nigeria. Several alternative models have been developed by many researchers for predicting global solar radiation in Nigeria. However, the artificialneural network techniques for global prediction have not been fully utilized for this purpose especially in Nigeria. These techniques offer a promising alternative to conventional modeling techniques becausethey have been used in a number of solar energy applications by several researchers in many developed countries and they found that the techniques serve as accurate alternatives to direct measurement. Tymvios et al.[3] trained seven ANN models to estimate the solar radiation on a horizontal surface using the back-propagation feed-forward method with tangent sigmoid as an activation function at Athalassa, Cyprus. They found that the mean biased error (MBE) and root mean square error (RMSE) values were 0.12% and 5.67% respectively better than other estimated models. Ahmad and Anderson[4] used the nonlinear autoregressiverecurrent neural networks with exogenous input (NARX) to predict global solar radiation across New Zealand. The predicted values of hourly global solar radiation were compared with the measured values, and it was found that the mean squared error (MSE) and regression (R) values showed a very good correlation. Other researchers include Moustris et al.[5], Mubiru et al.[6], Ghanbrazadeh et al.[8], Mellit, and Pavan.[9], Deng et al.[10], Wang et al.[11], and Alharbi[15] predicted global solar radiation using different forms of artificial neural network models and found that the predicted values compared well with the direct measurements. This present research uses minimum temperature, maximum temperature, relative humidity, and wind speed as input variables to create, train and validate the nonlinear autoregressive recurrent neural networkwith exogenous input (NARX) forthe prediction of global solar radiation (GSR) over four climatic regions in Nigeria. The generated outputs from the network (GSR) were compared with the multivariate linear regression predicted GSR and observed GSR using the statistical metricssuch as the correlation coefficient (CC), coefficient of determination (CD), index of agreement (dr), mean bias errors (MBE), root mean square errors (RMSE) and t-statistics (T-test).

MATERIALS AND METHOD

Data acquisition and treatment

The surface data of the minimum and maximum temperature, relative humidity, and wind speed were retrieved from the Archives of the Era-Interim database of the European Centre for Medium-Range Weather forecast (ECMWF) at grid point of 0.25x0.25. The data span the period of 1980-2015 for twelve stations averaged into four climatic regions in Nigeria as shown in Figure 1. The data was obtained in the NETCDF format and they were extracted into readable Excel format using ferret software.

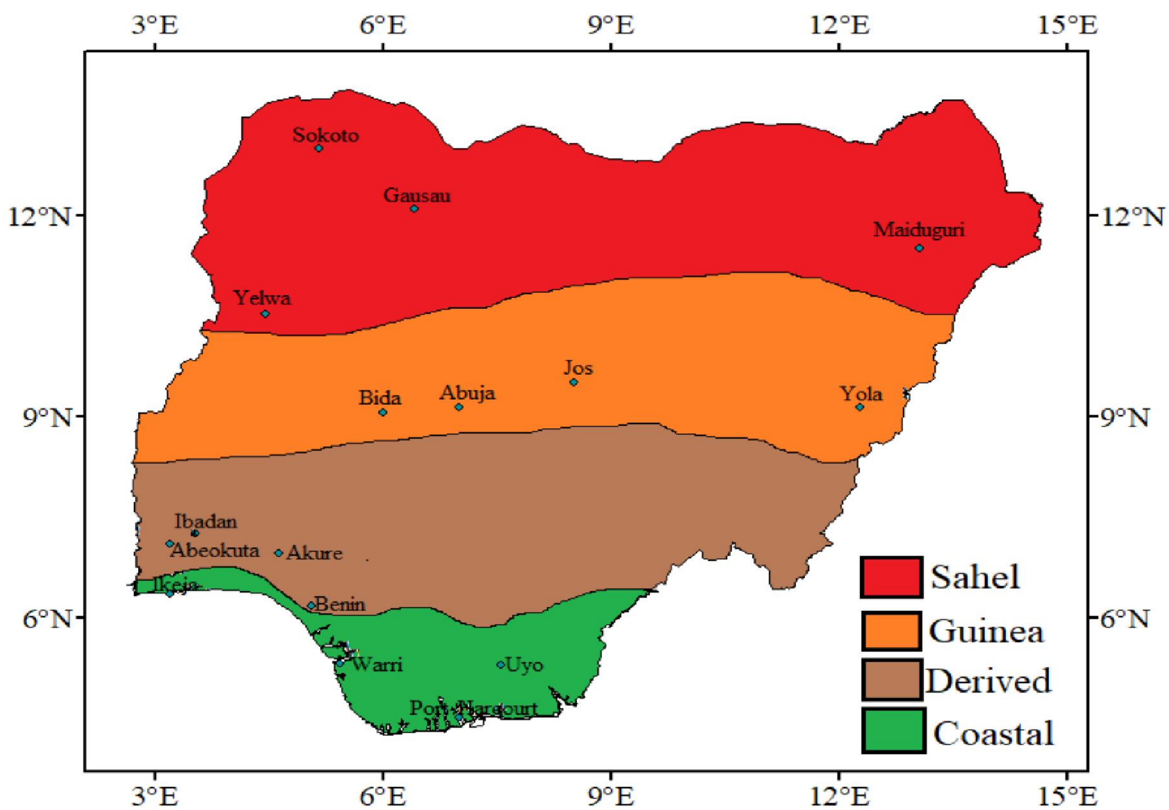

Figure 1: A map of Nigeria showing four climatic regions and the studied stations.

Artificial neural network model theory

Artificial neural network (ANNs) is a powerful forecasting tool that has led to a tremendous surge in research activities in the past decade. The interest in ANNs is largely due to their ability to mimic natural intelligence in its learning from experience[7]. They learn from examples by constructing an input-output mapping without explicit derivation of the model equation. ANNs have been used in a broad range of applications including pattern classification[18], function approximation, optimization, prediction, and automatic control[19] and many others. Additionally, ANNs have been used extensively for meteorological applications. Artificial neural network (ANN) consists of many interconnected identical simple processing units called neurons. It was developed to mimic the basic biological neural systems-the human brain. Each neuron receives an input signal from other neurons as shown in Figure 2. This processes the signal locally through an activation or transfer function and produces a transformed output signal to other external output[20].

For forecasting problem, the inputs to an artificial neural network are usually the independent or predictor variables with functional relationship estimated written as:

$$y = f(x_1, x_2, x_3, x_4..., xp) \quad (1)$$

where x1, x2,…, xpispindependent variables, and y is a dependent variable. In this article, global solar radiation was used as an output signal while minimum and maximum temperature, relative humidity, and wind speed served as an input signal. The NARX model was created and trained with 80% of the dataset (1980 – 2009) and the remaining 20% (2010 – 2015) was used to validate the model. On the other hand, the multivariate linear regression model (MLRM) of the form shown in the Equation 2 was developed and compared with the NARX model to ascertain its performance for the estimation of global solar radiation;

$$H = a + \beta_1 T_{min} + \beta_2 T_{max} + \beta_3 RH + \beta_4 WS \quad (2)$$

where H is the global solar radiation, β1, β2, β3, and β4 are the parameter estimates of minimum (Tmin), maximum (Tmax) temperatures and relative humidity (RH) and wind speed (WS) respectively and α is the multivariate intercept to be determined using the least square method.

Model testing and assessment

The models were validated using the surface data of minimum and maximum temperatures; relative humidity and wind speed span 2010-2015 as input variables. The performance of the developed models was tested with the coefficient of determination (CD), root means square error (RMSE), and means bias error (MBE), t-statistics (t-test), correlation coefficient (CC) and index of agreement (IA) using Equations 3 – 6.

$$MBE = \frac{1}{n}\sum_{n=1}^{n}(H_p - H_a) \quad (3)$$

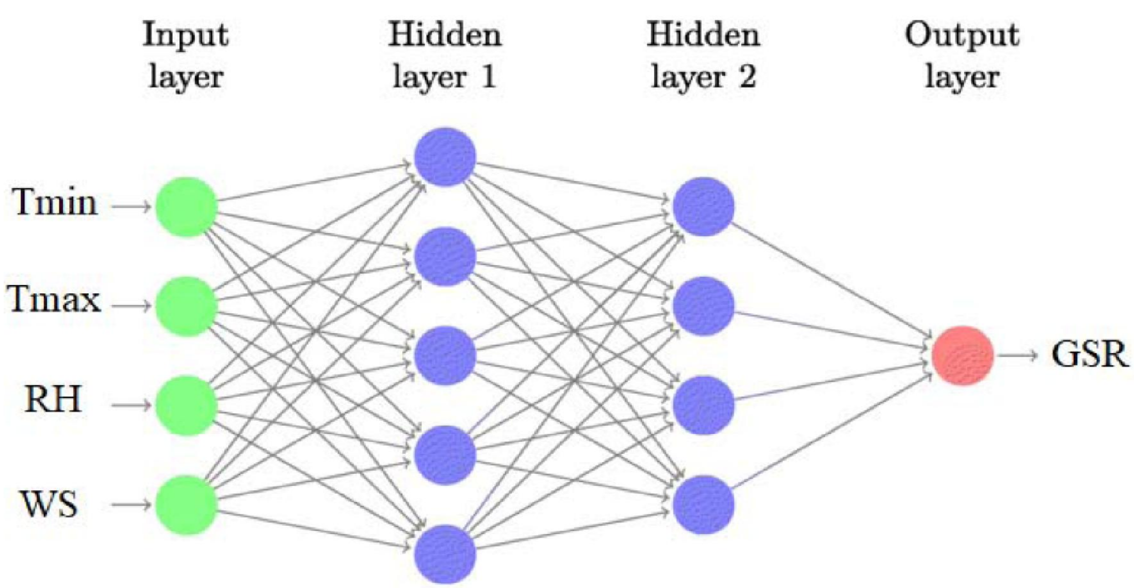

Figure 2: A NARX model architecture

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$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{n}(H_p - H_a)^2} \quad (4)$$

$$t - test = \frac{(P-1)(MBE)^2}{(RMSE)^2 - (MBE)^2} \quad (5)$$

$$IA = 1 - \frac{\sum_{n=1}^{n}(H_p - H_a)^2}{\sum_{n=1}^{n}\left([H_p - \overline{H}_a] + [\overline{H}_a - \overline{H_a}]\right)^2} \quad (6)$$

where Hp andHa are the predicted and measured values of solar radiation and n is the total number of observations,$\overline{H}$ is the mean of the measure of values. MBE indicates underestimation and overestimation if its values are negative and positive respectively. RMSE shows term by term relationship. Low values close to zero are desirable for MBE, RMSE, and t-test[1,12-14]. Meanwhile, CC which shows how predicted and observed values are related and CD and IAthat shows the predictive ability of the models requires values close to unity[1,16,17].

RESULTS AND DISCUSSION

Model development and evaluation

TABLE 1 shows the values of parameter estimates (PE) of the multivariate linear regression model (MLR) shown in Equation 2 and their significant properties over Sahel, Guinea Savannah, Derived Savannah and Coastal climate regions in Nigeria. Each of the PE indicates the relationship of each studied meteorological variable with the measured values of global solar radiation. For the fact that the probability values (p-value) were less than 0.05 alpha statistical level ($p < 0.05$) showed that all the parameter estimates of the meteorological variables and other properties have a very goodsignificant relationship with globalsolar radiation. It can be observed from the table that minimum and maximum temperatureshavea significant positive or increasing relationship with globalwarming solar radiation in all the regions except in the Sahel region where the maximum temperature has a negative or decreasing relationship with globalsolar radiation. On the other hand, relative humidity (RH) and wind speed have a significant negative relationship with globalsolar radiation in all the regions except in the Sahel region where wind speed showed a positive relationship.

Also, the significance of these variables' parameter estimates makes their combination as the multivariate linear regression models shown in Equations (7 – 10) suitable for the prediction of globalsolar radiation in the studied regions and their environs.

TABLE 1: Multivariate linear regression model parameter estimates and their properties over four climatic regions in Nigeria.

Station	Properties	Parameter Estimates					Estimates Test		
		α	β1	β2	β3	β4	R	R2	RMSE
Sahel	Estimate	-743.33	6.066	-2.751	-0.772	0.412	0.621	0.385	18.600
	SE	17.725	0.313	0.323	0.032	0.142			
	t-stat	-41.936	-9.364	-8.526	-24.47	-2.9			
	p-value	0.000	0.000	0.000	0.000	0.004			
Guinea	Estimate	-1133.3	2.576	2.111	-1.13	-2.523	0.668	0.446	26.100
	SE	36.055	0.471	0.436	0.050	0.216			
	t-stat	-31.433	5.713	4.839	-22.428	-11.685			
	p-value	0.000	0.000	0.000	0.000	0.000			
Derived	Estimate	-1931.8	2.549	4.516	-0.307	-3.805	0.603	0.363	25.900
	SE	50.559	0.488	0.428	0.0671	0.221			
	t-stat	-38.209	5.223	10.563	-4.573	-17.193			
	p-value	0.000	0.000	0.000	0.000	0.000			
Coastal	Estimate	-2188.9	4.145	3.777	-0.283	-3.886	0.560	0.313	25.000
	SE	60.796	0.531	0.456	0.088	0.214			
	t-stat	-36.004	7.803	8.278	-3.238	-18.16			
	p-value	0.000	0.000	0.000	0.0012	0.000			

Note: SE:Standard Error, t-stat: t-statistics and p-value: significant value at 0.05 alpha levels (95%).

Sahel zone model

$$H = -743.33 + 6.066T_{min} - 2.751T_{max} - 0.772RH + 0.412W_s \quad (7)$$

Guinea Savannah model

$$H = -1133.3 + 2.576T_{min} + 2.111T_{max} - 1.13RH - 2.523W_s \quad (8)$$

Derived Savannah model

$$H = -1931.8 + 2.549T_{min} + 4.516T_{max} - 0.307RH - 3.805W_s \quad (9)$$

Coastal zone model

$$H = -2188.9 + 4.145T_{min} + 3.777T_{max} - 0.283RH - 3.886W_s \quad (10)$$

The multivariate models (MLR) were used to predict global solar radiation (GSR) for each of the regions for a period of six years (2010 – 2015) on a daily and monthly basis. The MLR predicted GSR was then correlated with the observed GSR using scatterplots as shown in Figure 3. The results showed that the correlations have coefficient values of 0.6221 for the Sahelian region, 0.6317 for the Guinea Savannah region, 0.5797 for the Guinea Savannah region and 0.5779 for the Coastal Zone. They also have positive slopes in all the regions. Meanwhile, the global solar radiation was equally predicted for the same period of years using the NARX model in which minimum temperature, maximum temperature, relative humidity, and wind speed served as input variables. The NARX model'spredicted GSR values were then correlated with the observed GSR values using the scatterplots as shown in Figure 4. The results showed that the correlations have coefficient values of 0.8758 for the Sahelian region, 0.8462 for the Guinea Savannah region, 0.7599 for the Guinea Savannah region, and 0.7788 for the Coastal Zone. They also have positive slopes in all the regions. Comparatively, the NARX model predicted GSR hasa stronger relationship with observed GSR than MLR predicted GSR.

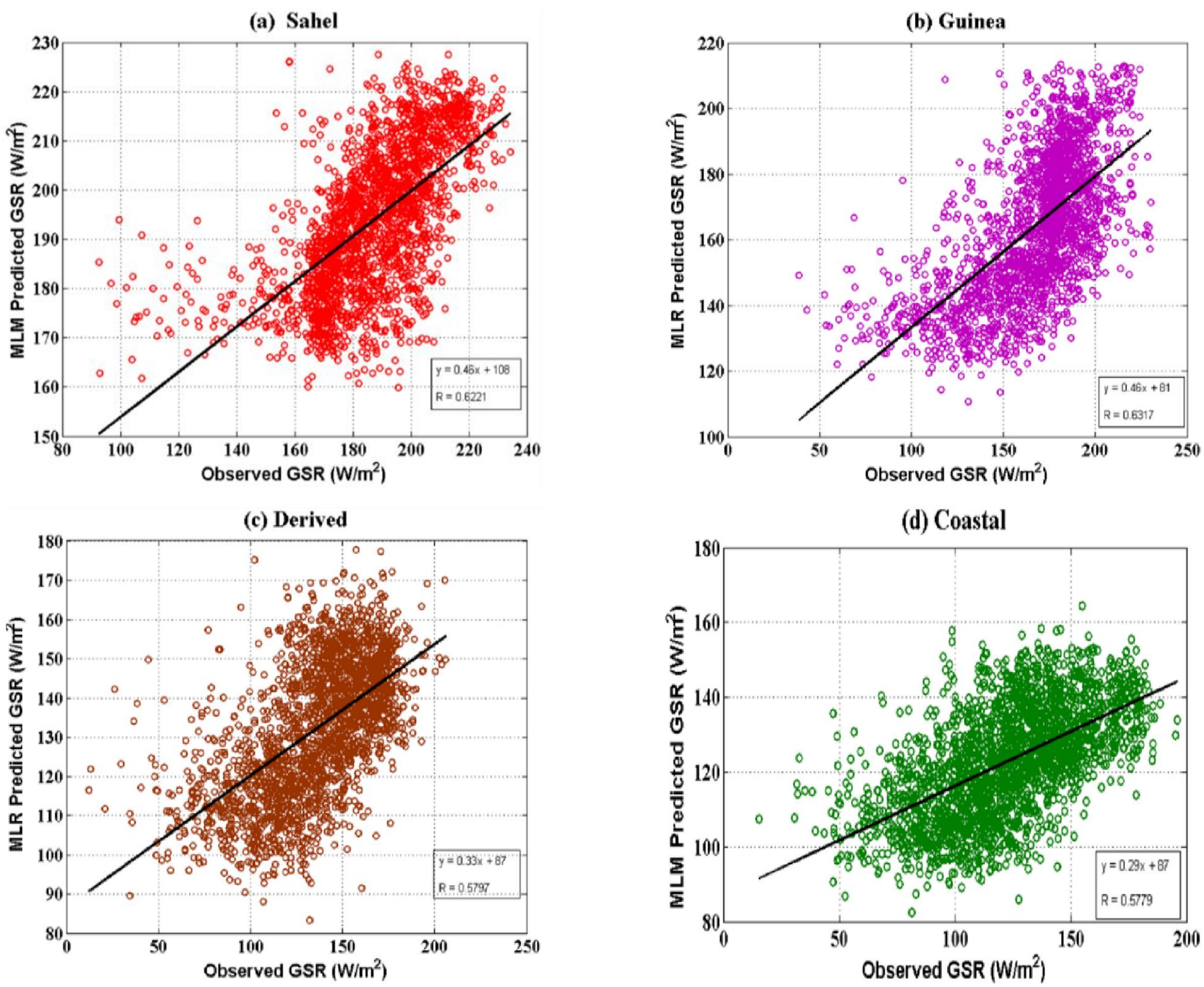

Figure 3: Scatterplots of relationship between MLR predicted and observed global solar radiation (GSR) over four climatic regions in Nigeria.

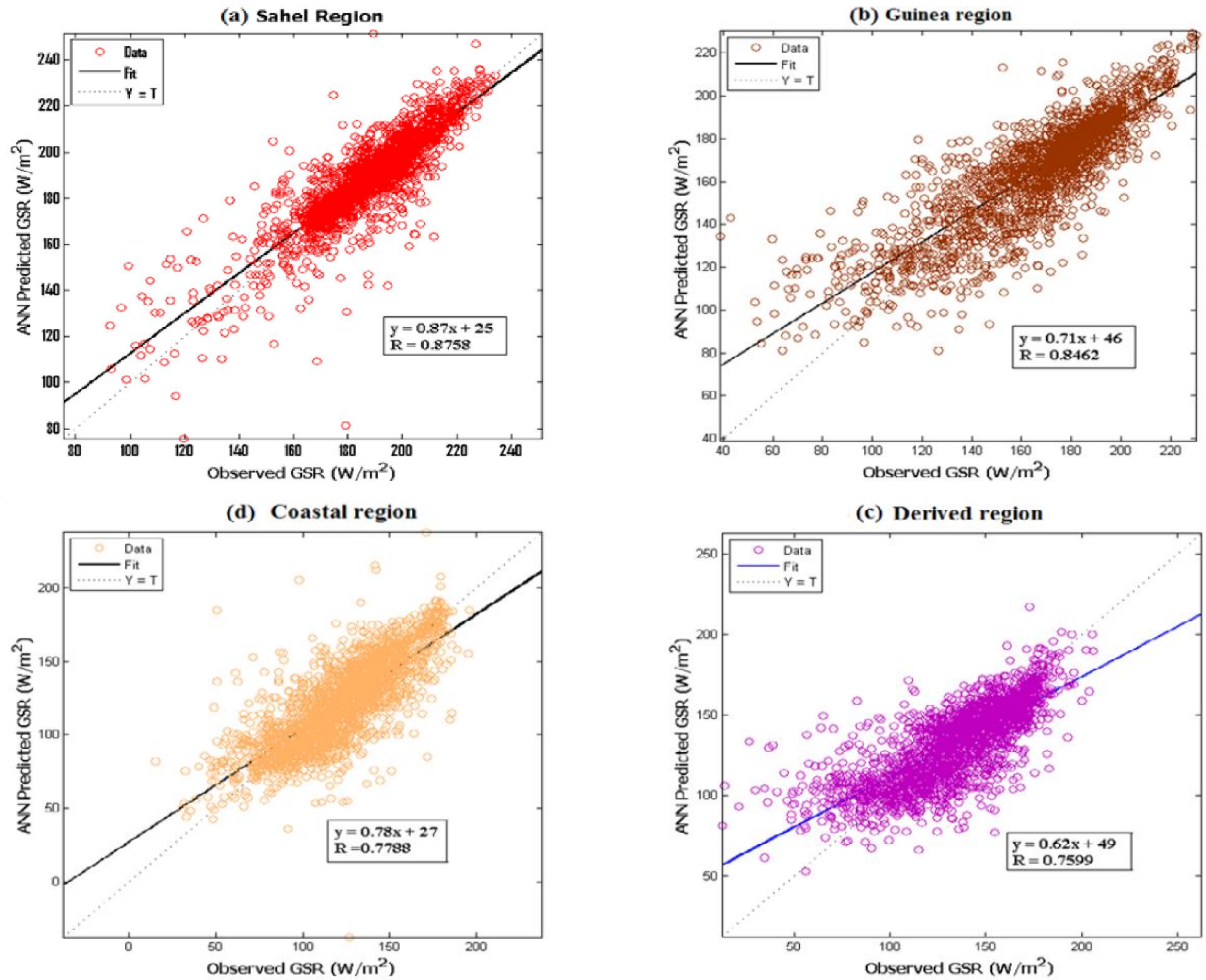

Figure 4: Scatterplots of relationship between NARX predicted and observed global solar radiation (GSR) over four climatic regions in Nigeria.

Model assessment test

The predictive performance of NARX and MLR modelsfor global solarradiation was evaluated using the coefficient of determination (CD), root mean square error (RMSE) and mean bias error (MBE), t-statistics (T-TEST), correlation coefficient (CC) and index of agreement (AI) as shown in Figure 5. In comparison, the values of CC, CD, and IA for the NARX model are closer to unity in all the four climatic regions more than those of the MLR model.

Also, the values of MBE, RMSE, T-TEST were smaller for the NARX model than those of the MLR model in all the regions. Considering the values of MBE, cases of underestimation were observed in Guinea and Derived savannah region for the two models but only the NARX model slightly underestimated in the Coastal region. The results of the statistical test further confirmed the suitability of the NARX model for the prediction of global solar radiation over the MLR empirical model in all the climatic regions of Nigeria.

Daily average and interannual monthly variations of the predicted and observed global solar radiation

Figures 6-7 show thedaily average and interannual monthlyvariations of observed and predicted global solar radiation (GSR) in the Sahel, Guinea, Derived, and Coastal Regions of Nigeria for 2010-2015. It can be observed from the figures that both MLR and NARX predicted values of GSR followed similar patterns with the observed values of GSR across the year.

The predicted values also monitored the observed values closely but slight cases of underestimation and overestimation were observed from the two models. However, the underestimation and overestimation of

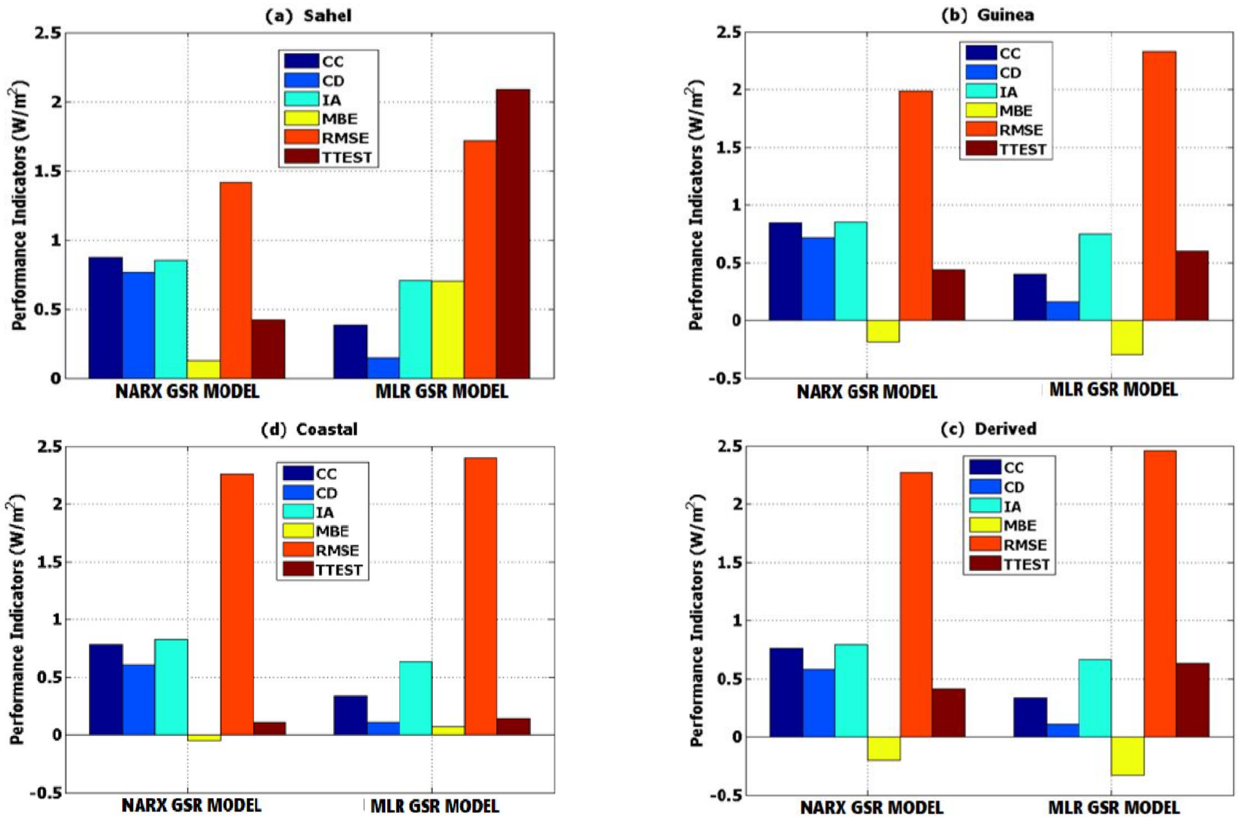

Figure 5: Statistical tests of artificial neural network (ANN) and multi-linear regression (MLR) models over four climatic regions in Nigeria.

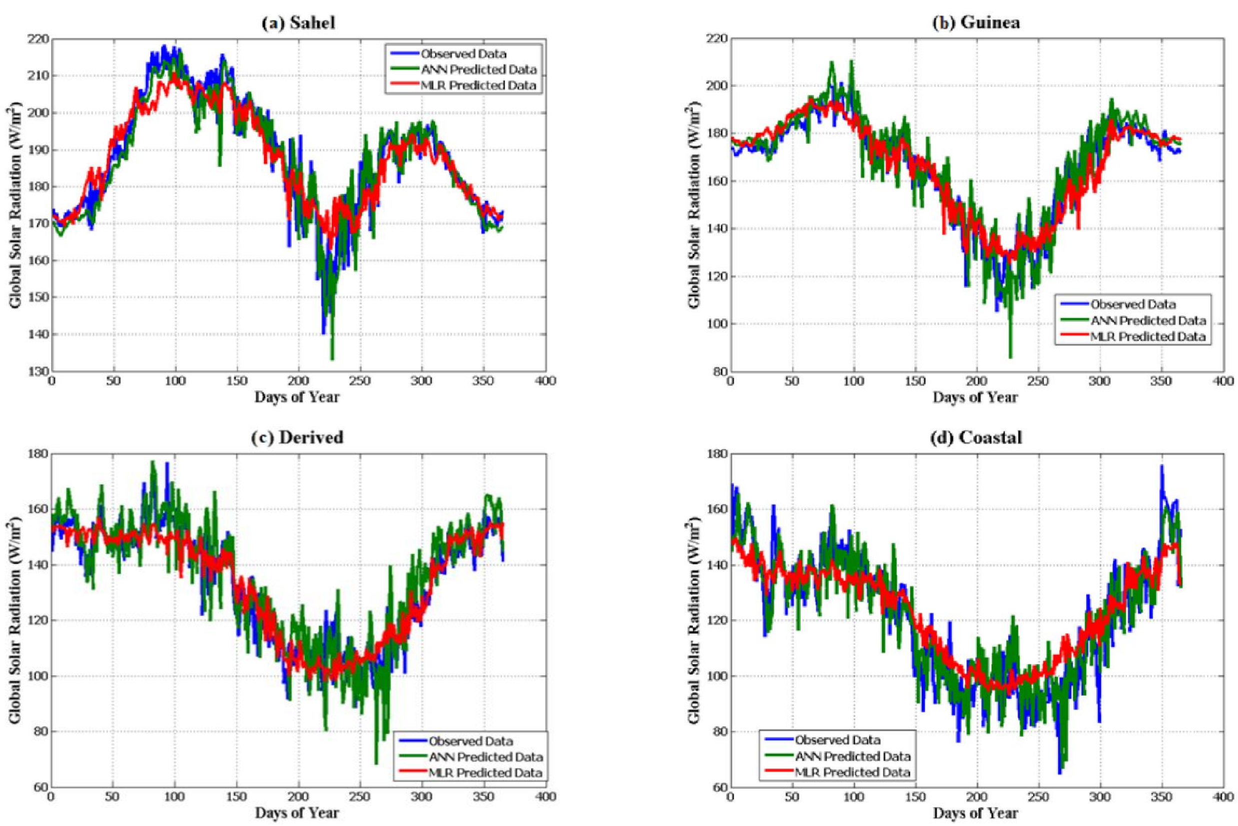

Figure 6: Daily variations of observed and predicted global solar radiation (GSR) over four climatic regions in Nigeria.

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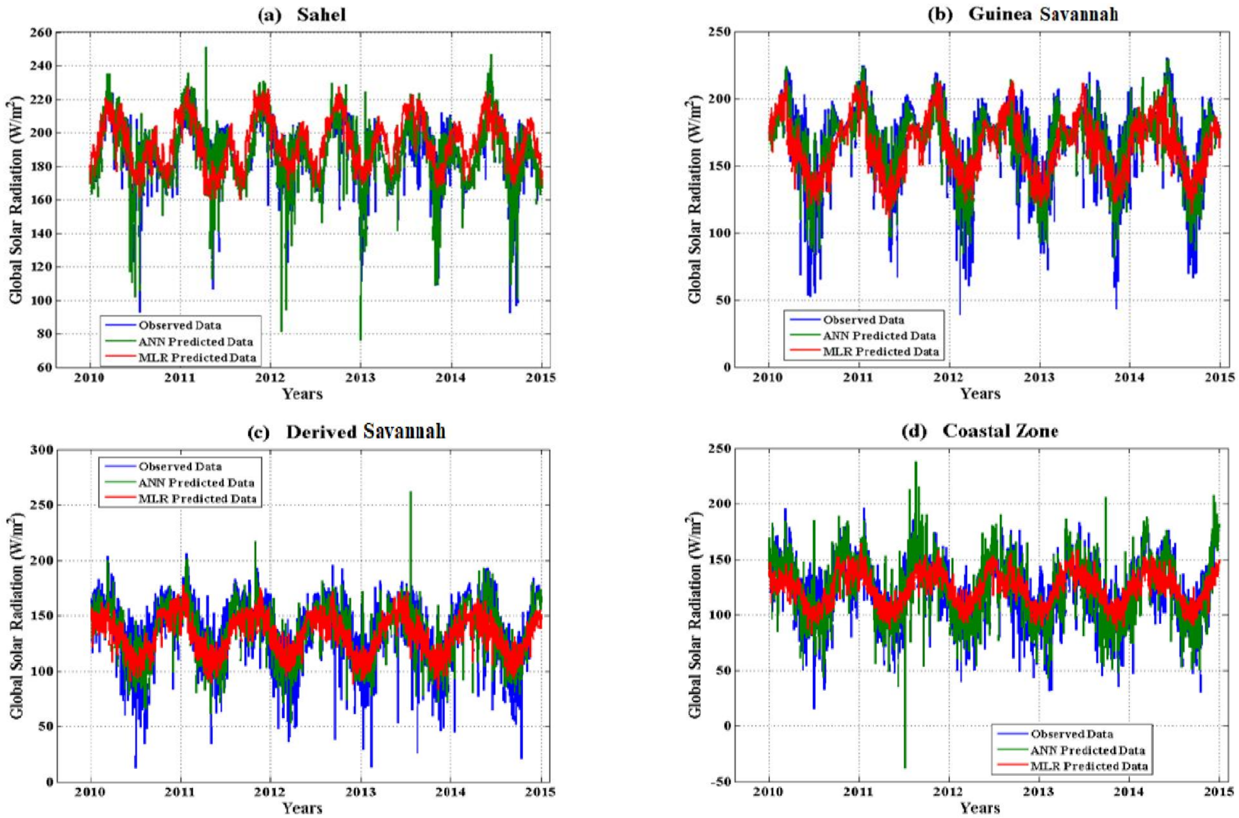

Figure 7: Inter-annual variations of observed and predicted global solar radiation (GSR) over four climatic regions in Nigeria.

GSR were more conspicuous forthe MLR model than the NARX model. This may be attributed to the fact that MLR predicted GSR was more sensitive to outliers than to observations near the mean leading to a bias toward extreme events. It can be concluded that the NARX model gave more accurate predictions of GSR than the MLR model.

CONCLUSION

The reanalysis data retrieved from the archive of the Era-Interim database of the European Centre for Medium-Range Weather forecast (ECMWF) were used to predict global solar radiation over the Sahel, Guinea Savannah, Derived Savannah and Coastal regions of Nigeria using the NARX and MLR models for 2010 – 2015. Surface data of minimum and maximum temperatures; relative humidity and wind speed were used as input variables. Multivariate linear regression analysis showed that minimum and maximum temperatures have a significant positive relationship while relative humidity and wind speed have a negative relationship with global solar radiation in all the three climatic regions of Nigeria. However, minimum and maximum temperatures have a significant negative relationship while relative humidity and wind speed have a positive relationship with global solar radiation in Sahel region only. The results of the correlation analysis between the predicted and observed global solar radiation showed that the NARX model had a stronger correlation than the MLR model. Finally, the comparative analyses using the statistical performance tests confirm that the NARX artificial intelligence model is suitable for thepredictionof global solar radiation to greater accuracy than the traditional regression model over Nigeria.

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