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Evaluation of methane emission distributions in Nigeria using neural network model

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ABSTRACT

The earth is becoming warmer because of solar energy trapped in the lower atmosphere and less heat radiated into space due to radiative forcing of greenhouse gases. This study assesses the distributions of greenhouse gas (methane) concentration over Nigeria with neural network model. The variation of methane reveals that higher concentration occurs in the South in dry season than the North, while slightly higher concentration occurs in the South in wet season in comparison with the Northern part of Nigeria. In addition, it could be noted that methane concentration covered almost over Nigeria during the wet season. This could imply influence of weather conditions on methane and several anthropogenic sources of methane during the wet season such as the production of rice, decomposition of some plants, high moisture content etc. The similarity in the estimated and observed signatures shows good performance of the Neural Network model used in this study. The result reveals that the contributions of

methane in Nigeria if left unchecked will increase adverse effects on livelihoods, such as crop production, livestock production, fisheries, forestry and post-harvest activities, because the rainfall regimes and patterns will be altered, floods which devastate farmlands would occur. It will also result in increase in temperature and other natural disasters like floods, ocean and storm surges, earth tremors which not only damage Nigerians' livelihood but also cause harm to life and property.

Keywords: Radiative forcing, Greenhouse gases, Methane, Neural network, Signatures, Nigeria.

1. INTRODUCTION

Several chemical mixtures found in the troposphere act as greenhouse gases. The green house gases allow light to enter the troposphere freely. Some of the light reflects back towards space as infrared radiation (heat) when the solar radiation strikes the earth’s surface. As the short wave energy hit the surface, some of the longer wave energy emits back into the space through the atmosphere. Greenhouse gases absorb some of the energy trapped in the lower atmosphere and less heat radiates into space due to radiative forcing and the earth becomes warmer. These are the fundamental causes of the greenhouse effect which results in increased temperatures on the earth (Langa, *et al*., 2016).

According to Cooper (2000) the greenhouse emissions is precipitated from gas flaring, deforestation, agricultural product, bush burning, fumes from generators and vehicular movement, and burning of coal amongst others. Similarly, Keeling and Whorf (2009) affirmed that there has been an increase in the concentration of greenhouse gases CO_2, CFC, CH_4etc in earth’s atmosphere system over the years.

Methane’s (CH_4) mixtures characteristics and connections in the atmosphere contribute significantly as a greenhouse gas. It is formed and released to the atmosphere by natural and anthropogenic process. Once methane is in the atmosphere absorbs terrestrial infrared radiation that would escape to space. This contributes to the warming of the atmosphere as part of greenhouse gases (Houghton, *et al*., 1992). Methane's chemical lifetime in the atmosphere is approximately 12 years (Ayodele and Emmanuel, 2007).

Methane is the second largest gaseous contributor to anthropogenic radiative forcing after CO_2 (Forste, 2007). The major anthropogenic sources of atmospheric CH_4 are rice paddies, ruminants, and fossil fuel. They contributes about 60 % to the global CH_4 budget (Chen and Prinn, 2006; Schneising, *et al.,* 2009). The remaining fraction is contributed by biogenic sources such as wetlands and the fermentation of organic matter by microbes in anaerobic conditions (Conrad, 1996; Khadak, *et al*., 2017).

Many researchers have employed different methods to determine the concentration and distributions of methane. Burgett and Green (1976) use an automatic gas chromatographic system in measuring CH_4concentration. Cooper *et al*. (1974) determined methane in air by separating it from other hydrocarbons using a cryogenic trap, while Ayodele and Emmanuel (2007) determine the level of methane in different parts of Kano Municipal environment using automatic gas sensors. This paper uses neural network model to determine the variations and distributions of methane concentration over Nigeria.

2. MATERIALS AND METHODS

The Study Area

The study areas used in this work are thirty six (36) points station over Nigeria as shown in Figure 1, which is the gridded map of selected stations in Nigeria, while 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 the order) of the gridded map to cover Nigeria.

Sources of Data

The methane data used in this work were gotten from www.gmes-atmosphere.eu/data between 2009-2012. Satellite data were used for this study because greenhouse gases have no ground based measurement in Nigeria. The data which was in NetCDF format were extracted, converted to binary format, sorted and merged to file using MATLAB software program. The data collected 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.

Neural Network Architecture

Neural networks can be trained using different algorithms. 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 architecture used in this study for the training comprises three main layers; an input layer, a hidden layer and an output layer. The architecture were 4-20-1, which means that we have 4 neurons in the input layer, 20 neurons in the hidden layer and 1 neuron in the output layer. The Levenberg-Marquardt (LM) algorithm used in this study is designed to minimize the sum of square error functions that arise during neural network training (Otugo *et al*., 2019). Prior to training, the entire available data was randomly split into three portions: 70% for the training, 15% for validation and the remaining 15% for testing during the simulation. 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, using MATLAB, we normalized 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 a 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 (Beale *et al.,* 2014).

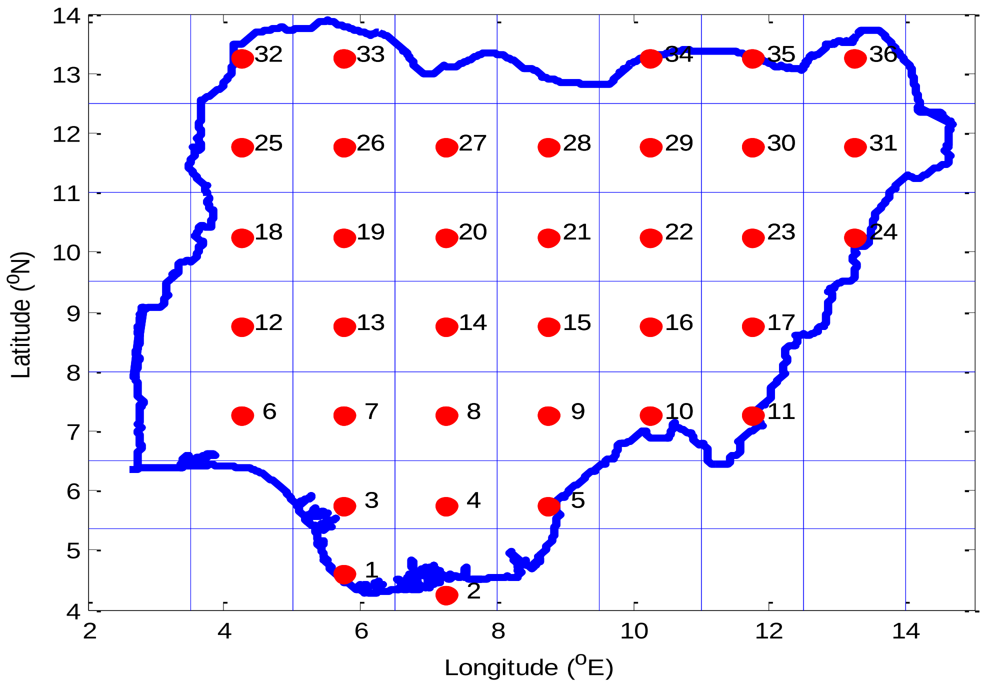

Figure 1 Gridded Map of Nigeria Showing Data Points of the selected stations in Nigeria

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

Equations (1) - (7) respectively were the mathematical models of the Neural Network architecture used to transfer the input layer neurons to the hidden layer neurons and from the hidden layer neurons to the output layer neurons. Figure 2 is the model structure for the network training, while Figure 3 is the drop down window of the model. Thus,

$$\sum(\mathrm{I}_{\mathrm{wm}} * \mathrm{I}_{\mathrm{m}} + \mathrm{b}_1) = \mathrm{n}_1 \quad 1$$

$$\mathrm{f}_1\,(\mathrm{n}_1) = \mathrm{tansig}(\mathrm{n}_1) = \frac{e^{\mathrm{n}_1} - e^{-\mathrm{n}_1}}{e^{\mathrm{n}_1} + e^{-\mathrm{n}_1}} = \mathrm{H}_{\mathrm{vm}} \quad 2$$

$$\sum(L_{wm} * H_{vm} + b_2) = \mathrm{n}_2 \quad 3$$

$$\mathrm{f}_2(\mathrm{n}_2) = \mathrm{purelin}(\mathrm{n}_2) = \mathrm{O}_{\mathrm{m}} \quad 4$$

$$\mathrm{f}_2(\mathrm{n}_2) = \mathrm{purelin}\,(L_{wm} * H_{vm} + b_2) = \mathrm{O}_{\mathrm{m}} \quad 5$$

$$\mathrm{O}_{\mathrm{m}} = \mathrm{L}_{\mathrm{wm}} * \mathrm{H}_{\mathrm{vm}} + \mathrm{b}_2 \quad 6$$

$$\mathrm{O}_{\mathrm{m}} = \mathrm{L}_{\mathrm{wm}} * (\mathrm{tansig}(\mathrm{I}_{\mathrm{wm}} * \mathrm{I}_{\mathrm{m}} + \mathrm{b}_1)) + \mathrm{B}_2 \quad 7$$

Where O_m depicts the output matrix containing the desired outputs. The output matrix (O_m) at the end of the neural network training using Levenberg-Marquardt back propagation algorithm and multilayer perceptron network were generated from the mathematical expressions of equation (7). While I_{m} is the input matrix (year, day of the year (DOY), latitude, longitude), I_{wm} depict 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 function used 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 are available on request. There are no specific or perfect rules for deciding the most appropriate number of neurons in a hidden layer. Using an extreme number of hidden-layer neurons can leads to over-fitting, while a lesser number brings about under-fitting. Either scenario greatly degrades the generalization capability of the network with significant deviance in prediction and forecasting accuracy of the model (Sheela and Deepa, 2013). 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.

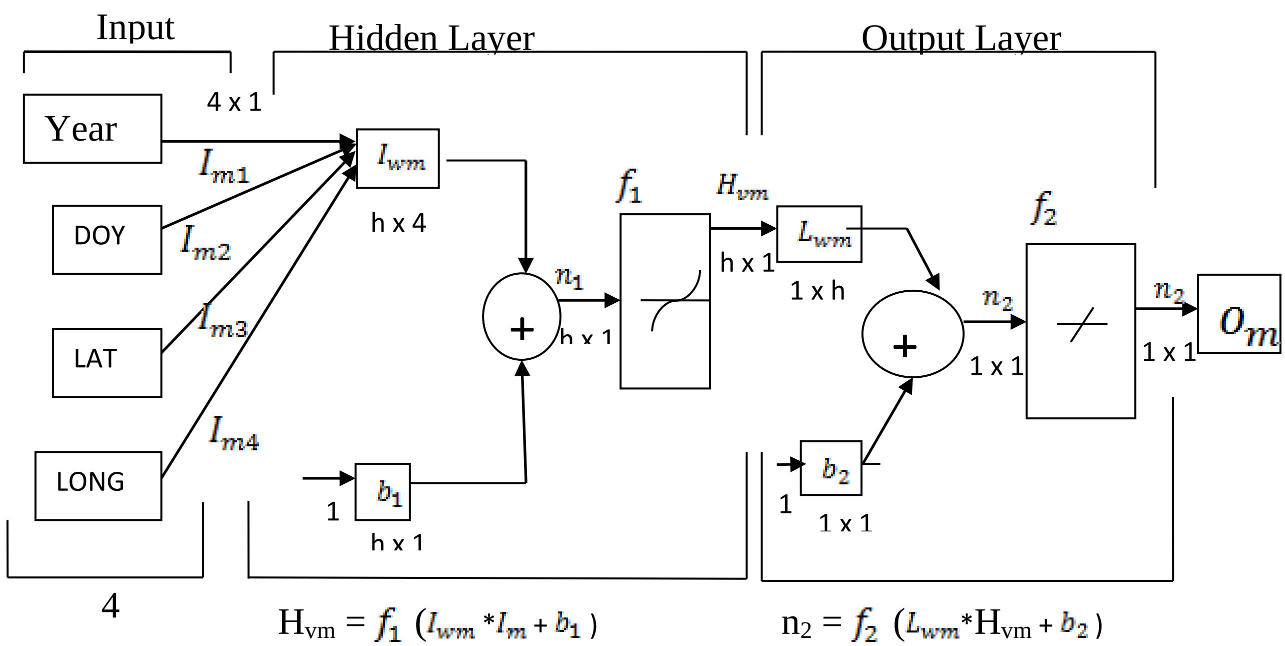

Figure 2 Feed Forward Neural Network Training Structure from Input to Output

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 1 and 1 x 1 respectively, where h is the number of hidden layer neurons.

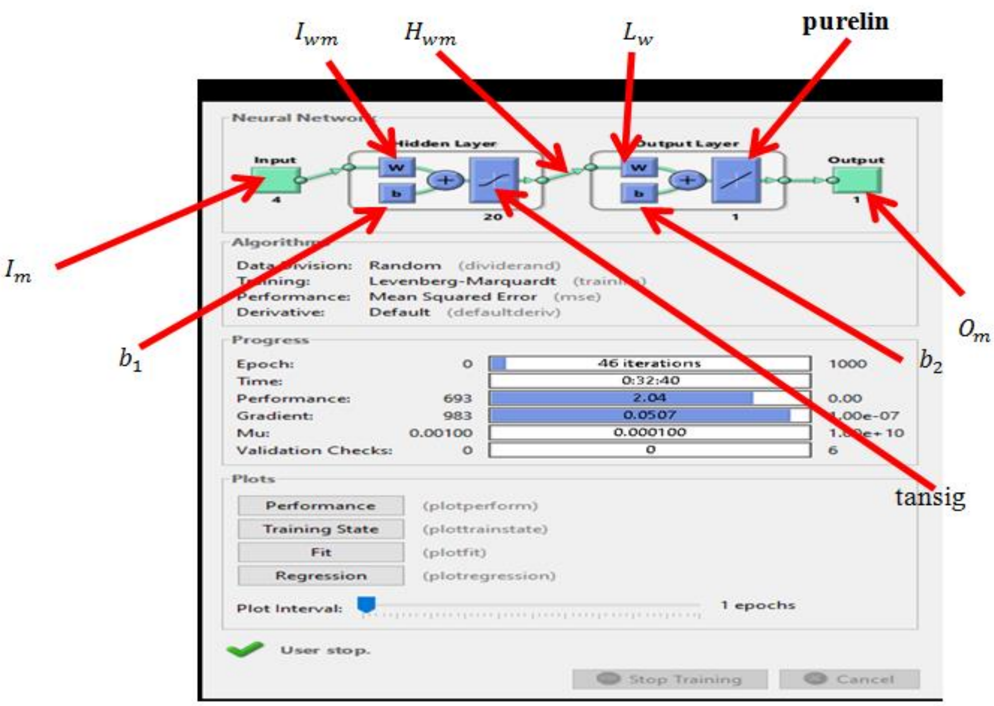

Figure 3 Schematic Diagram of Neural Network Training Window

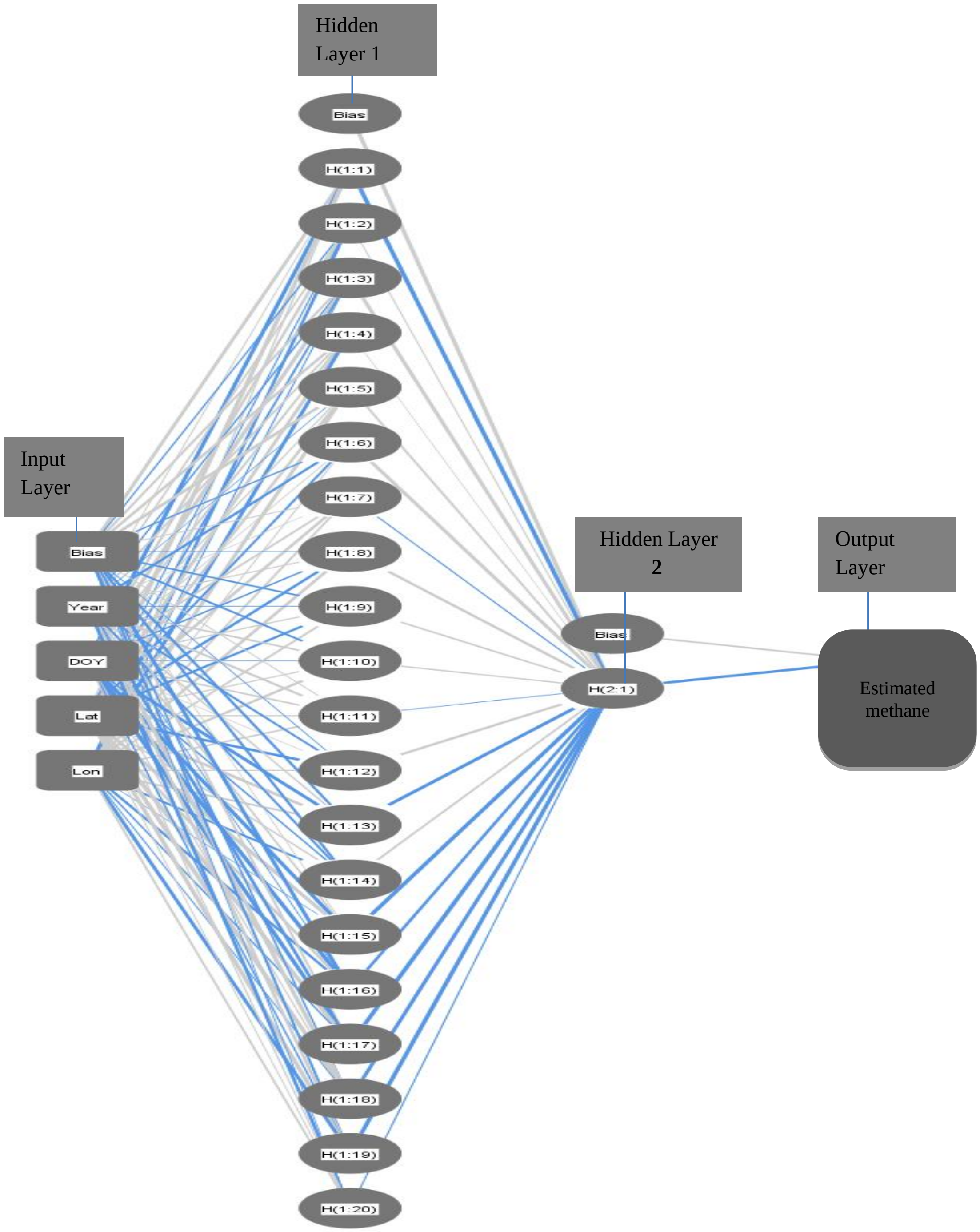

Figure 4 Network Diagram of the Model

To decide an optimal number of hidden-layer neurons in this work, the performance of the simulation was tested using root mean square error (RMSE) computations as given in equation (8) amongst the 20 hidden neurons.

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

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

We define the best network as the one that gives the least estimated error on forecasted data using root means square errors (RMSE). In this work, the best network obtained was network 18, thus, net 18 were employed in the model to determine the following:

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

It is pertinent to note that the model has the ability of studying the distributions of methane for each day from January to December, but the month of January (1^{st}) was taken to represent dry period or season, while the month of July (1^{st}) was used to represent wet season to study the distributions of methane. This was done in order to study the seasonal variation of methane.

3. RESULTS AND DISCUSSION

Figure 5 gives the result of the simulation of a system of networks which indicates net 18 (indicated by a downward arrow) as the best network of methane. Figure 5 reveals that the RMSEs generally keep decreasing as the number of hidden layer neurons increases. 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, Figures 6 and 7 present, respectively, the plots of spatial variations in methane for the periods of dry and wet seasons in Nigeria, while Figures8and 9gives the trend in variation of the average annual values of both the estimated and observed methane in Nigeria and annual Nigeria milled rice Production.

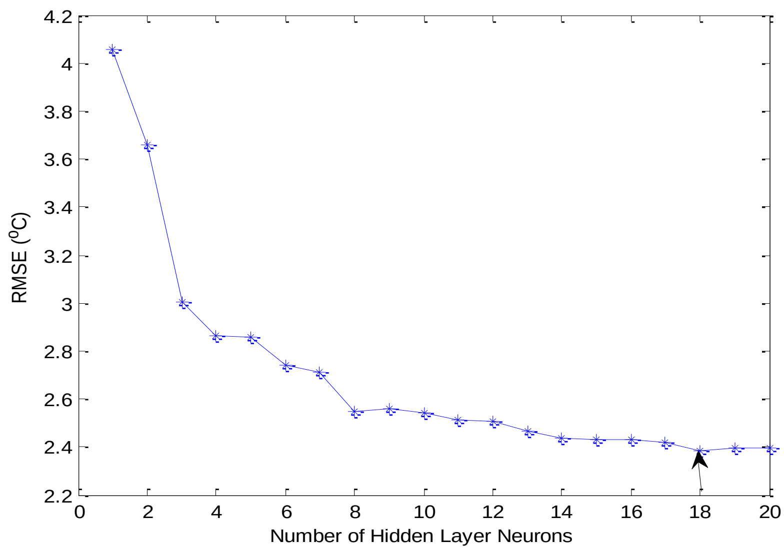

Figure 5 Variations of root means square errors (rmse) and number of hidden layer neuron of methane

The dry season distribution ofCH_4 concentration (Figure 6 a – c) shows that in 2003, the CH_4 concentration varies between 1780 – 1810 ppm, where as in 2008, 2012 and 2014, the ranges in CH_4 concentration are between 1730 – 1770 ppm, 1745 – 1785 ppm and 1800 – 1845 ppm respectively. This implies yearly increase in CH_4 concentrations. In addition, it could be observed that in 2003, the highest concentration of CH_4 (about 1800 – 1810 ppm) is found within the South-South regions of the country, while the lowest concentration of about 1790 – 1785 ppm are obtained between Central and Northern Nigeria. It is interesting to note that the existence of peak concentrations of CH_4 in the South-South part of the country is predominant in all the years under study. This could be attributed to the possible existence of hydrocarbon and gas flaring activities in the area (Ubani and Onyejekwe, 2013). Figure 7 (a – d) revealed that the variations of CH_4 shows uniformly high concentration of CH_4in all the stations through all the years under study in wet seasons. Comparison of Figures 6 and 7 revealed that methane were present in Nigeria both in dry and wet seasons. It could be observed that higher concentration occur in the South in dry season than the North, while slightly higher concentration occurred in the South in wet season in comparison with the North. In addition, it could be noted that methane concentration covered almost over Nigeria during the wet seasons. High concentration of CH_4in wet season is as a result of methane produced from wetland, decomposition of plants, rice paddies (anaerobic process), enteric fermentation in mammals (ruminants) and termites. This could imply that the concentrations of CH_4 depend on the moisture content of the environment (which may enhance decomposition) and also from many plants such as water hyacinths which release CH_4. This agrees with Delgado, *et al.* (2008), which states that water hyacinth (Eichhornia crassipes) which is from biomass are converted to methane. It could also be due to increase in the rate of rice farming in Nigeria that occurs during the wet season and a source of methane generation. This agrees with Delgado *et al*. (2008), which state that water hyacinth (Eichhornia crassipes) is potential biomass source able to be converted into methane. It could also be due to increase in the rate of rice paddies in Nigeria that occurs in wetland during the wet season and a source of methane generation (Babu *et al.,* 2005). Termite emits methane due to methanogenesis in the synergetic metabolic collapse in termite hindguts (Philipp *et al.,* 2018).

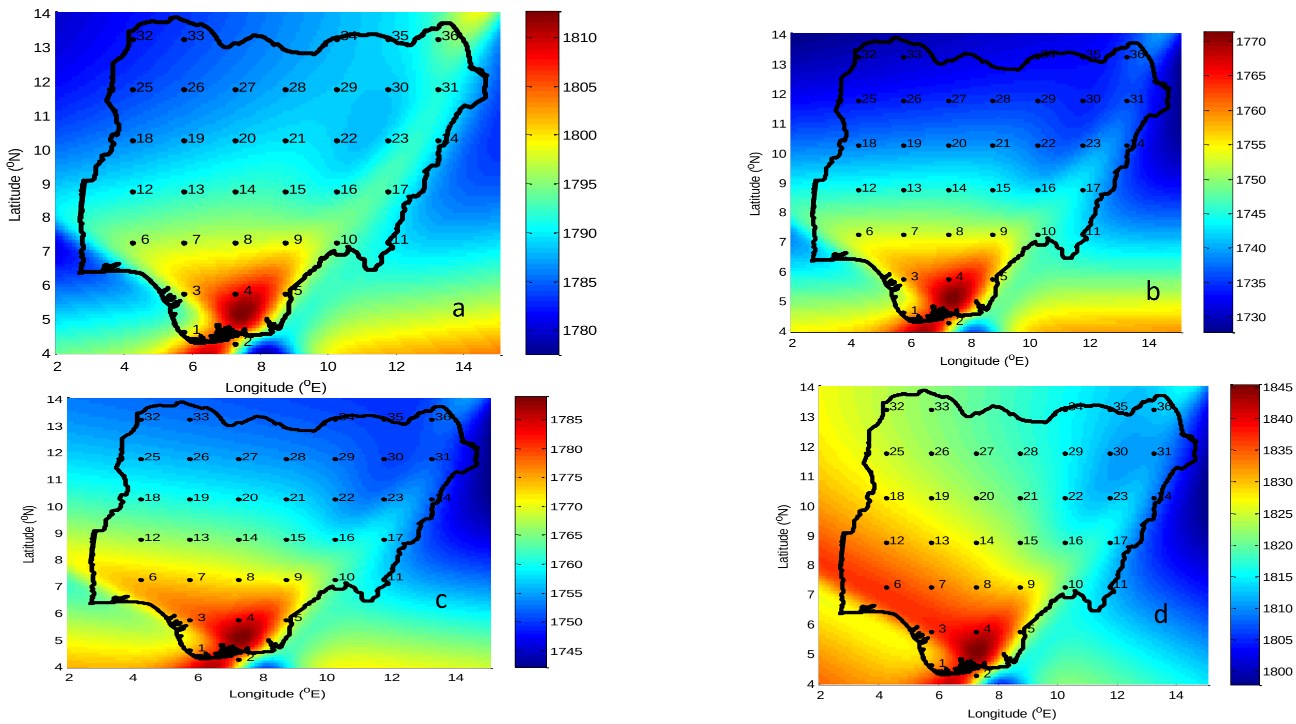

Figure 6 The spatial variations in methane (ppm) in dry season over Nigeria for the periods: (a) 2003 (b) 2008 (c) 2012 and (d) 2014

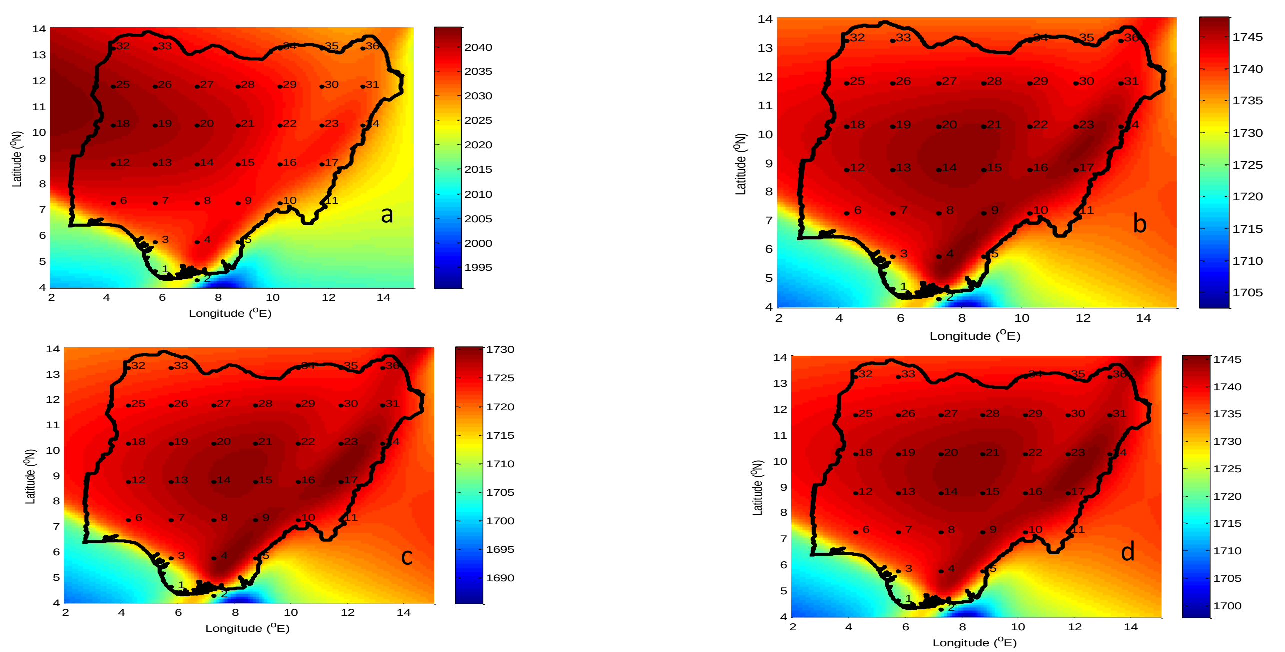

Figure 7 The spatial variations in methane (ppm) in wet season over Nigeria for the periods: (a) 2003 (b) 2008 (c) 2012 and (d) 2014

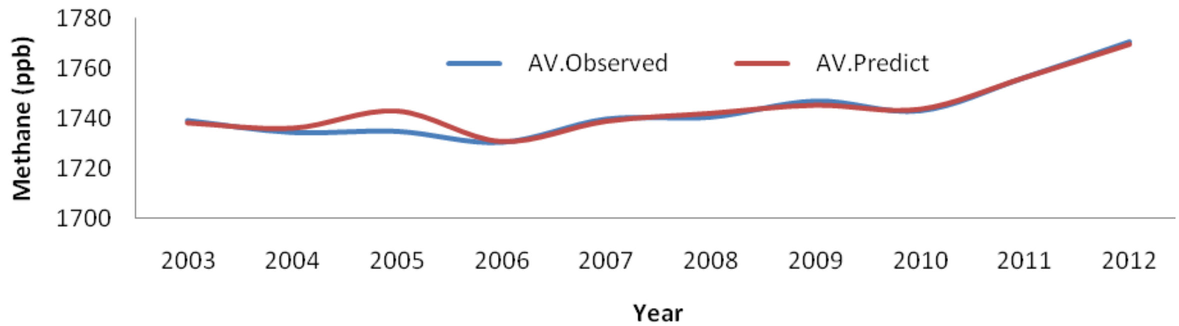

Figure 8 Annual Average variations of estimated and observed values of methane in Nigeria

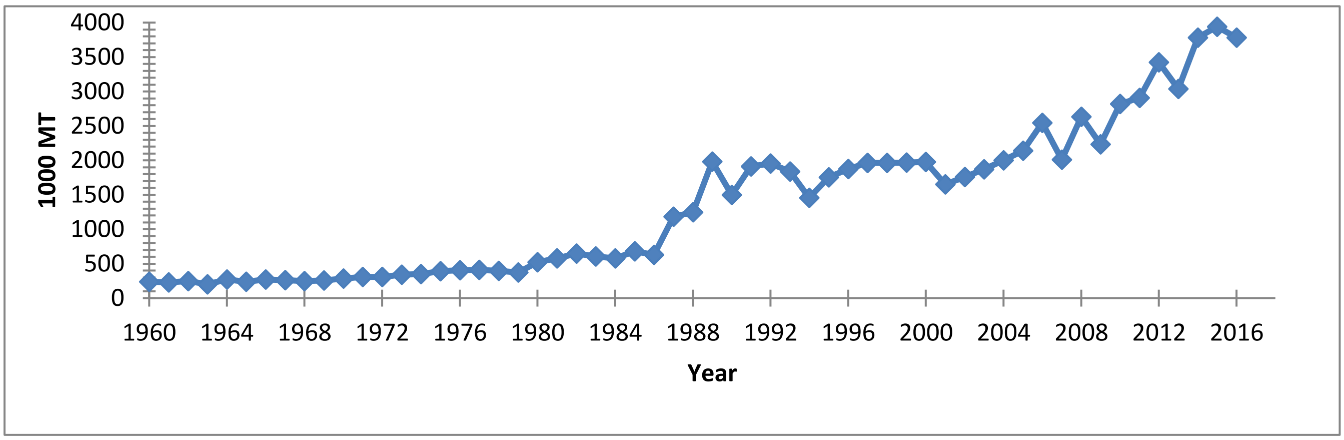

Figure 9 Annual Nigeria Milled Rice Production (Index Mundi, 2018)

Figure 8 shows in phase trend in the annual variation of observed and estimated values of CH_4, except in 2005 where there is over estimation of the observed data. The similarity in the estimated and observed signatures of Figure (8) proves the good performance of the Neural Network model used in this study.

The variation in Figure 8 is in correspondence with Figure 9, which is the annual Nigeria Milled rice production as obtained from the United States Department of Agriculture-Index Mundi (2018). The correlation between Figures 8 and 9 shows that the annual variation of methane is in line with the annual variations of rice productions in Nigeria. This reveals and affirmed that rice production could be a major contributor of methane emission. This is in line with Schneising (2009), which stated that rice paddies are among the major contributors of global CH_4. The high methane contributes to climate change and global warming in Nigeria is increasing continuously from Figure 8. This contribution in Nigeria if left unchecked will increase adverse effects on livelihoods, such as crop production, livestock production, fisheries, forestry and post-harvest activities. This will alter the patterns of rainfall régimes, which could cause floods and devastate farmlands. It will also result in increase in temperature and other natural disasters like floods, ocean and storm surges, earth tremors which not only damage Nigerians' livelihood but also cause harm to life and property.

Figures 10 present the daily multi-steps ahead forecasts (2018 and 2019)of methane for two stations, one from the North (Danjuma-Taraba State) with latitude 7.25 ^oN and longitude 10.25^oE and the other from the South, Apoi Creek–Bayelsa with latitude 4.59^0N and longitude 5.84^0N. It could be observed that methane variations will be between about 2099 - 2180 ppm in 2018, but will range between 2030 - 2210 ppm in 2019. This could imply obvious increase in 2019 as compared to 2018. It is observe that high value will be between June and July, while low value will be December and January. The result reviewed that the concentrations of methane in the south will be higher than the one in the north. The high concentrations occurring in wet season and southern part of Nigeria confirmed that wetland, rice paddies, termites and ruminants animal (cattle) major sources of methane production. The result revealed that the model used has the capacity of modeling greenhouse gases and other atmospheric parameters. This affirmed Daniel, *et al.* (2015) assertion, which stated that impressive performance of the neural networks model supports the application of neural networks in modeling atmospheric parameters.

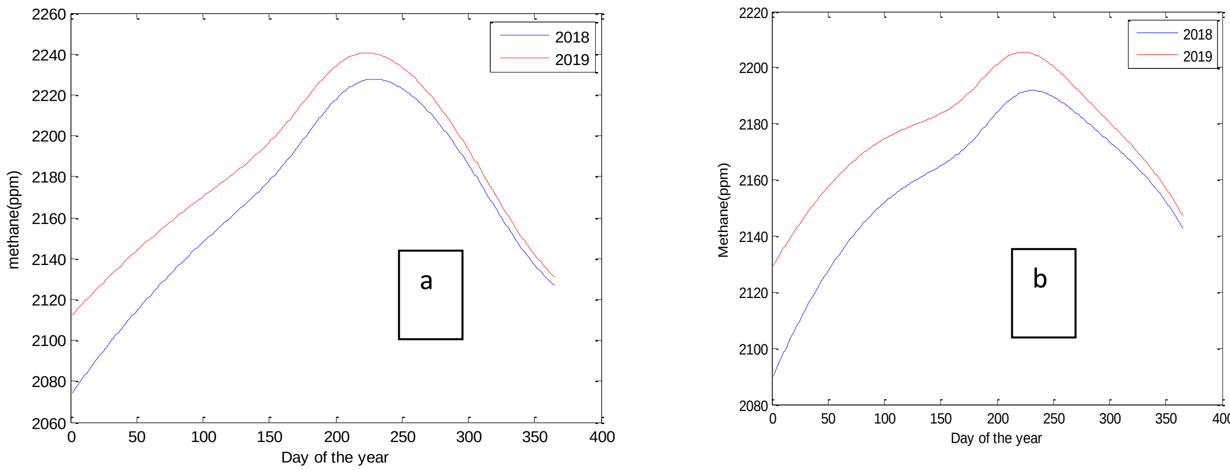

Figure 10 Variations of forecasts of 2018 and 2019 at (a) Apoi Creek, Bayelsa State (4.59 °N: 5.84 °E) and (b) Danjuma, Taraba State (7.25 °N: 10.25 °E) for Methane

4. CONCLUSION

The assessment of methane distributions over Nigeria was studied using neural network model. The variation reveals that higher concentration occurs in the South in dry season than the North, while slightly higher concentration occurred in the South in wet season in comparison with the Northern part of Nigeria. In addition, it could be noted that methane concentration covered almost over Nigeria during the wet seasons. This could imply that the concentrations of CH_4 depend on the moisture content of the environment which may enhance decomposition of many plants such as water hyacinths which release CH_4. This agrees with Delgado, *et al.* (2008), which states that water hyacinth is from biomass and is converted to methane. It could also be due to increase in the rate of rice farming in Nigeria that occurs during the wet season, which is also major source of methane generation. This is in line with Babu *et al.* (2005) that reveal that rice cultivation is a source of methane (CH_4). The similarity in the estimated and observed signatures of the average annual methane show good performance of the Neural Network model used in this study. The result is dominated by phase changes and increases from rice emitting relative to the methane data.

Acknowledgments

www.gmes-atmosphere.eu/data is acknowledged for making the data used in this work available. This work was carried out in collaboration between both authors. Author Ibeh G.F[1] designed the draft of the manuscript, performed the analysis and coordination, Author Udochukwu B.C wrote the protocol and supervised the study, author Ibeh L.M managed the literature searches and the analyses of the study and author Okoh D wrote the scripts for the model and performed the modeling. Both authors read and approved the final manuscript (no conflict of interests). The work was jointly funded.

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