__Original Research Article__

Investigation of Carbon Dioxide Variations in Selected Points in Nigeria Using Neural Network Model

ABSTRACT

Atmospheric pollution due to carbon dioxide emission from different fossil fuels and deforestations are considered as a great and important international challenge to the societies. This study is to investigate carbon dioxide (CO_2) distributions in selected points in Nigeria using neural network. Neural network model were used to estimate daily values of carbon dioxide, study spatial temporal variations of carbon dioxide, and study the annual variations of estimated and observed carbon dioxide in Nigeria. The study areas used in this work are thirty six (36) points location over Nigeria. The data used in this work is a satellite carbon dioxide (CO_2) data were obtained from Global Monitoring for Environment and Security (GMES) under the programme of Monitoring Atmospheric Composition And Climate (MACC)www.gmes-atmosphere.eu/data between 2009-2014**.** The neural network architecture used comprises of three main layers; an input layer, a hidden layer and an output layer. Four input data were considered which include year, day of year (DOY) representing the time, latitude and longitude. Twenty hidden neurons were employed, while the output is the desired data of carbon dioxide. The results show that the increase in trend of CO_2 in dry season in every part of the country is on yearly bases. In the wet season, the concentration of CO_2 in Nigeria is not as much as in the dry season case, probably due to absorption of the gas by precipitation. The continuous annual increase of CO_2 distribution suggests continuous increase of the greenhouse gas in Nigeria. This reveals continuous contribution of CO_2 in Nigeria. The similarity in the estimated and observed signatures reveals that neural network model performance were excellent and efficient in determination of spatial distribution of CO_2, thereby proving to be useful tool in modeling the greenhouse gases. The results show that neural network model has the capacity of investigating greenhouse gases variations in Nigeria.

Keywords: Fossil Fuels; Deforestation; Carbon dioxide Emission; Spatial Variation; Temporal variation; Neural Networks; Architecture**,** climate change**.**

1. INTRODUCTION

Climate change is a topical issue worldwide because of its attendant problems that are threatening the sustenance of man and his environment. This is evident in an increase in average global temperatures due to increased emission of greenhouse gases, such as carbon dioxide [1]. These are particularly becoming more severe in the under-developed and developing countries of which Nigeria is one. It has become a reality in developing countries like Nigeria, Ghana etc with grievous repercussions on human beings. These changes result in upsetting seasonal cycles, affecting water supply, agriculture and food production, rise in sea-levels, recurring flooding, off season rains, drought and famine, overheating, drying up of lakes and reduction in river. These cause harm to ecosystem. The effect of carbon dioxide emission in developing and under developed country like Nigeria motivated this study. Nigeria is in West African region bordered by Benin Republic in the west, Chad and Cameroon in the east, and Niger in the north. Its coast in the south lies on the

Gulf of Guinea in the Atlantic Ocean. Nigeria comprises of thirty-six states with the Federal Capital Territory in Abuja. It has a total land area of 923,768 km², populated by over 140,003,542 people [2]. The country is found in the Tropics, where the climate is seasonally damp and very humid. It is affected by four climate types; these climate types are distinguishable, as one moves from the southern part of Nigeria to the northern part of the country through its middle belt. The geographical information about the study area (Nigeria) has reveals its climatic nature. For developed countries which are the major contributors to climate change, the impacts are less severe due to, high adaptation techniques, and technologies, effective research proven policies, mechanized agricultural system and wealthy economic status [3].

Neural network has been largely used in solving different problems in numerous fields such as rainfall-runoff, water quality, sedimentation, variations of greenhouse gases, distributions and estimations of meteorological parameters and rainfall forecasting [4]. It has proven to be a good model for estimations, providing good accuracy for long term estimations, an impressive performance for modeling climatic parameters and proved to be an excellent modeling for gaseous pollutants [5, 6, 7]. Neural networks (also called computer neural networks) belong to a branch of artificial intelligence called machine learning. They are a system of information processing techniques inspired by the manner in which the human brain works, and so the name neural network. Neural networks can learn trends and patterns in data and consequently be able to correctly predict future trends and data patterns.

Although there are some researches on the variations of greenhouse gases and gaseous pollutants in some regions of Nigeria [8, 9], but none has been known at the time of this study to have studied the Neural Network based modeling of spatial variations with respect to carbon dioxide over Nigeria. [10] stated that the problems in trying to establish a weather station networks in Africa includes the technological and scientific underdevelopment of many African countries exacerbated by extensive poverty and political instability. These have given advantages to satellite data monitoring. Researchers have revealed that satellite data could be used in place of ground based data if equipment for in-situ measurements is not available [11, 12]. They opined that the advent of satellite monitoring will provide a more detailed analysis of atmospheric studies over a wide region in Nigeria and Africa in extension.

2. MATERIALS AND METHODS

2.1 The Study Area and Data Source

The study areas used in this work are thirty six (36) location points over Nigeria as shown in Figure 1, which is the gridded map of the selected stations in Nigeria. Table 1 shows the coordinates of the selected stations over Nigeria. These stations were selected based on the interval of 1.5^0 (from one point to another) of the gridded map to cover Nigeria.

The data used in this work is a satellite carbon dioxide (CO_2) data obtained from Global Monitoring for Environment and Security (GMES) under the programme of Monitoring Atmospheric Composition And Climate (MACC) www.gmes-atmosphere.eu/data between 2009-2014**.** Satellite data were used for this study because there were no ground based measured greenhouse gases in Nigeria at the time of this research. The data which were in NetCDF format were extracted, converted to binary format, sorted and merged to file using Matlab program. The data were daily data. The interval between one point and another in the study area (Figure 2) is 1.5^o, where 1^o represents about 111 km

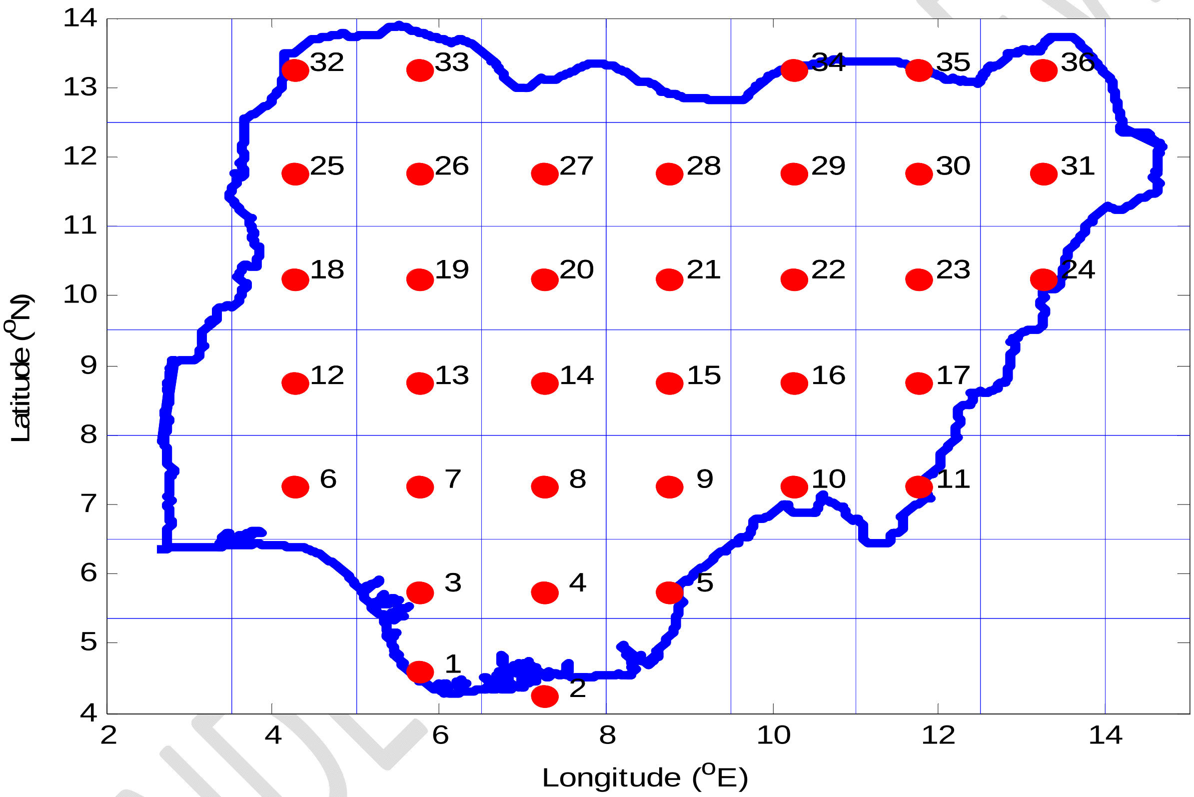


Figure 1: Gridded Map Showing Data Points of the selected stations in Nigeria

Table 1: Coordinates of the selected Stations and their Data Points over Nigeria

Points	Y Latitude (^oN)	X Longitude (^oE)	Stations	Local Government Area	State
1	4.59	5.84	Apoi Creek	Southern Ijaw	Bayelsa
2	4.25	7.25	Offshore	Atlantic Ocean	Atlantic Ocean
3	5.75	5.75	Ukpe Sobo	Okpe	Delta
4	5.75	7.25	Obiohoro Osu	Unuimo	Imo
5	5.75	8.75	Nsarum	Etung	Cross River
6	7.25	4.25	Mowo	Isokan	Osun State
7	7.25	5.75	Idosale	Ose	Ondo State
8	7.25	7.25	Allomo	Ofu	Kogi
9	7.25	8.75	Ahile	Gboko	Benue
10	7.25	10.25	Danjuma	Ussa	Taraba
11	7.25	11.75	Filinga Sekenoma	Gashaka	Taraba
12	8.75	4.25	Alajere	Moro	Kwara
13	8.75	5.75	Pategi	Pategi	Kwara
14	8.75	7.25	Kabi	Kuje	Abuja
15	8.75	8.75	Arugwadu	Lafia	Nassarawa
16	8.75	10.25	Ibi	Ibi	Taraba
17	8.75	11.75	Tainho	Yorro	Taraba
18	10.25	4.25	Luma	Borgu	Niger
19	10.25	5.75	Beri	Mariga	Niger
20	10.25	7.25	Gwagwada	Chikun	Kaduna
21	10.25	8.75	Bauda	Lere	Kaduna
22	10.25	10.25	Dindima	Bauchi	Bauchi
23	10.25	11.75	Pelakombo	Bayo	Borno
24	10.25	13.25	Mubi	Hong	Adamawa
25	11.75	4.25	Giro	Suru	Kebbi
26	11.75	5.75	Bukkuyum	Bukkuyum	Zamfara
27	11.75	7.25	Lugel	Faskari	Katsina
28	11.75	8.75	River Armatai	Dawakin Kudu	Kano
29	11.75	10.25	Galadao	Katagum	Bauchi
30	11.75	11.75	Damaturu	Fune	Yobe
31	11.75	13.25	Dalori	Jere	Borno
32	13.25	4.25	Gudu	Gudu	Sokoto
33	13.25	5.75	Kadagiwa	Wurno	Sokoto
34	13.25	10.25	Nguru	Yusufari	Yobe
35	13.25	11.75	Yunusari	Yunusari	Yobe
36	13.25	13.25	Abadam	Abadam	Borno

2.2. Methods

A total of 20 neural networks were trained; the difference between them is in the number of hidden layer neurons we applied (we varied the number of hidden layer neurons from 1 to 20). The neural network architecture used for the training was 4-20-1. The architecture comprises of three main layers; an input layer, a hidden layer and an output layer. The available data is split into three portions: 70% for the training, 15% for validation and the remaining 15% for testing before the neural network training. The performance of the simulation was tested using root mean square error (RMSE) computed to determine the best network. MATLAB codes were used to implement the neural network algorithm for the training. In the MATLAB implementation of this algorithm, MATLAB had to normalize the data by default before presenting it as input data to the network. Normalization of the training data was done using the mapminmax processing function, which is default for the MATLAB training algorithm used in this work. The mapminmax function normalizes the training data so that inputs fall in the range (-1, 1) by mapping the minimum and the maximum values to -1 and 1, respectively [13].

There are no specific or perfect rules for deciding the most appropriate number of neurons in a hidden layer. Using an excessive number of hidden-layer neurons causes over-fitting, while a lesser number leads to under-fitting. Either scenario greatly degrades the generalization capability of the network with significant deviance in prediction and forecasting accuracy of the model [14]. Using a larger number of hidden layer neurons usually leads to better predictions (because the prediction errors will reduce) for data within the range of the training data set. If however, the same network is used to predict data outside the range of the training data set, the errors decreases, and then increase after a certain number of hidden layer neurons. We define the best network as the one that gives the least prediction error on forecasted data using root means square errors (RMSE).

Equations (1) - (7) were the mathematical illustrations of the processes of the Neural Network training from input to the output of the parameter as shown in Figures 2 and 3. Thus,

$$\sum(\mathrm{I_{wm}} * \mathrm{I_m} + \mathrm{b_1}) = \mathrm{n_1} \tag{1}$$

$$\mathrm{f_1}\ (\mathrm{n_1}) = \mathrm{tansig}(\mathrm{n_1}) = \frac{e^{\mathrm{n_1}} - e^{-\mathrm{n_1}}}{e^{\mathrm{n_1}} + e^{-\mathrm{n_1}}} = \mathrm{H_{vm}} \tag{2}$$

$$\sum(L_{wm} * H_{vm} + b_2) = \mathrm{n_2} \tag{3}$$

$$\mathrm{f_2}(\mathrm{n_2}) = \mathrm{purelin}(\mathrm{n_2}) = \mathrm{O_m} \tag{4}$$

$$\mathrm{f_2}(\mathrm{n_2}) = \mathrm{purelin}\ (L_{wm} * H_{vm} + b_2) = \mathrm{n_2} = \mathrm{O_m} \tag{5}$$

$$\mathrm{O_m} = \mathrm{L_{wm}} * \mathrm{H_{vm}} + \mathrm{b_2} \tag{6}$$

$$\mathrm{O_m} = \mathrm{L_{wm}} * (\mathrm{tansig}(\mathrm{I_{wm}} * \mathrm{I_m} + \mathrm{b_1})) + \mathrm{B_2} \tag{7}$$

where $\mathrm{I_m}$ is the input matrix containing inputs variables of the study (year, day of the year, latitude, longitude), $\mathrm{I_{wm}}$ depict input weight matrix, $\mathrm{b_1}$ is bias vector one, $\mathrm{H_{vm}}$ is the hidden variable matrix, $\mathrm{L_{wm}}$ is layer weight matrix, $\mathrm{b_2}$ is bias vector two, $\mathrm{O_m}$ is the output matrix, while tansig ($\mathrm{f_1}$) and purelin ($\mathrm{f_2}$) were hyperbolic tangent sigmoid function used between the input and the hidden layers and linear transfer functions used from hidden layers to the output layer as activation functions.

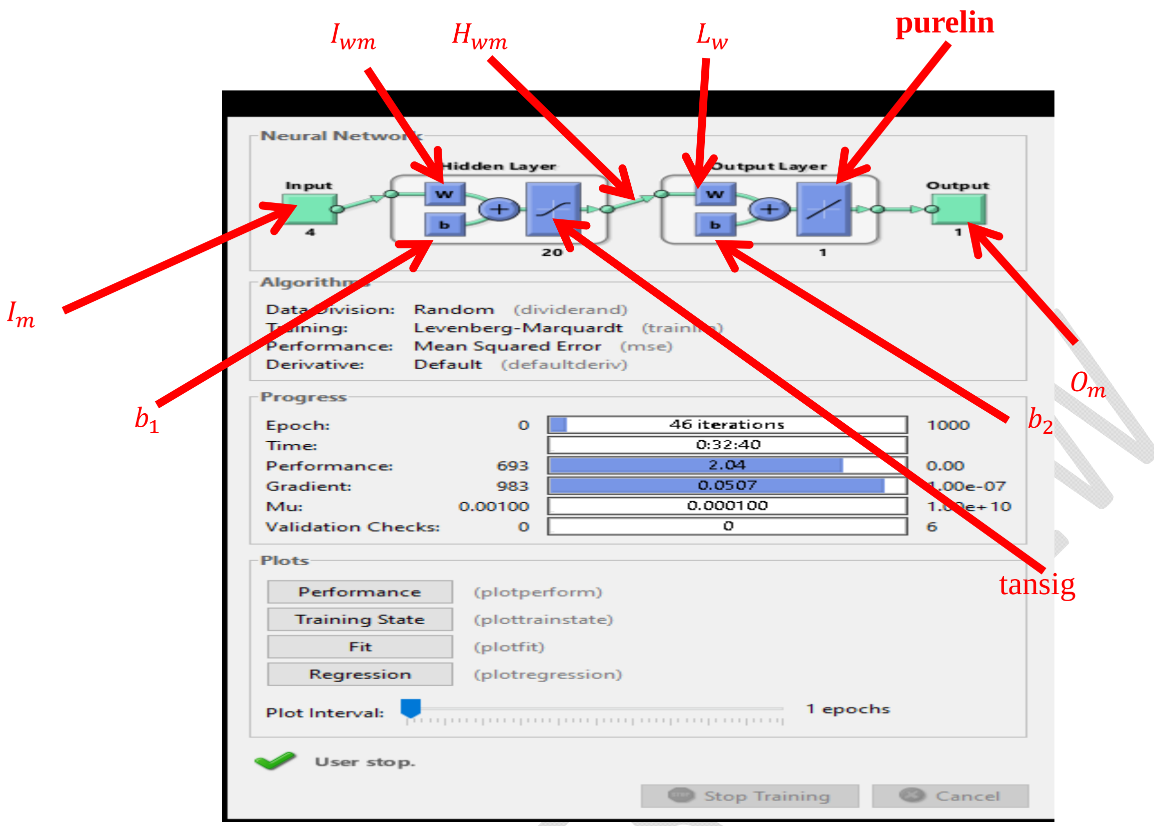
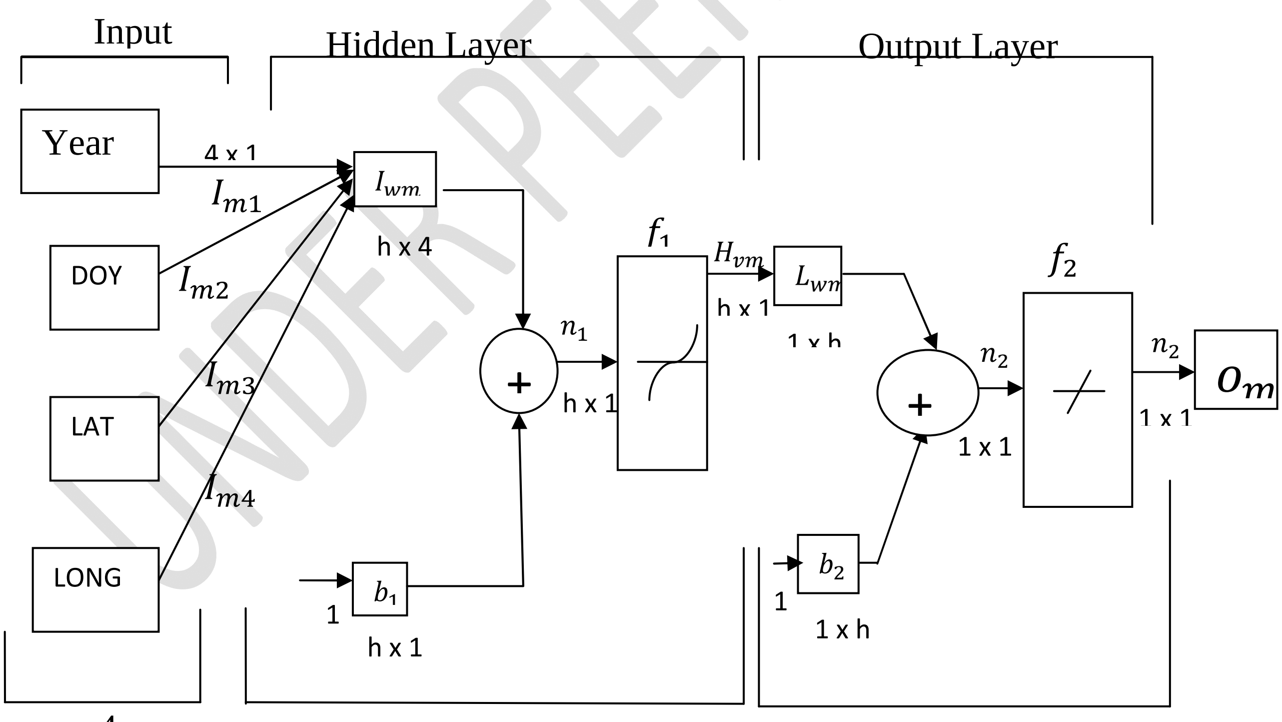


Figure 2: Schematic Diagram of Neural Network Training Window



$$\mathrm{H_{vm}} = f_1\ (I_{wm} * I_m\ +\ b_1\ ) \qquad \mathrm{n_2} = f_2\ (L_{wm} *\ \mathrm{H_{vm}}\ +\ b_2\ )$$

Figure 3: Feed Forward Neural Network Training Structure from Input to Output

The size of I_{wm} is h-by-4 because there are 4 input layer neurons. The size of L_{wm} is 1-by-h because there is one output layer neuron. The sizes of b_1, n_1, H_{vm}, b_2 and n_2 are h x 1, h x 1, h x 1, 1 x h and 1 x 1 respectively, where h is the number of hidden layer neurons.

To decide an optimal number of hidden-layer neurons in this work, we simulated a system of networks, varying the number of hidden-layer neurons in the networks from 1 to 20. Finally, the performance of the simulation was tested using root mean square error (RMSE) computations as given by [13]

$$\text{RMSE} = \sqrt{\frac{(p-obs)^2}{N}} \qquad 8$$

where p and obs depict estimated and observed data, while N represent the total number of sample respectively.

In this work, the best network obtained using the RMSE values at the end of the training was network (net) 13, that means at net 13 the best neural network model were observed. Thus, nets 13 were employed in the model to generate the following:

1. The estimated values of CO_2;
2. The plots of the spatial and temporal distributions of CO_2;
3. The plots of the annual variations of the estimated and observed CO_2.

. It is important to note that in this work, the month of January represents dry period or season, while the month of July was used to represent wet season. Furthermore, for temporal consideration, few stations in the Northern part (Dindima in Bauchi State and Damaduru in Yobe State) and Southern part (Apoi Creek in Bayelsa state) were used as case studies between the periods 2009 and 2014.

4. RESULTS AND DISCUSSION

The result of the simulation of a system of networks indicates net 13 (indicated by a downward arrow) as the best network of CO_2 data, because it has the lowest RMSE value from networks 1 to 20. This shows that point 13 will statistically give significant results compared to other points. Figure 4 also reveals that the values of RMSEs at points 10, 17 and 19 are closer to the best network (point 13). This suggests that these points will provide results that are close, but statistically different compared to point 13

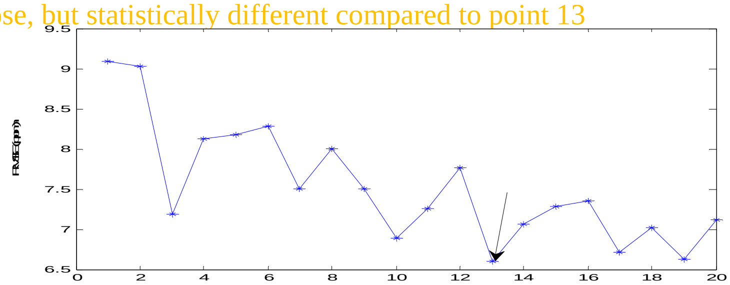


Figure 4: Variations of the Number of hidden layer neuron with root means square errors (rmse) of CO_2.

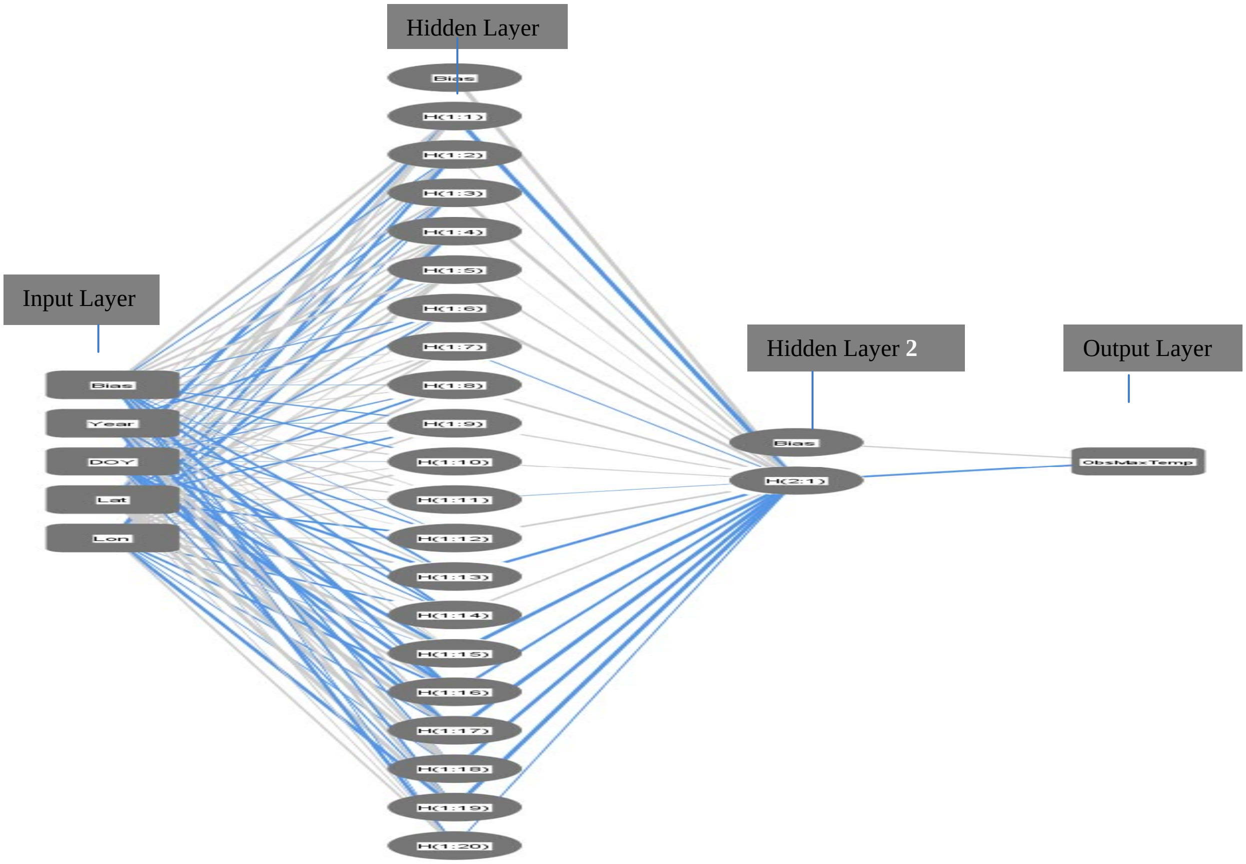


Figure 5: Network Diagram of the Model

Figure 5 shows the networks of the simulation from input layer through the hidden layers to the output layer. On the other hand, Figures 6 and 7 present, respectively, the plots of spatial variations in CO_2 for the period of dry and wet seasons in Nigeria. The temporal variation in estimated and observed values of CO_2 for Apoi Creek, Dindima and Damaturu are shown in Figures 8-9 respectively, while Figure 10 gives the trend in variation of the average annual values of both the estimated and observed CO_2.

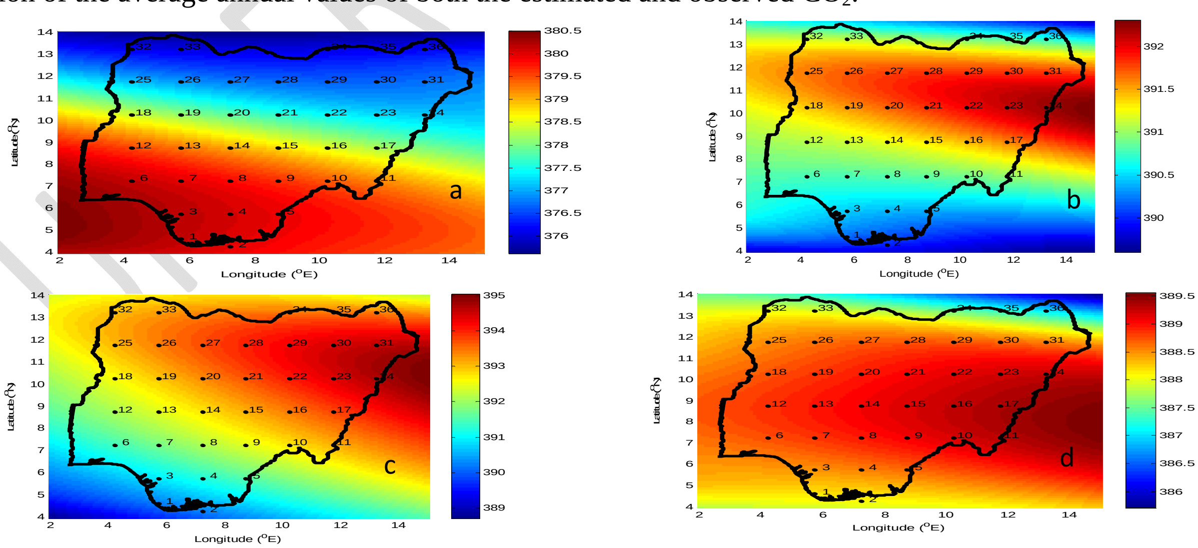


Figure 6: The spatial variations in CO_2 (ppm) for dry season over Nigeria for the periods: (a) 2009 (b) 2010 (c) 2011 and (d) 2012

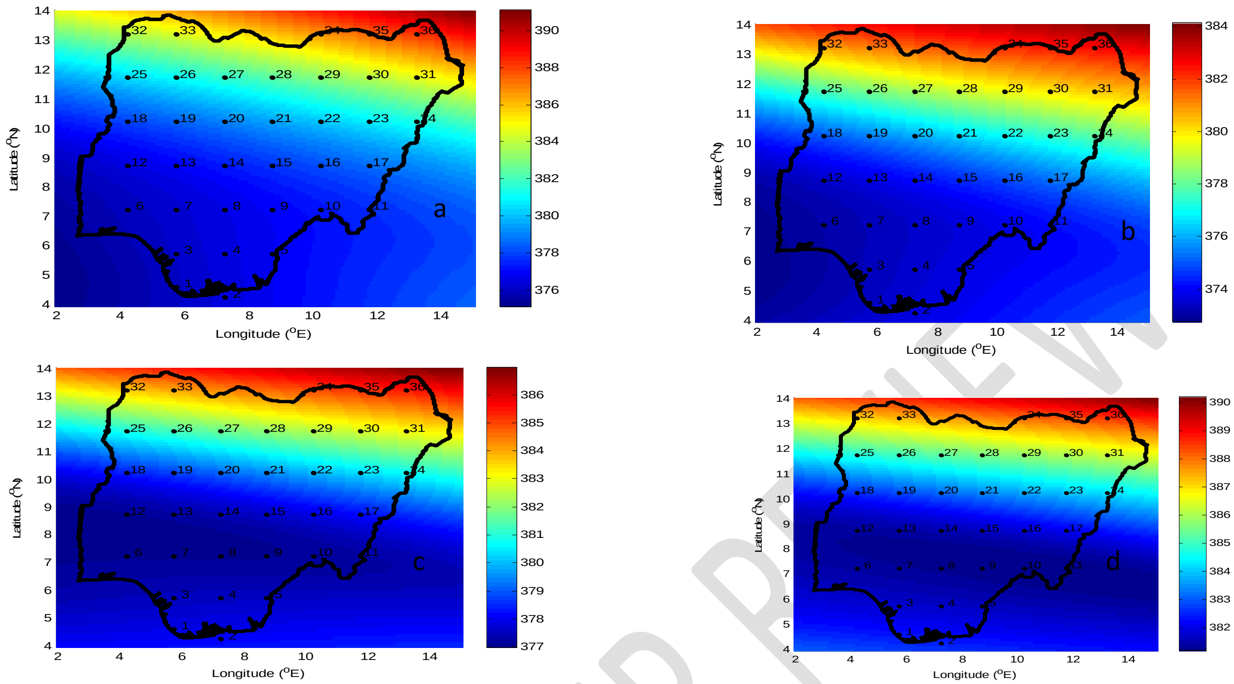


Figure 7: The spatial variations in CO_2 (ppm) for wet season over Nigeria for the periods: (a) 2009 (b) 2010 (c) 2011 and (d) 2012

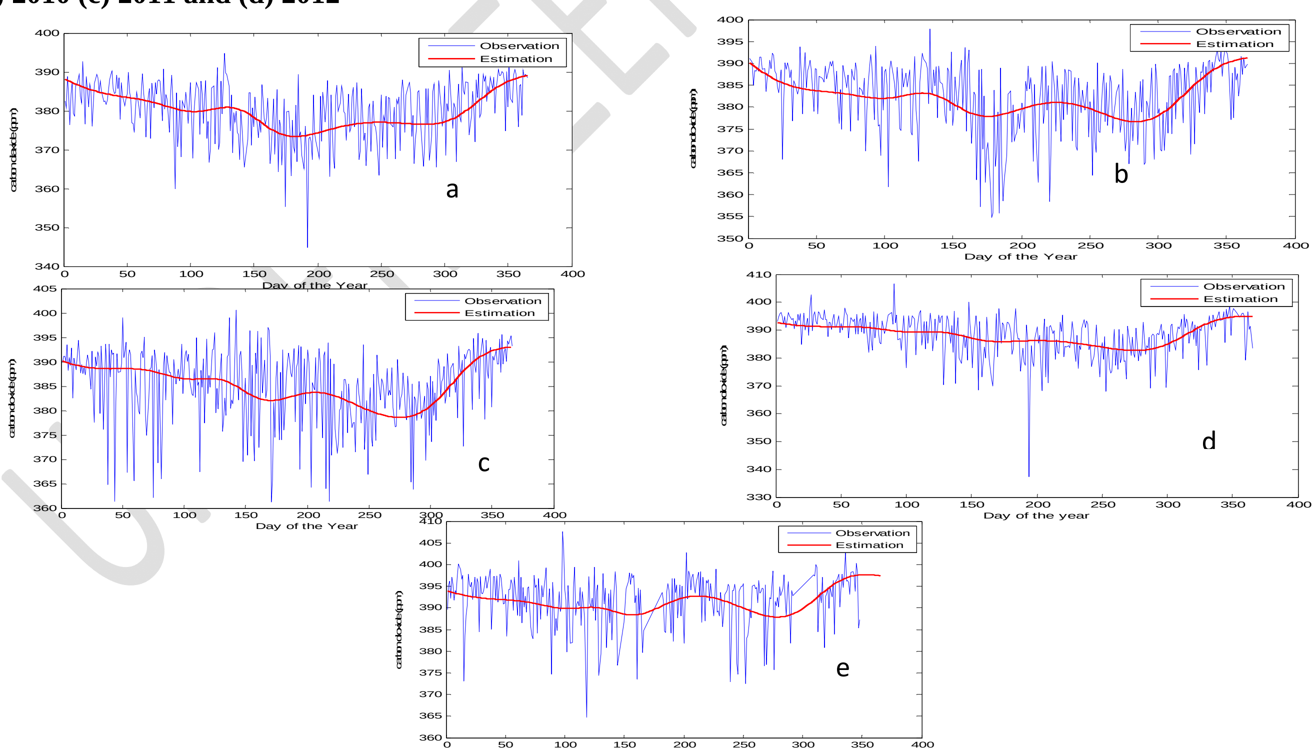


Figure 8: The temporal variations in carbon dioxide at Apoi Creek, Bayelsa State (4.59 °N: 5.84 °E) for the periods: (a) 2010 (b) 2011 (c) 2012 (d) 2013 and (e) 2014

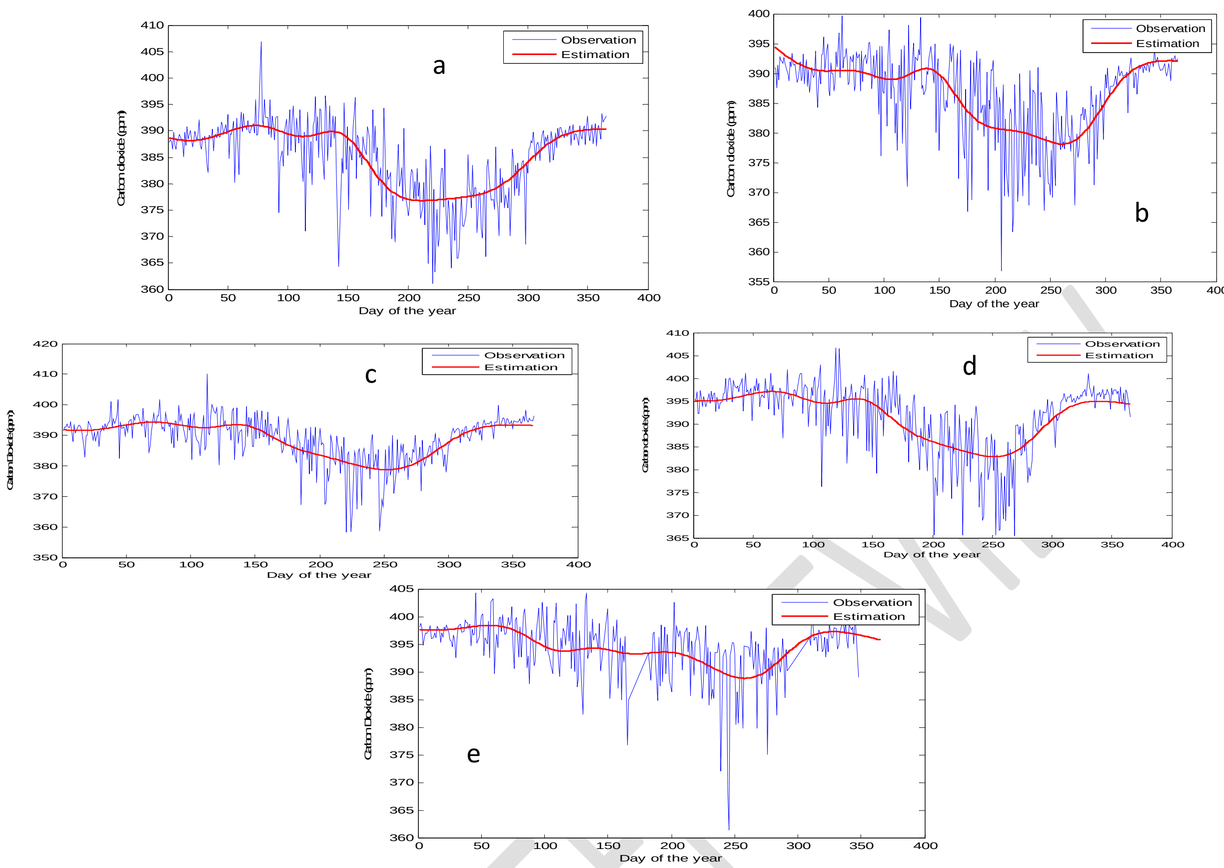


Figure 9: Temporal variations in carbon dioxide at Damaturu, Yobe State (11.75 ^{o}N: 11.75 ^{o}E) for the periods: (a) 2010 (b) 2011 (c) 2012 (d) 2013 and (e) 2014

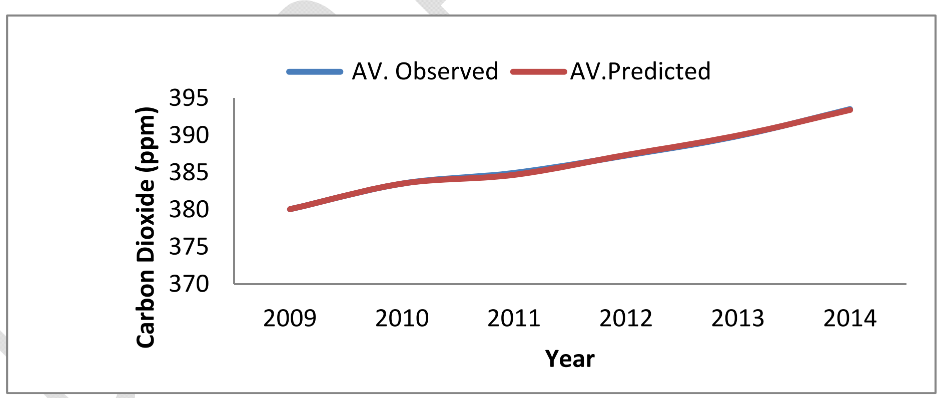


Figure 10: The yearly variations of estimated and observed value of Carbon dioxide.

The dry season distribution of CO_2 in Nigeria between 2009 and 2012 (fig. 6 (a – d)) shows a trend where by in 2009, high CO_2 concentration (378.5 – 380.5 ppm) were identified with stations in the South and South-West. By 2010 and 2011, the concentration of CO_2 shifted to about two-third of the locations in Nigeria with more predominance in the Eastern part of the country. Surprisingly, by 2012, the concentration of CO_2 has increased in all parts of the country. This implies that the trend in variation of dry season CO_2 in every part of the country is on yearly bases. This trend of increase of CO_2 is supported by [15] who suggests that human activities cause emissions of greenhouse gases such as CO_2 into the atmosphere, thereby causing climate change and unpredictable weather conditions in the world.

In the wet season, the concentration of CO_2 in Nigeria is not as much as it is in the dry season case (fig. 7 (a – d)), probably due to absorption of the gas by precipitation. It is interesting to also note that CO_2 concentrations from Figure 7 (a – d) are higher in the Northern parts of Nigeria which could be due to heavy rain in the South. In Figures 6 and 7, therefore, show that during wet seasons we have lower concentrations of CO_2 in South, while the higher concentration occur in the North-East during the dry season for 2010 and 2011. The reverses were the case in 2009 during dry seasons, while in 2012 the concentrations were all over Nigeria. In wet season, the highest concentration of carbon (iv) oxide occurs in the North, while the lowest occurs in the South. This could be as a result of heavy rain fall occurring in the Southern part of Nigeria during the periods under study, implying that rain washes away carbon (iv) oxide from the atmosphere.

From Figures 8 and 9, it could be observed that the signatures of the estimated and observed CO_2 vary in similar manner with lowest values occurring between days 150-300 (May-August). This reveals high performance and accurate estimations of the model. This agrees with [5, 6, 7]. Neural network model, therefore, can be used to estimates carbon dioxide and other atmospheric parameters if equipment for in-situ measurements is not available. Figure 10 reveals that concentrations of carbon dioxide increase significantly between 2009 – 2014 in Nigeria with the observed and estimated varies showing the same trend. The increase in carbon dioxide concentrations suggest that contribution of human activities to carbon dioxide concentration in Nigeria were continuous and are becoming alarming. This agrees with [16, 17], who stated that atmospheric concentrations of greenhouse gases, which include carbon dioxide and methane, were increasing daily in Nigeria, mainly due to human activities, such as use of fossil fuel. The increase reveals contributions of CO_2 in Nigeria. According to Olaniyi [12], the increase in average global temperatures is due to increase in greenhouse gases emission such as carbon dioxide.

5. Conclusion

The investigation on the spatial and temporal distributions of CO_2 has been carried out in Nigeria using Neural Network model. The spatial variations of CO_2 reveal that the least concentration occurs in the South, while the highest concentration occurs in the North-East during the dry season for 2010 and 2011. The reverses were the case in 2009 during dry seasons, while in 2012 the concentrations were all over Nigeria. In wet season, the highest concentration of carbon dioxide occurred in the North, while the lowest occurred in the South. This could imply that heavy rainfall and high concentration of relative humidity during wet periods in Southern part of Nigeria has the ability of reducing carbon dioxide concentrations. According to Andreas and Jacek [18] in their study of humidity measurement in carbon dioxide at low temperature and pressure, state that gaseous carbon dioxide is easily soluble in liquid water, especially at low temperatures. Southern parts of Nigeria are prone to high relative humidity and low temperature during the rainy season due to Atlantic Ocean and coast. The yearly variations show continuous increase of CO_2 in Nigeria. The close agreement between the estimated and observed CO_2 data within the years of study (2010-2014) shows that the model has the ability and potential of predicting 2015 and onwards. The study has successfully investigated carbon dioxide distributions in Nigeria using neural network model. The results show that neural network model has the capacity of investigating greenhouse gases variations in Nigeria. Finally, we recommend that investigations of carbon dioxide distributions in Nigeria of more years and points location should be carried out. Again, mitigation of carbon dioxide emissions in Nigeria should also be carried out.

COMPETING INTERESTS

Authors have declared that no competing interests exist

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