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Investigation of the Distributions of Nitrogen Dioxide in Nigeria using Neural Network

G. F. Ibeh[1*], B. C. Udochukwu[2] and T. Sombo[2]

[1]Department of Physics with Electronics, Evangel University, Akaeze, Ebonyi State, Nigeria.
[2]Department of Physics, Federal University of Agriculture, Makurdi, Benue State, Nigeria.

Authors' contributions

This work was carried out in collaboration among all authors. Author GFI designed the study, wrote the first draft of the manuscript and performed the statistical analysis and author BCU managed the literature searches and author TS wrote the protocol and managed the analyses of the study. All authors read and approved the final manuscript.

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ABSTRACT

Nitrogen dioxide emission is part of atmospheric pollutant that has been linked to climate change. Artificial neural network model were used to investigate nitrogen dioxide distributions in Nigeria at a selected points. The study areas used in this work are thirty six (36) points over Nigeria as shown in Fig. 1. The data used in this work is a satellite nitrogen dioxide (NO_2) obtained from Global Monitoring for Environment and Security (GMES) under the programme of Monitoring Atmospheric Composition and Climate (MACC). The data used in this work is a satellite nitrogen dioxide data obtained from 2003-2014. The neural network processed the available data by dividing them into three portions randomly: 70% for the training, 15% for validation and the remaining 15% for testing. Input parameters were chosen to be latitude, longitude, day of the year, year. Observed nitrogen dioxide was inputted as targeted data, while the output nitrogen dioxide data were the estimated data. The results reveal that dry and wet season variations differ in Nigeria. Nitrogen dioxide concentrations were observed to be higher in the North during dry season, but were higher in the South during the wet season. This could imply that weather condition and seasons influences the concentrations and variations of nitrogen dioxide in Nigeria. The similar trend of the estimated and

**Corresponding author: E-mail: ibehgabrielfriday@evangeluniversity.edu.ng, ibehgabrielfriday@gmail.com, ibehgabriel@ymail.com;*

observed nitrogen dioxide of both diurnal and annual distributions suggests good performance of the model. The result shows that high concentrations of nitrogen dioxide contribute to climate change in Nigeria, resulting to global warming. Consequently, if left unchecked, increase in nitrogen dioxide may cause alteration in rainfall regimes and patterns, floods, and so on. These in turn will bring about adverse effects on livelihoods, such as crop production, livestock production, fisheries, forestry and post-harvest activities. Finally, we recommend analysis of nitrogen dioxide distributions in Nigeria to be regular.

Keywords: Neural network; nitrogen dioxide; Nigeria; seasons; global warming; climate change

1. INTRODUCTION

Atmospheric pollution affects human and ecosystem health as well as being intrinsically linked to climate change in the present and coming decades [1]. Atmospheric pollution is as a result of greenhouse gases and gaseous pollutants such as nitrogen dioxide. Nitrogen dioxide is the chemical compound with the formula NO_2 and part of gaseous pollutants. It is one of several nitrogen oxides (NOx), others include nitric oxide, nitrous oxide etc. Nitrogen oxides (NOx) play critical roles in many atmospheric processes including the catalytic production of tropospheric ozone and the formation of nitric acid being key elements of local air quality with effects felt across global tropospheric chemistry [1]. NO_2 is a pollutant with both anthropogenic (fossil fuel / bio-fuel burning and incomplete combustion) and natural sources (soil emissions).

According to Nesim [2], nitrogen dioxide is a ubiquitous secondary pollutant arising mainly as a by-product of combustion processes. Ambient concentrations of NO_2 can vary widely, ranging from a few parts per billion (ppb; 10-9 by volume) to peaks of several 100s ppb during particular episodes of high pollution. There has been increasing concern about the buildup of NO_2 concentrations in the atmosphere [3]. International scientific consensus has concluded that the increase of NO_2 in the atmosphere is one of the causes of global climate change [4].

He et al. [5] reveal their study that the trend in NO_2 concentration has been on the decline in the developed Europe in the last decade while the reverse is the case in the developing countries of Asia. This was reveal in their study on variations of the increasing trend of tropospheric NO_2 over central east China during the past decade. Shiva [6] used artificial neural network approach for modeling nitrogen dioxide dispersion from vehicular exhaust emissions in India. The results show satisfactory performance of the ANN-based NO_2 models on the evaluation data at the two stations. Yeboah et al. [3] uses ANN to Observe and forecast NO_2 emissions using satellite data for Ghana. The result reveals that MATLAB neural network time series prediction algorithm has the capacity to forecast NO_2 concentration in Ghana.

Ugboma and Nwobi [7] state that nitrogen dioxide (NO_2) is one of the most essential air pollutants in the troposphere. The lifetime of NO_2 varies from one hour at the surface to several days high in the atmosphere. A spatial variation of NO_2 concentration was conducted in Owerri, Imo state of Nigeria for a period of six months [8]. They observed from the study that the levels of NO_2 concentration in the area of 29.10 ppm exceeded WHO standard for 1-hour mean of 4.89 ppm. They recommended that urgent need for serious awareness campaign on air pollution, regular air quality studies and enforcement of air quality guidelines in Owerri should be carried out.

The use of ANN in MATLAB to study variations and distributions of gaseous pollutants such as carbon dioxide, nitrogen dioxide, tropospheric ozone etc. has been done in America, Europe, Asia, Africa (Ghana) but is almost nonexistent in Nigeria. Some regional study on nitrogen dioxide distribution without the use of ANN has been observed. These observations on the methods and pattern of nitrogen dioxide studies from the literatures motivated this study. This work intends, therefore, using ANN in MATLAB to investigate the distributions of nitrogen dioxide across Nigeria. This we help to generate a model that could be used in places where in situ measurement will not be available.

An artificial neural network is a computing method inspired by structure of brains and nerve systems. A typical neural network consists of a group of inter-connected processing units, which are also called neurons. Each neuron makes its independent computation based upon a weighted sum of its inputs, and passes the results to other neurons in an organized fashion. Neurons that receive the input data form the input layer, while those generate output to users form the output layer. A neural network must be trained by data for a certain problem. The training process is the adjustment of the connecting weights between neurons so that the network can generalize the features of a problem and therefore obtain desired results. A neural network is trained from training data set. This makes neural network a desirable tool in dealing with complex systems [9].

2. MATERIALS AND METHODOLOGY

2.1 Study Area

The study areas used in this work are thirty six (36) location points over Nigeria as shown in Fig. 1.The data used in this work is a satellite Nitrogen dioxide (NO_2) obtained from Global Monitoring for Environment and Security (GMES) under the programme of Monitoring Atmospheric Composition and Climate (MACC). 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 (Fig. 1) is 1.5^o, where 1^o represents about 111 km

2.2 Research Method

A total of 20 neural networks were trained; the difference between them is in the number of hidden layer neurons that was applied (the number of hidden layer neurons were varied from 1 to 20). The feed-forward neural network architecture was use. The neural network architecture built for the training was 4-20-1, which means 4 neurons in the input layer, 20 neurons in the hidden layer and 1 neuron in the output layer. The inputted data through the input neurons were; year, DOY representing the time, latitude and longitude represent the coordinates. The architecture comprised of three main layers; an input layer, a hidden layer and an output layer. The available data were 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. Normalization of the training data was done using the mapminmax processing function, which is the default for the MATLAB training algorithm used in this work.

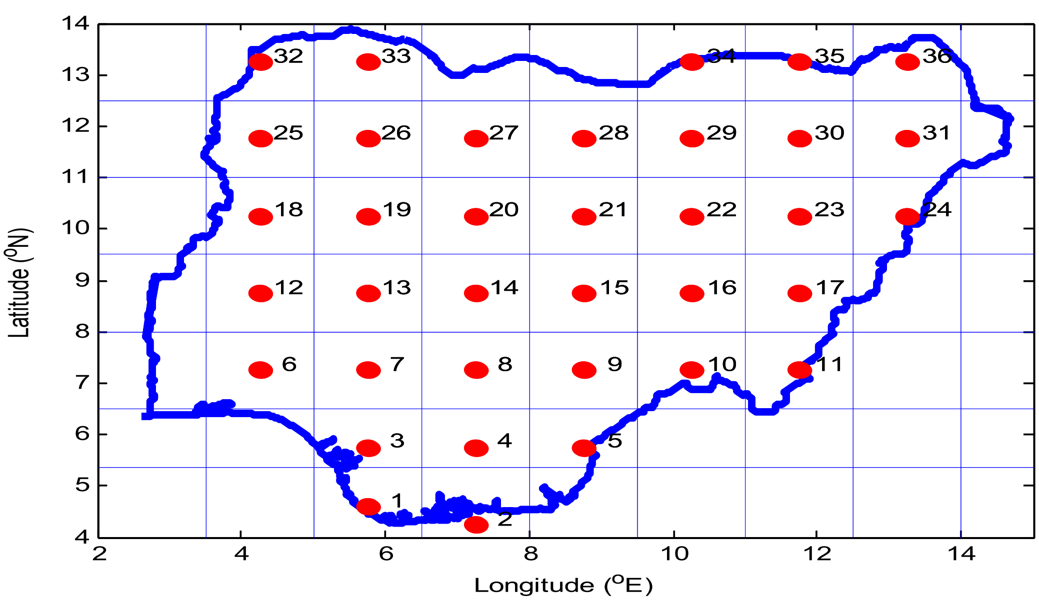

Fig. 1. Gridded map of nigeria showing data points of the selected stations in Nigeria

Table 1. Coordinates of the selected stations and their data points over Nigeria

Points	Y latitude (°N)	X longitude (°E)	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	UkpeSobo	Okpe	Delta
4	5.75	7.25	ObiohoroOsu	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	FilingaSekenoma	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

The feed-forward neural network equations from input layer to hidden layer give the net input (n_1) in equation at the hidden layer and the net out (n_2) from the hidden layer to the output layer are shown in equations (1) and (2).

$$n_1 = I_{wm1} * I_{m1} + I_{wm2} * I_{m2} + \ldots + I_{wmh} * I_{m4} + b_1 \quad (1)$$

$$n_2 = L_{wm_1} * H_{vm} + L_{wm_2} * H_{vm} + \ldots + L_{wm_{h,1}} * H_{vm} + b_2 \quad (2)$$

The express of equation (1) and (2) are written with MATLAB codes as equation (3) and (6) [10]. Hyperbolic tangent sigmoid transfer function (f_1) (4) is applied to equation (3) to have hidden layer matrix (H_{vm}) (5). Equation (3) is the sum of the input weight matrix multiplied with input matrix plus the bias vector one.

$$\sum(I_{wm} * I_m + b_1) = n_1 \quad (3)$$

$$f_1\ (n_1) = \text{tansig}(n_1) = \frac{e^{n_1} - e^{-n_1}}{e^{n_1} + e^{-n_1}} = H_{vm} \quad (4)$$

$$H_{vm} = f_1\ (I_{wm} * I_m + b_1) \quad (5)$$

The sum of the layer weight matrix multiplied with hidden variable matrix plus the bias vector two gives net out (n_2) as shown in equation (6). Linear function is applied to equation (6) as shown in equation (7) to predict the targeted output called the output matrix as expressed in equation (8) in the network model. The combination of equations (1 – 7) gives the straight line equation (8) for the model that is used for this study.

$$\sum(L_{wm} * H_{vm} + b_2) = n_2 \quad (6)$$

$$f_2(n_2) = \text{purelin}(n_2) = \text{purelin}(L_{wm} * H_{vm} + b_2) = O_m \quad (7)$$

$$O_m = \text{purelin}\,(L_{wm} * (\text{tansig}(I_{wm} * I_m + b_1)) + b_2) \quad (8)$$

where O_m depicts the output matrix which contains the predicted data with the network model, while I_m depict the input matrix (year, day of the year (DOY), latitude, longitude), I_{wm} represent inputs weight matrix, b_1 is bias vector one, H_{vm} is the hidden variable matrix, L_{wm} is layer weight matrix, b_2 is bias vector two, tansig (f_1) is hyperbolic tangent sigmoid transfer function used between the input and the hidden layers as activation function, while purelin (f_2) is the linear transfer functionused from hidden layers to the output layer as the activation function. The values of I_{wm}, L_{wm}, b_1 and b_2 of this study we be made available on request. The application of Neural Network architecture used for building the network and training from input to output is shown in Fig. (2), while Fig. (3) is the drop down window showing the neural network training (nntraintool) process at network 20.

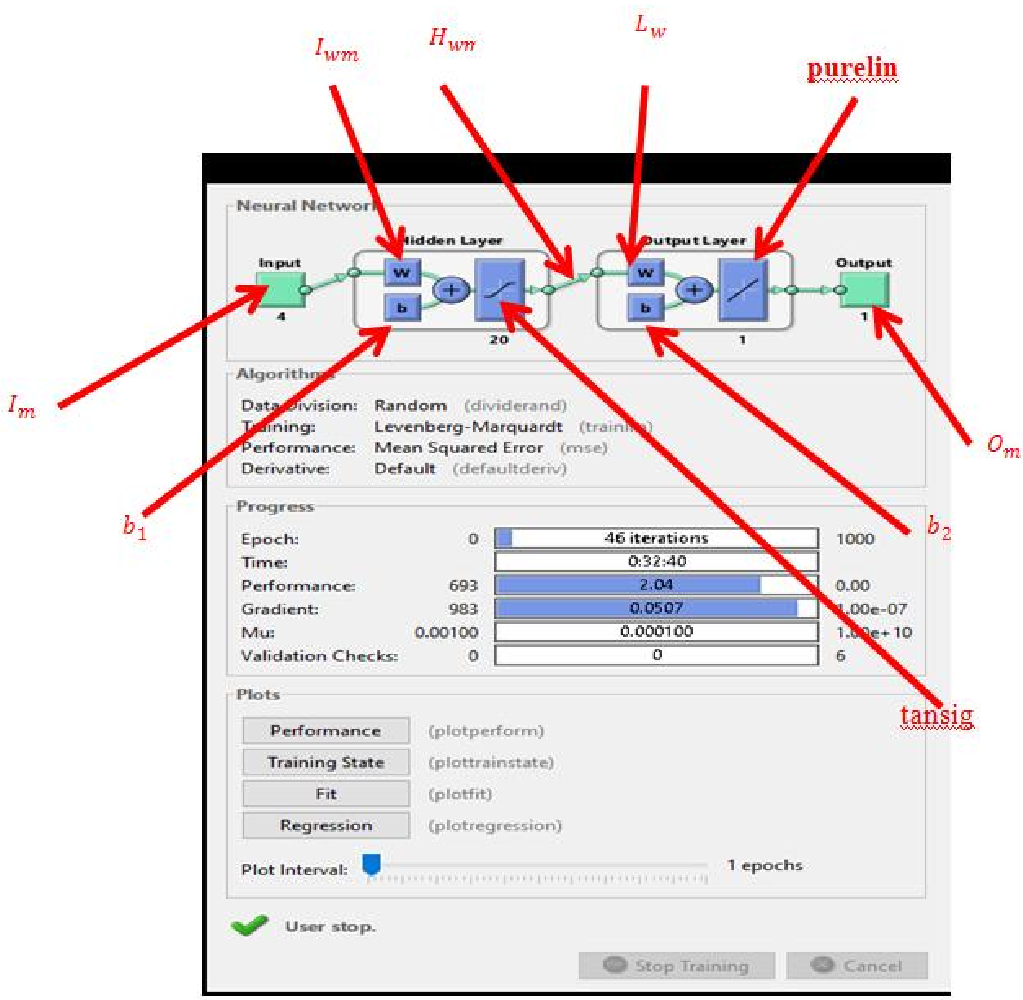

Fig. 2. Schematic diagram of neural network training window

Fig. 3 shows that 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. Fig. 4 is the network diagram of the model.

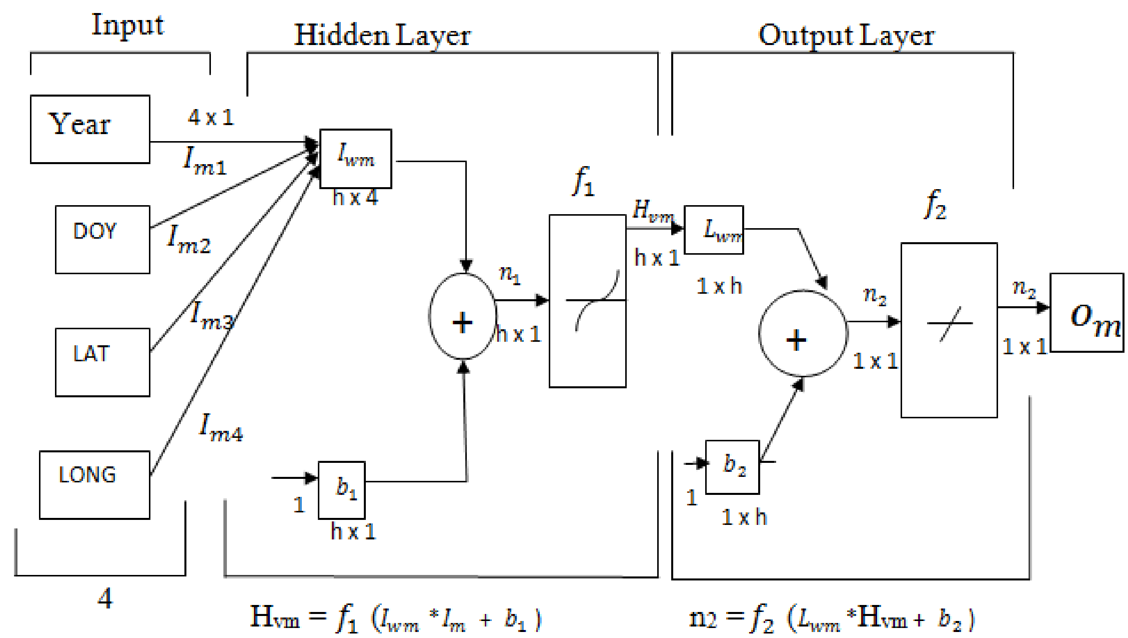

Fig. 3. Topology of neural network model

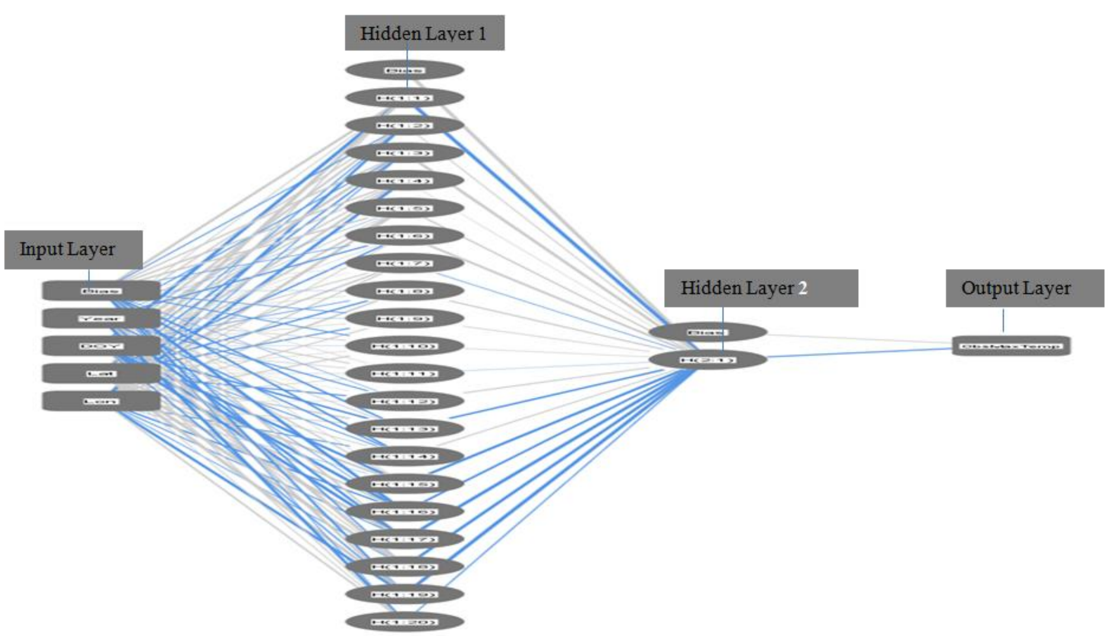

Fig. 4. Network 4:20:1 ANN -based NO_2 model

To decide an optimal number of hidden-layer neurons in this work, the performance of the training was tested using root mean square error (RMSE) computations as given in equation (9) amongst the 20 hidden neurons.

$$\text{RMSE} = \sqrt{\frac{(p-obs)^2}{N}} \tag{9}$$

where p and obs depict estimated and observed data respectively.

In this work, the best network obtained was network (net) 18, thus, net 18 models were employed to determine the spatial distributions of nitrogen dioxide, estimate the daily values of nitrogen dioxide and the annual average variations of the estimated and observed nitrogen dioxide. It is pertinent to note that the model has the ability of studying the distributions of nitrogen dioxide for each day from January to December across the years of study, but the month of January (1^{st}) has taken to represents dry season, while the month of July (1^{st}) was used to represent wet season for the study. This was done in order to determine the seasonal variations of nitrogen dioxide in Nigeria.

3. RESULTS AND DISCUSSION

Fig. 5 is the RMSE networks values from 1 to 20. It indicates net 18 (indicated by a downward arrow) as the best network for the training of nitrogen dioxide data. Fig. 5 reveals that the RMSEs generally keep decreasing as the number of hidden layer neurons increase. This trend suggests that using an excessive number of hidden layer neurons will lead to an improved neural network; this is not correct because using an excessive number of hidden layer neurons will cause the neural network to predict interpolated data so well, whereas the prediction accuracy grows worse for extrapolated data. On the other hand, Figs. 6 and 7 present, respectively, the plots of spatial variations in nitrogen dioxide for the periods of wet and dry seasons in Nigeria, while Fig. 8 gives the trend in variation of the average annual values of both the estimated and observed nitrogen dioxide in Nigeria.

4. DISCUSSION

In Fig. 6 (a – e), it could be observed that the amount of nitrogen dioxide (NO_2) in dry season between 2004 and 2014 is very high in the range of about 50 – 150 ppb. This could be due to high emission of this gas from different sources of air pollution. However, it is interesting to note that the amount of NO_2 in Nsarum in Cross River and Ibi in Taraba is about 50 ppb which is remarkably smaller than that in any other place within the same period of investigations. This could be as a result of reductions in the activities (burning of fuel, power plants, off-road equipment etc) in the area that leads to low emissions of NO_2 in the locations.

It could be observed from Fig. 7 (a – e) that the concentration of NO_2 has become more reduced than in the dry season case, probably due to the absorption of the gas by precipitation. Hence, the NO_2 in the wet season trend towards the Southern region, probably due to high concentration of hydrocarbons in the areas.

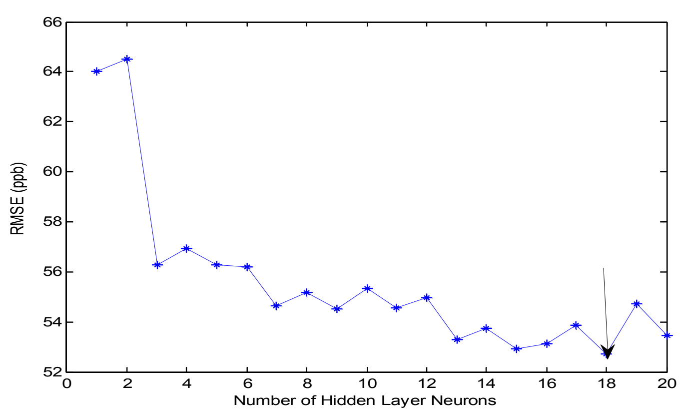

Fig. 5. Variations of the number of hidden layer neuron with root means square errors (rmse) of Nitrogen dioxide

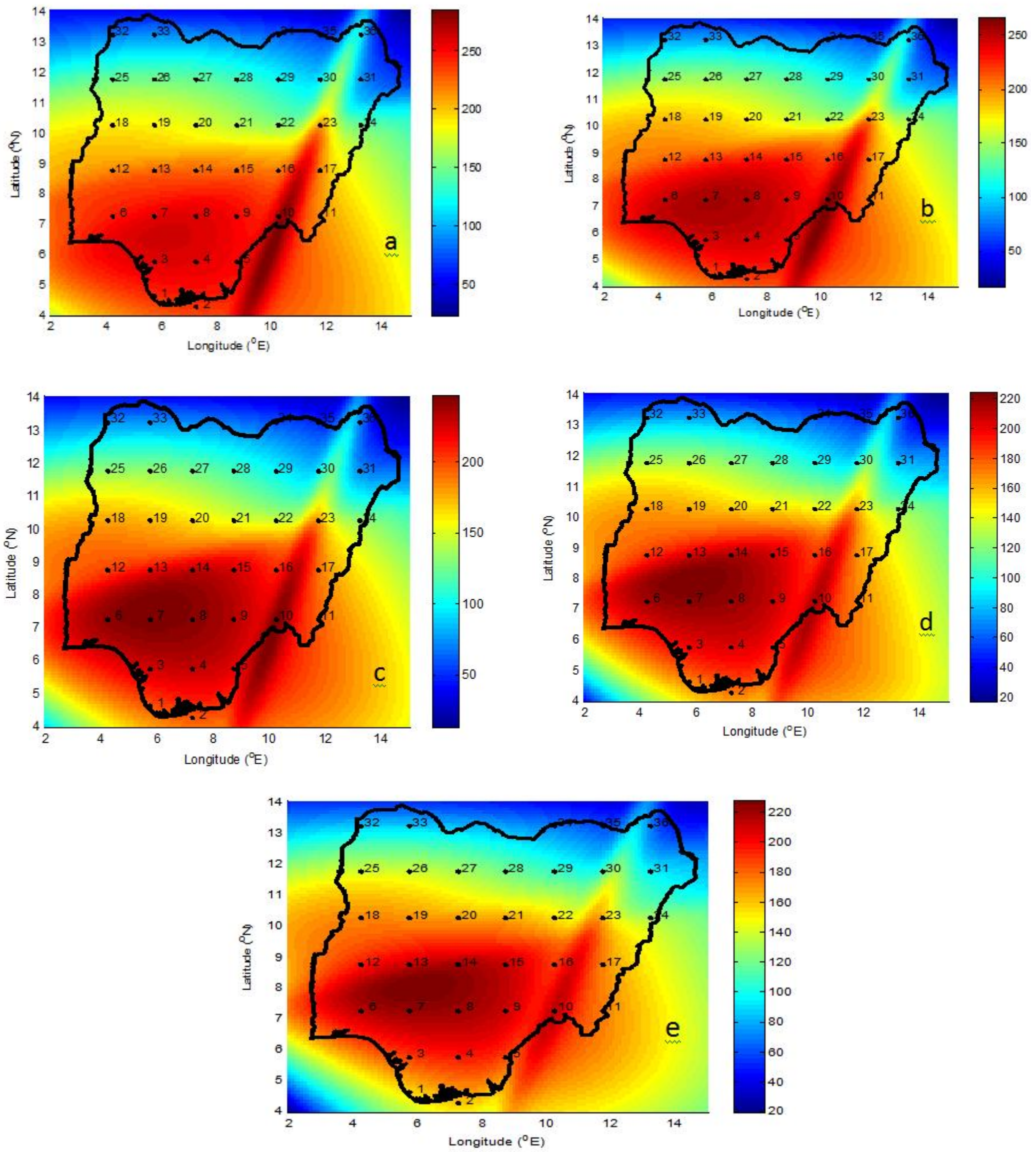

Fig. 6. The spatial variations in nitrogen dioxide (ppb) in wet season over Nigeria for the periods: (a) 2004 (b) 2008 (c) 2012 and (d) 2014

For Fig. 8, the similar trend of the estimated and observed nitrogen dioxide at Mowo, Osun State (4.25^{o}N: 7.25^{o}E) for the periods: (a) 2005 (b) 2008 (c) 2012 and (d) 2014 suggests good performance of the model. Observations show that in some cases, there are unsteady variations of the observed as compared to the estimated parameter, but generally, it is important to note that places where the observed and the estimated data are in phase reveal the good performance of the model. On the other hand, although there is a drop in NO_2 from 2004 to 2005; there is a steady level of NO_2 until 2012, when it has started increasing. The in phase relationship between the observed and estimated NO_2 shows that the model has a good performance for estimating annual NO_2. High concentration of Nitrogen dioxide in Figs. 5 and 6 reveals its high contribution to climate change in Nigeria. The daily estimated data were computed to yearly data. The daily observed data were also computed to yearly data. The annual comparisons of both estimated and observed were shown in Fig. 9. The variations reveal similar trend all through the years of study.

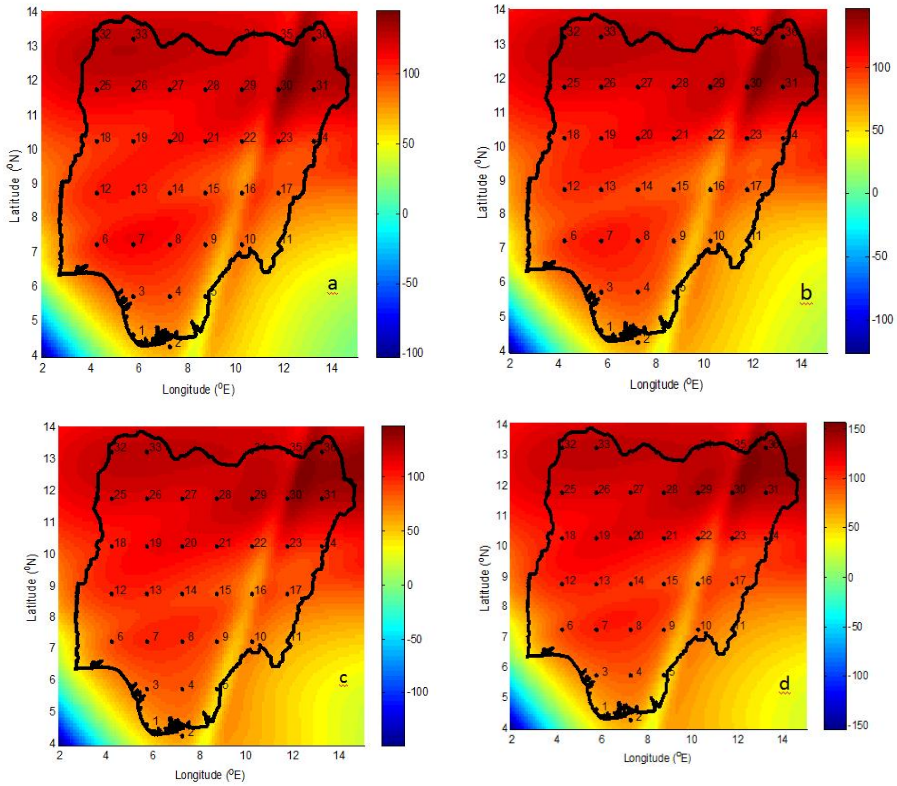

Fig. 7. The spatial variations in nitrogen dioxide (ppb) in dry season over Nigeria for the periods: (a) 2004 (b) 2008 (c) 2010 and (d) 2014

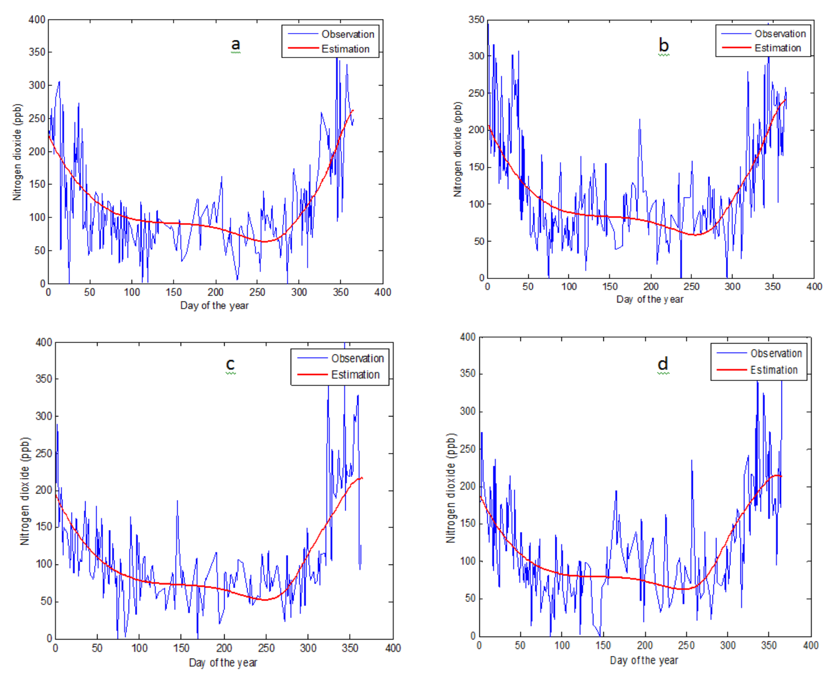

Fig. 8. The diurnal variations of observed and estimated nitrogen dioxide at Mowo, Osun State (4.25°N: 7.25°E) for the periods: (a) 2005 (b) 2008 (c) 2012 and (d) 2014

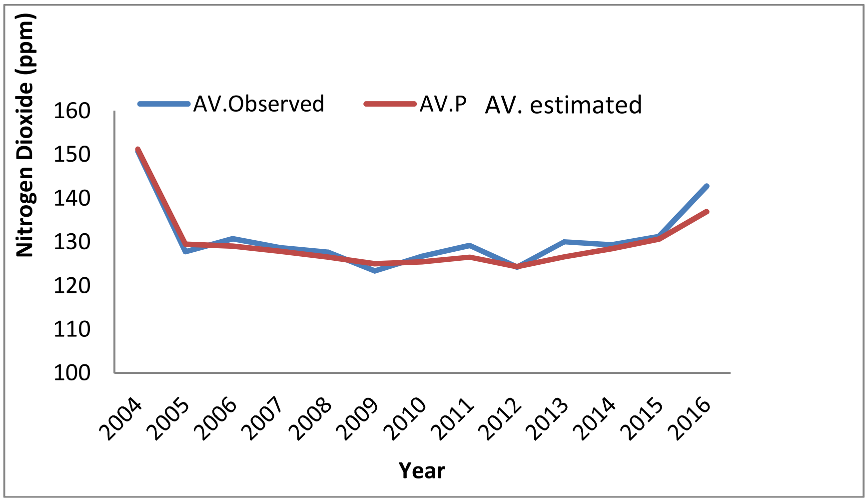

Fig. 9. The Annual Average variations of estimated and observed nitrogen dioxide

5. CONCLUSION

Applications of neural network can be used to study the distributions of atmospheric parameters such as gaseous pollutants and greenhouse gases. This has been used in Europe, Asia, etc. In this study, Neural Network was used to study the distributions of nitrogen dioxide in Nigeria. The model shows the ability of studying the distributions of nitrogen dioxide with respect to its variations in Nigeria. It revealed the signatures of the estimated and observed data to be equivalent, which implies good performance of the model. The result also reveals that the variations of nitrogen dioxide in the South are at variance with that of the North. The result shows that the concentration of Nitrogen dioxide could be contributing to climate change in Nigeria. This could be resulted to global warming. The result reveals that the contributions of Nitrogen dioxide in Nigeria, if left unchecked will increase adverse effects on livelihoods, such as crop production, livestock production, fisheries, forestry and post-harvest activities. The alteration of climate change resulting in increase in rainfall regimes and patterns, incessant increase in floods which devastate farmlands will continue in a high magnitude.

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COMPETING INTERESTS

Authors have declared that no competing interests exist

REFERENCES

1. Von SE, Monks PS, Allan JD, Bruhwiler L, Forster P, Fowler D, Lauer A, Morgan WT, Paasonen P, Righi M, Sindelarova K, Sutton MA. Chemistry and the linkages between air quality and climate change, Chem Rev. 2015;1:3856–3897.
2. Nesimi O. Spatio-temporal distributions of Nitrogen Dioxide around Can-Bayramic region in Canakkale: A comparative exposure and model study. 2011;20:6.
3. Yeboah IK, Obeng P, Akrofi G. Observation and forecast of NO_2 emissions using satellite data for Ghana. MOJ Proteomics Bioinform. 2017;6(2):263–268. DOI: 10.15406/mojpb.2017.06.00192
4. Moretti AL, Jones CS. Advanced emissions control technologies for coal–fired power plants. USA: Power Generation Group, Inc, Barberton. 2012;1–11.
5. He Y, Uno I, Wang Z, Variations of the increasing trend of tropospheric NO2 over central east China during the past decade. Atmos. Environ. 2007;41:4865–4876.
6. Shiva SN, Mukesh K. Artificial neural network approach for modelling nitrogen dioxide dispersion from vehicular exhaust

emissions. Ecological Modelling. 2006;99–115
7. Ugboma EA, Nwobi FN. Spatial distribution of NO_2 concentration in southeastern region of Nigeria Academic Journal of Applied Mathematical Sciences. 2017; 3(1):1-7
8. Ibe FC, Njoku PC, Alinnor JI, Opara AI. Spatial variation of NO_2 and SO_2 in the ambient environment of Imo State Nigeria. International Journal of Science, Environment and Technology. 2016;5:33–46.
9. Haykin S. Neural network: A comprehensive Foundation. Second Edition, Prentice - Hall, Incoporation, Canada. 1999;2-10.
10. Beale MH, Haaga MT, Demuth BH. Neural network Toolbox[TM]. User's Guide (R2015a). The Math Works, Incorporation. 2015;10- 20.

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