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Application of nonlinear autoregressive neural network to estimation of global solar radiation over Nigeria

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ABSTRACT

In this paper, surface data meteorological were used as input variables to create, train and validate the network in which global solar radiation serves as a target. These surface data were obtained from the archives of the European centre for Medium-Range weather forecast for a span of 36 years (1980-2015) over Nigeria. 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 using the statistical metrics. Model selection analysis using the index of agreement (d_r) metric showed that the MLR and NARX models have values of 0.710 and 0.853 in the Sahel, 0.748 and 0.849 in the Guinea Savannah, 0.664 and 0.791 in the Derived Savannah, 0.634 and 0.824 in the Coastal regions, and 0.771 and 0.806 in entire Nigeria respectively. Meanwhile, error analyses of the models using root mean square errors (RMSE) showed the values of 1.720 W/m^2 and 1.417 in the Sahel region, 2.329 W/m^2 and 1.985 W/m^2 in the Guinea Savannah region, 2.459 W/m^2 and 2.272 W/m^2 in the Derived Savannah region, 2.397 W/m^2 and 2.261 W/m^2 in the Coastal region and 1.691 W/m^2 and 1.600 W/m^2 in entire Nigeria for MLR and NARX models respectively. These showed that the NARX model has higher d_r values and lower RMSE values over all the climatic regions and entire Nigeria than the MLR model. Finally, it can be inferred from these metrics that the NARX model gives a better prediction of global solar radiation than the traditional common MLR models in all the zones in Nigeria.

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1. 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 can be modified when it passes through the atmosphere to the ground surface via reflection, scattering, and absorption by the atmospheric constituents like water vapour, aerosols, ozone, air molecules, and the clouds [2]. Global solar radiation (GSR) comprises the direct solar radiation and the diffuse radiation resulting from scattered or reflected sunlight. Knowledge of solar radiation as well as its temporal distribution is needed for architectural designs, solar energy systems, meteorological forecasting, crop growth models, to mention but a few [3]. Although the amount of solar radiation reaching the earth's surface can be measured using a

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pyranometer, the cost of installing this actual measuring equipment is high which has made it impossible for it to be installed in many locations, especially in Nigeria. The dearth of the instruments in many locations results in the usage of atmospheric parameters to estimate the GSR in a given site using different models. This is because the solar radiation reaching the earth's surface varies with the site meteorology [4]. This prompted different authors to develop alternative techniques for accurate modelling and estimate of global solar irradiance.

Many empirical and statistical models have been developed by many researchers for forecasting GSR in Nigeria [4]–[13]. Artificial intelligence methods have a greater ability to handle nonlinearity and complex relations between the GSR and other meteorological data, and provide better efficiency and accuracy. Meanwhile, some researchers in many developed countries have found the techniques to be accurate alternatives to direct measurement [14]–[22]. Specifically, nonlinear autoregressive recurrent neural networks with exogenous input (NARX) was used in [19] to estimate the GSR across New Zealand using air pressure, rain amount, temperature, relative humidity, azimuth angle, solar zenith angle, wind speed and wind direction. The predicted values of hourly global solar radiation compared favourably with the measured values. The NARX model was also used in [23] to predict solar radiation over India. The study used temperature, sunshine hour, and humidity as input variables and found that goodness-of-fit is 0.6431. In [24] an enhanced estimation of solar radiation using NARX models with corrected input vectors was studied over three locations in Mexico. The study used wind speed, pressure, relative humidity and temperature as input vectors and the performance evaluation showed the coefficient of determination (R) of 0.947 for Chihuahua, 0.968 for Temixco and 0.957 for Zacatecas stations in Mexico. However, the artificial neural network techniques for the estimation of GSR have not been fully utilised in Nigeria [3], [25]. Among the few researchers in Nigeria who have used the NARX model for estimation of solar radiation, include [26] that introduced a hybrid SARIMA-NARX neural network model for solar radiation estimation in Makurdi, Nigeria. The study used minimum and maximum temperatures as input variables and concluded the model has good accuracy after validation with R of 0.771. Also, [27] predicted solar radiation using the NARX model over six locations in Nigeria. The study found that the model performed best in Abuja with an R of 0.78.

This present research uses minimum temperature, maximum temperature, wind speed and relative humidity as input variables to create, train and validate the NARX model for the estimation of GSR over four climatic regions in Nigeria. The overall aim of the study was to estimate the predictive accuracy of the NARX model for global radiation over the multivariate linear regression model. The NARX predicted GSR was compared with the multivariate linear regression (MLR) predicted GSR and observed GSR using the statistical metrics such as the correlation coefficient (R), coefficient of determination (R^2), index of agreement (d_r), mean bias errors (MBE), root mean square errors (RMSE) and t-statistics (t-test).

2. Materials and Method

2.1. Data Acquisition and Treatment

The surface data of the minimum and maximum temperature, wind speed and relative humidity were retrieved from the Era-Interim archives of the European Centre for Medium-Range Weather forecast at grid point of 0.25x0.25. The data span the period of 1980-2015 for sixteen stations averaged into four climatic regions in Nigeria as shown in Fig. 1. The data obtained in the network common data form format were extracted into readable Excel format using ferret software.

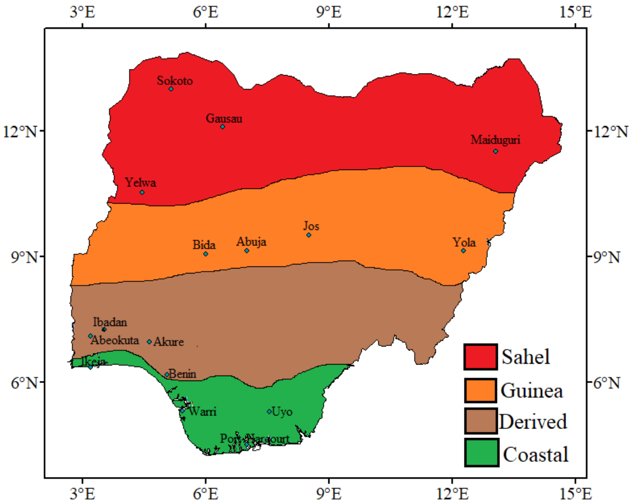

Fig. 1 A map of Nigeria showing sixteen stations and four climatic regions

2.2. Theory of Nonlinear Autoregressive Recurrent Neural Networks with Exogenous Input (NARX)

The NARX is a nonlinear recurring dynamic neural network model that can be built with feedback connections with multiple layers

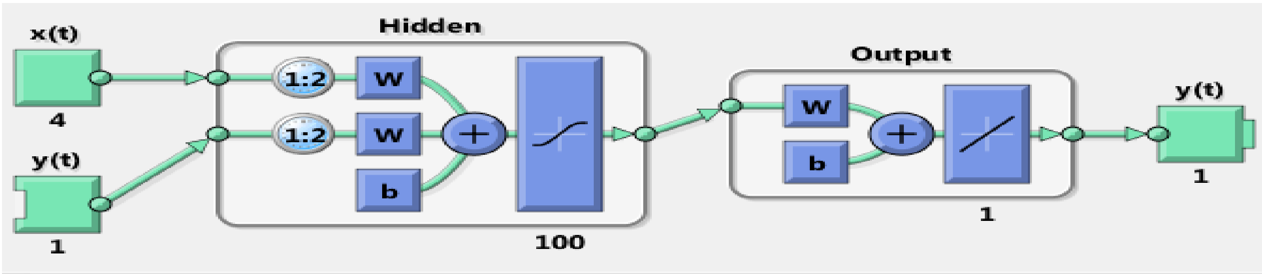

Fig. 3 Series-parallel NARX network

based on the ARX linear model for time series [28], [29] modelling. The main advantage of NARX over feed-back neural networks is that it can accept time series represented dynamic inputs [30]. Also, NARX models are better at discovering long-term characteristics and behaviour than traditional recurring networks based on the Back-Through-Time (BPTT-) algorithm [31]. NARX has been extensively utilised in applications including pattern classification [32], optimisation, function approximation, prediction, and automatic control [33]. The NARX model is expressed as:

$$y(t) = f\big(y(t-1), y(t-2), \dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u)\big) \quad (1)$$

where y(t) is the dependent output signal and u(t) the independent (exogenous) input signal. The next value of the dependent output signal y(t) is regressed on the previous values of the output signal and previous values of an independent/external (exogenous) input signal. A block diagram which represents a NARX model is shown in Fig. 2.

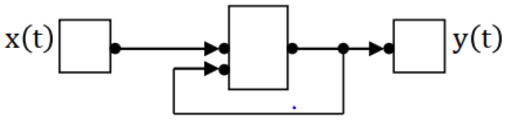

Fig. 2 NARX block diagram

The output of the NARX model is considered an approximation of the actual output of a nonlinear dynamic system because the actual output is produced during the network training phase, a series-parallel design is used to replace the estimated goal by the actual output.

In this study, the NARX model with 100 neurons in the hidden layer was created (Fig. 3). This is used to train and test models for the estimation of GSR using four input variables as shown in Fig. 4.

The GSR was used as an output signal while minimum and maximum temperature, wind speed and relative humidity served as input signals. 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.

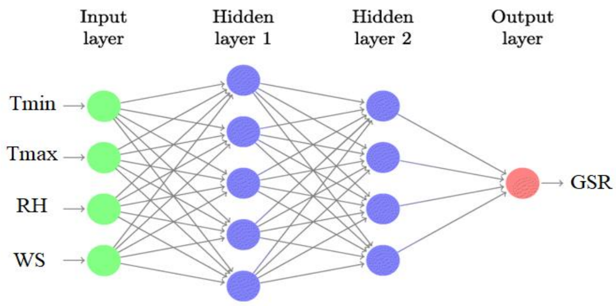

Fig. 4 A NARX model architecture

On the other hand, the multivariate linear regression (MLR) model shown in Eq. (2) was developed and compared with the NARX model to ascertain its performance for the estimation of GSR:

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

where H is the GSR, β_1, β_2, β_3, and β_4 are the parameter estimates of minimum temperature (T_{min}), maximum temperature (T_{max}), relative humidity (RH) and wind speed (WS) respectively and α is the multivariate intercept to be determined using the least square method.

2.3. Model Testing and Assessment

The models were validated using the surface data of wind speed, relative humidity and the minimum and maximum temperatures with time span 2010-2015 as input variables. The performance of the developed models was tested with the following statistical metrics:

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

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

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

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

$$R = \frac{n\sum H_a.H_p - (\sum H_a)(\sum H_p)}{\sqrt{\left(n(\sum H_a{}^2)-(\sum H_a)^2\right)}\sqrt{\left(n(\sum H_p{}^2)-(\sum H_p)^2\right)}} \quad (7)$$

$$R^2 = 1 - \frac{SS_R}{SS_T} \quad (8)$$

H_p and H_a are the predicted and measured values of GSR and n is the number of observations, $\overline{H}$ is the mean of the measure of values, SS_R is the sum of square due to regression and SS_T is the total sum of squares. MBE indicates underestimation and over-estimation 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], [34]–[36]. Meanwhile, *R* that shows how predicted and observed values are related and R-squared and d_r that shows the predictive ability of the models requires values close to unity [1], [37], [38].

3. Results and Discussion

3.1. Model Development and Evaluation

Table 1 shows the values of parameter estimates (PE) of the multivariate linear regression model (MLR) 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 of the studied meteorological variables with global solar radiation. 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 good significant relationship with GSR. It can be observed (Table 1) that minimum and maximum temperatures have a significant positive or increasing relationship with GSR in all the regions except in the Sahel region and entire Nigeria where the maximum temperature has a negative or decreasing relationship with GSR. On the other hand, relative humidity (RH) and wind speed have a significant negative relationship with global solar radiation in all the regions except in the Sahel region and entire Nigeria where wind speed showed a positive relationship. The negative relationship between maximum temperature and global solar radiation especially in Sahel region may be due to prevalence of trade winds such as Continental Tropical wind popular known as Harmattan hays in the region. This was supported by the positive wind speed relationship that was also observed in the region (Table 1). Also, the significance of these variables' parameter estimates makes their combination as the multivariate linear regression models shown in Eq. (9) – Eq. (13) suitable for the prediction of GSR in the studied regions and their environs.

Table 1 MLR model parameter estimates and their properties over four climatic regions in Nigeria

Station	Properties	Parameter Estimates					Estimates Test		
		α	β_1	β_2	β_3	β_4	R	R^2	RMSE
Sahel Region	Estimate	-743.330	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	-24.470	-2.900			
	p-value	0.0000	0.0000	0.0000	0.0000	0.0040			
Guinea Savannah Region	Estimate	-1133.3	2.576	2.111	-1.130	-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	0.0000	0.0000	0.0000	0.0000	0.0000			
Derived Savannah Region	Estimate	-1931.8	2.549	4.516	-0.307	-3.805	0.603	0.363	25.900
	SE	50.559	0.488	0.428	0.067	0.221			
	t-stat	-38.209	5.223	10.563	-4.573	-17.193			
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000			
Coastal Region	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	0.0000	0.0000	0.0000	0.0012	0.0000			
Entire Nigeria	Estimate	-1038.9	-3.304	4.821	-1.603	-3.381	0.704	0.495	18.400
	SE	31.000	0.351	0.362	0.045	0.193			
	t-Stat	-33.513	-0.864	13.320	-35.912	-17.554			
	p-value	0.0000	0.3876	0.0000	0.0000	0.0000			

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

Sahel Zone model

$$H = -743.33 + 6.066T_{min} - 2.751T_{max} - 0.772RH + 0.412WS \quad (9)$$

Guinea Savannah model

$$H = -1133.3 + 2.576T_{min} + 2.111T_{max} - 1.13RH - 2.523WS \quad (10)$$

Derived Savannah Model

$$H = -1931.8 + 2.549T_{min} + 4.516T_{max} - 0.307RH - 3.805WS \quad (11)$$

Coastal Zone Model

$$H = -2188.9 + 4.145T_{min} + 3.777T_{max} - 0.283RH - 3.886WS \quad (12)$$

Entire Nigeria Model

$$H = -1038.9 - 3.304T_{min} + 4.821T_{max} - 1.603RH - 3.381WS \quad (13)$$

The MLR models were utilised to predict the 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 Fig. 5. The results showed that the correlations have coefficient values of 0.6221 for the Sahel 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 GSR was equally predicted for the same period of years using the NARX model in which minimum temperature, maximum temperature, wind speed and relative humidity served as input variables.

On the other hand, the NARX model's predicted GSR were validated with the observed GSR using the scatterplots as shown in Fig. 6. 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 has a stronger relationship with observed GSR than MLR predicted GSR based on the higher values of the correlation coefficient.

3.2. Model Assessment Test

The predictive performance of NARX and MLR models for global solar radiation was assessed using the six metrics (R, R^2, d_r, RMSE, MBE, and t-test) as shown in Fig. 7.

Comparatively, from Fig. 7, the values of R, R^2, and d_r for the NARX model were closer to unity in all the four climatic regions than those of the MLR model. For instance, the values of the index of agreement (d_r) for validation of the MLR and NARX models were 0. 710 and 0.853 in the Sahel, 0.748 and 0.849 in the Guinea Savannah, 0.664 and 0.791 in the Derived Savannah, and 0.634 and 0.824 in the Coastal regions respectively.

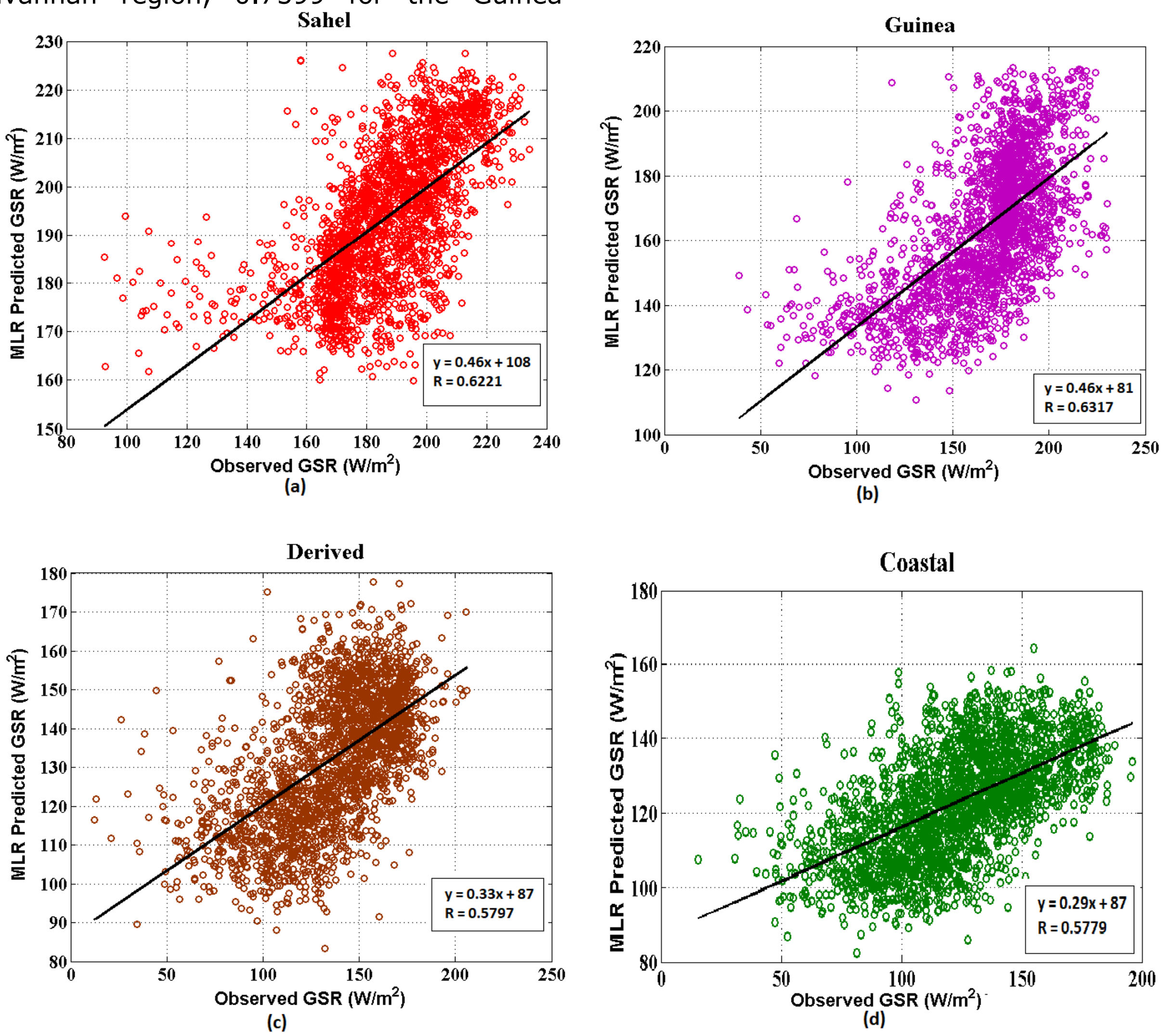

Fig. 5 Scatterplots of relationship between MLR predicted and observed GSR over four climatic regions in Nigeria

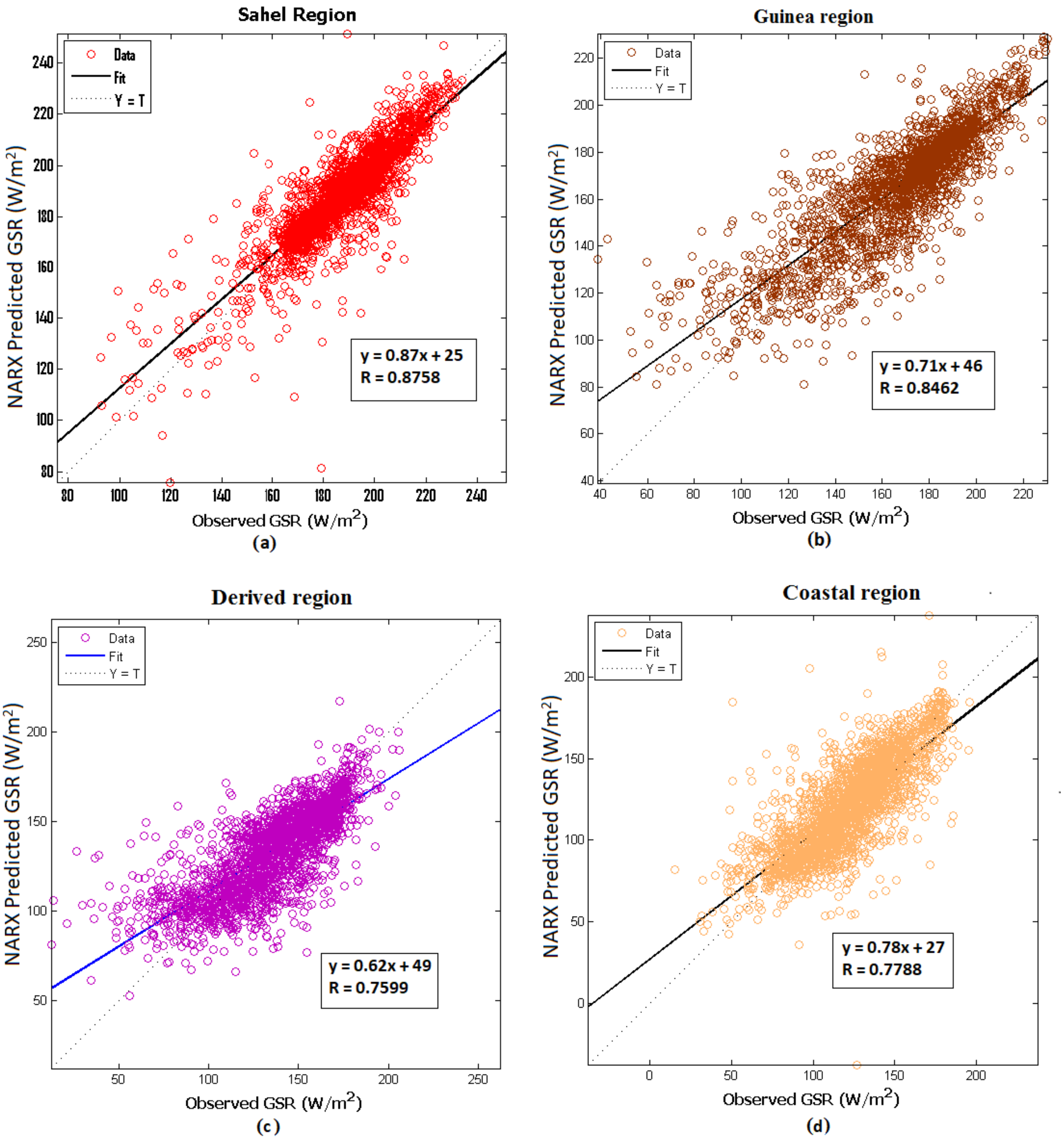

Fig. 6 Scatterplots of relationship between NARX predicted and observed GSR over four climatic regions in Nigeria

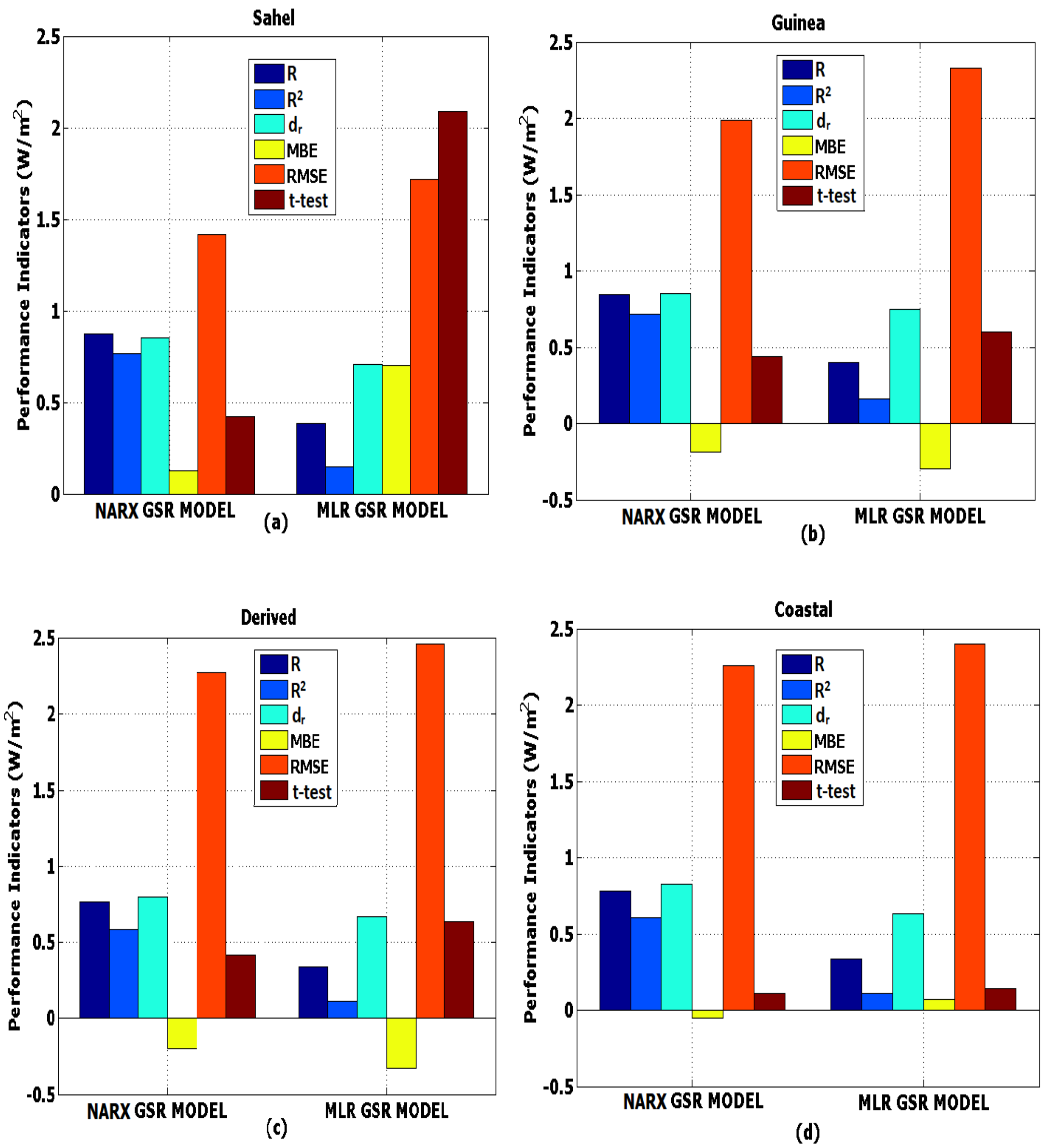

Fig. 7 Statistical tests of NARX and MLR models over four climatic regions in Nigeria

Also, the values of MBE, RMSE, t-test were smaller for the NARX model than those of the MLR model in all the regions. For instance, the values of the RMSE for MLR and NARX models are 1.720 W/m^2 and 1.417 in the Sahel, 2.329 W/m^2 and 1.985 W/m^2 in the Guinea Savannah, 2.459 W/m^2 and 2.272 W/m^2 in the Guinea Savannah, and 2.397 W/m^2 and 2.261 W/m^2 in the Coastal regions respectively. 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 GSR over the MLR empirical model in all the climatic regions of Nigeria.

3.3. Daily Average and Inter-annual Monthly Variations of the Predicted and Observed GSR

Figs. 8 - 9 show the daily average and inter-annual monthly variations of observed and predicted 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.

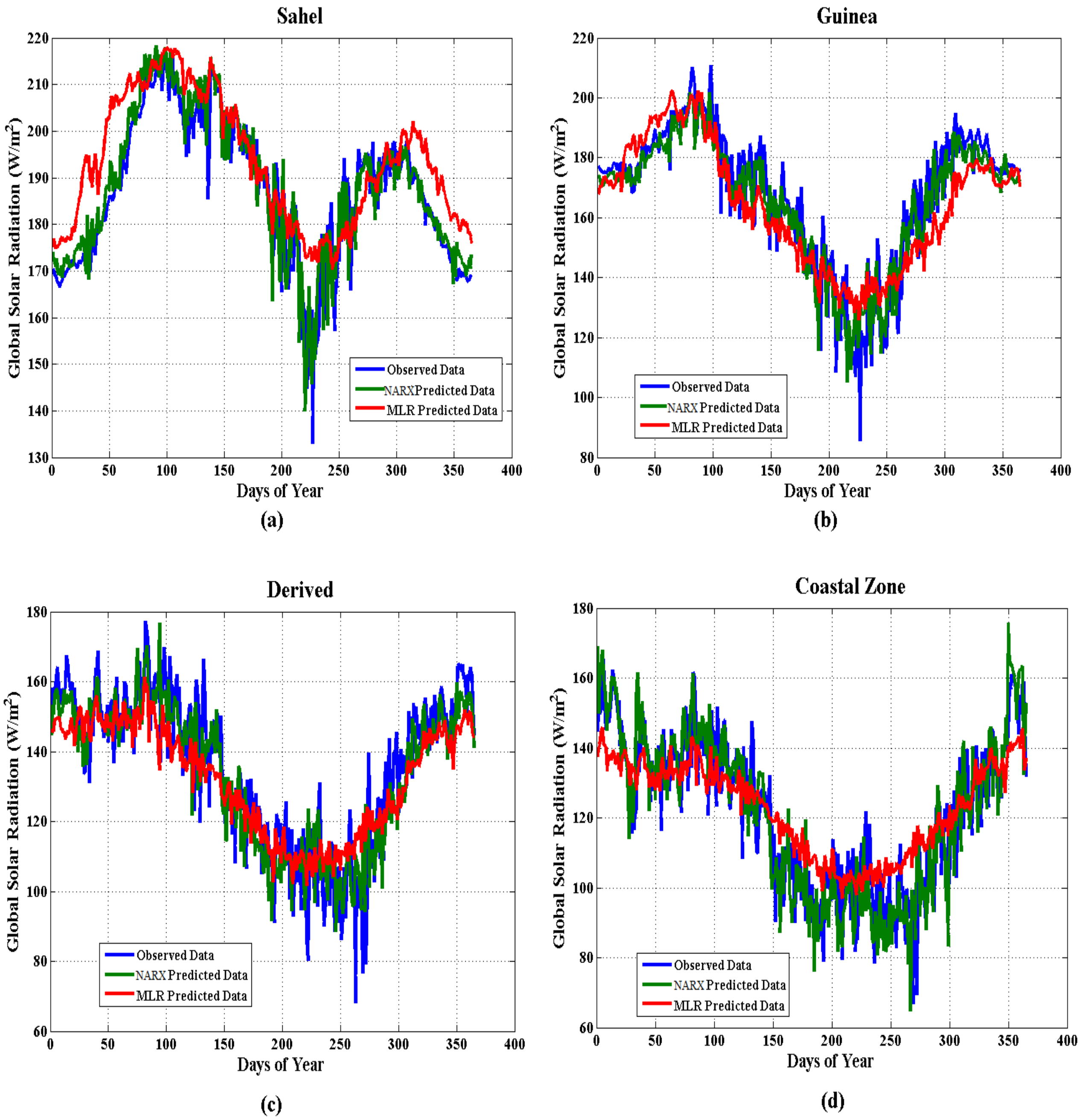

Fig. 8 Daily variations of observed and predicted GSR over four climatic regions in Nigeria

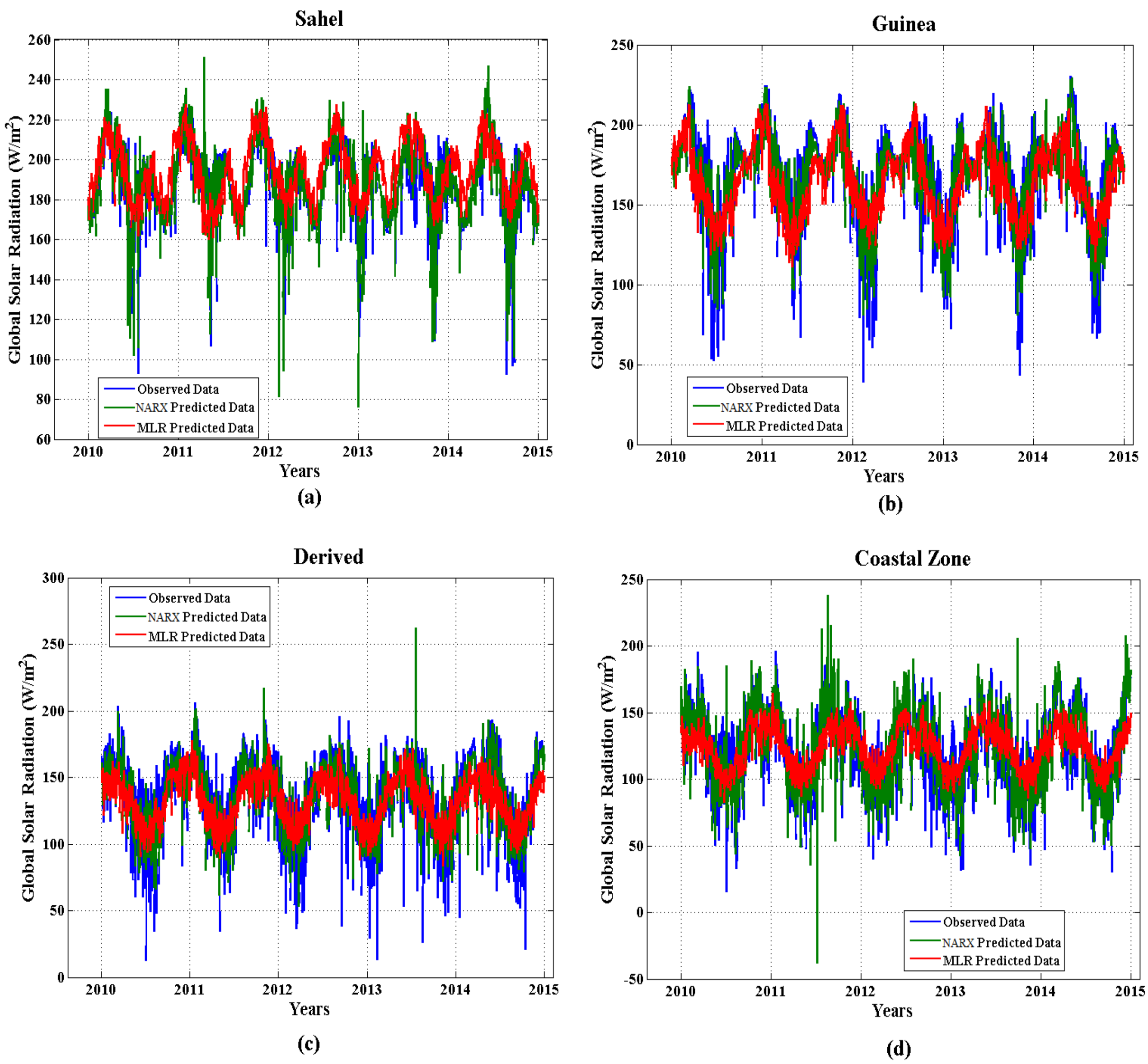

Fig. 9 Inter-annual variations of observed and predicted GSR over four climatic regions in Nigeria

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 GSR were more conspicuous for the 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.

Fig. 10 (a-b) shows the scatterplots of the relationship between predicted GSR by MLR and the NARX model and observed GSR over the entire Nigeria. The figure showed that the correlations between observed GSR and MLR and NARX predicted GSR are 0.6596 and 0.8267 respectively.

The performance evaluation of MLR and NARX models using the R, R^2 and d_r showed that the NARX model has higher values closer to unity than the MLR model (Figure 8c). Specifically, the index of agreement (d_r) has values of 0.771 and 0.806 for MLR and NARX models respectively. Nevertheless, the values of MBE, RMSE, and t-test for the NARX model are lower than those of the MLR model. The root mean square errors have the values of 1.691 for the MLR model and 1.600 for the NARX model over entire Nigeria (Fig. 10c). Therefore, it can be inferred that the NARX model performs better than the MLR model for the estimation of GSR. Finally, the prediction and observed GSR followed the same patterns but the cases of overestimation and under-estimation are more conspicuous for the MLR model than the NARX model (Fig. 10d).

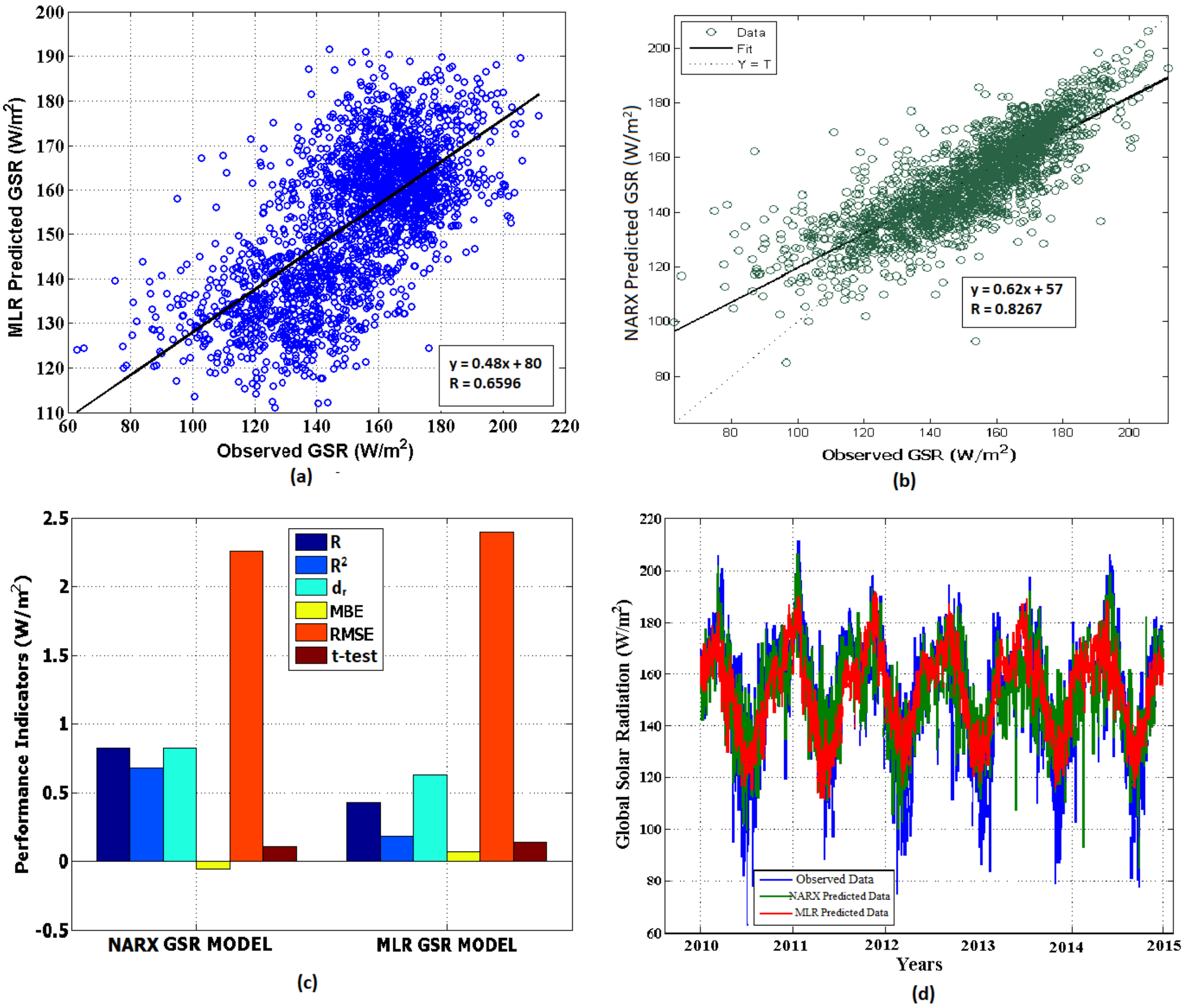

Fig. 10 Performance assessment of the MLR and NARX models for prediction of GSR over entire Nigeria

4. Conclusion

The reanalysis data collected from the Era-Interim archive of the European Centre for Medium-Range Weather forecast were used to estimate the GSR over the Sahel, Guinea Savannah, Derived Savannah and Coastal regions in Nigeria using the NARX and MLR models for 2010 – 2015. The Surface data of minimum and maximum temperatures; relative humidity and wind speed for a period of 30 years (1980 – 2009) were used as input variables to develop the models. 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 four climatic regions in Nigeria. However, minimum and maximum temperatures have a significant negative relationship while relative humidity and wind speed have a positive relationship with GSR in Sahel region only. The results of the correlation analysis between the predicted and observed GSR showed that the NARX model had a stronger relationship than the MLR model. Finally, the comparative analyses using the statistical performance tests confirm that the NARX artificial intelligence model is suitable for the estimation of GSR to greater accuracy than the traditional regression model over Nigeria. The proposed models can also be used to predict GSR in any location within each of the four climatic regions in Nigeria. Other machine learnings techniques should be explored for estimation of GSR in Nigeria and the results should be compared with this study.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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