Original Research Article
Geostatistical Analysis for Monitoring and Modelling Atmospheric Pollutants.

Abstract. Urbanisation and industrialization are predominant indicators of regional growth with some adverse effect especially in ambient air quality often prone to contamination by emissions. Vehicular emissions have been identified as a consistent air pollutant in urban areas. However, meteorological conditions such as rainfall also affect air pollution concentration level. In this study, we used rainfall temporal resolution and vehicular load to model air pollution variation in Effurun City, Delta State. In-situ sampling of CO, VOC and NO_2 and Geostatistical analysis were used to obtain concentration level and relationships between air pollutant concentration, vehicular load and rainfall which was used to predict spatial trend for efficient monitoring.

INTRODUCTION

Air contamination a key challenge of the 21st century, with majority of these pollution occurring due to urbanization posing a major health hazard worldwide (Avogbe et al., 2011). Air pollution is a major part of the overall atmospheric pollution with vehicular emissions constituting the most significant source of ultrafine particles in an urban environment (Zhu et al., 2002). Important chemical pollutants emitted by land vehicles are Carbon monoxide, Sulphur dioxide, Nitrogen dioxide and Total Suspended Particle (Najceba et al.,1997). Vehicle emissions have become one of the most difficult environmental problems to solve especially in cities that rely on a significant number of vehicles for daily transit and have few efficient public mass transportation modes (Salami, 2007). An efficient internal combustion engine would burn fuel to create only water and carbon dioxide, but worn-out engines, lowgrade fuel types, irregular maintenance, physical aging of engines, intensive use of vehicles, and incorrect lubricant use all work together to limit the efficiency of fuel combustion. (Dey et al., 2020). Carbon monoxide, hydrocarbons, Nitrogen dioxide and Sulphur dioxide emissions from the exhaust system and engine components of automobiles are the result (Bhandarkar et al., 2013). As a result of the absence of countermeasures, air pollution has become a serious environmental problem (Zaghaet et al., 2015).

Globally, the hazardous impact of air pollution on human health and the environment has been on the rise, particularly in developing countries where most people still generate their own electricity by burning fossil fuel for both commercial and domestic use. (Wilkinson, P., Smith, K. R., Joffe, M., & Haines, A. (2007). Air pollutants of concern are carbon monoxide, carbon dioxide, oxides of nitrogen, oxides of Sulphur, Particulate Matter, noise and Volatile Organic Compounds such as Benzene, Polycyclic Hydrocarbons and Formaldehyde (Bernstein et al., 2018). Each of these pollutants can have severe consequences in both the short- and long-term, resulting in acute and chronic toxicity effects. Many of these substances have harmful effects on bone marrow, the spleen and lymph nodes. The circulatory system is especially vulnerable to toxins in exhaust fumes and exposures have been linked to asphyxiation and anaemia (Wargo et al., 2006). Exposure to air pollutants has been associated with increased risk of upper respiratory tract diseases such as asthma, inflammation, fibrosis and chronic obstructive pulmonary disease, exacerbation of heart disease due to hypertension and degeneration of the cells which line blood vessels, irreparable damage to the central nervous system, as well as cancers (Wegesser et al, 2009).

Cities in developing nations, such as Nigeria, have seen increased air pollution. There is a significant incidence of rural-to-urban migration, resulting in traffic congestion, squatter settlements, and poor air quality. Uvwie and Effurun, a huge city in Nigeria in terms of area, has seen this kind of population boom. The city's automobile population has increased at an alarming rate, with a disproportionately large number of taxis. Refineries, gas plants, food and drinks, paint, and pharmaceuticals are the main industries connected with air pollution in the city's industrial region. However, many megacities, such as Uvwie, have insufficient air quality monitoring. Gas flaring, motor vehicles, industrial activities, and household heating are all obvious causes of air pollution in Uvwie. Gas flaring, motor vehicles, industrial activities, residential heating, and coal burning in commercial areas are all obvious causes of air pollution in Uvwie. According to studies, cars are the primary cause of air pollution in most cities (Pandey et al., 2014; Eibir et al., 2017).

The vast number of cars on congested streets, low quality vehicles, poor quality fuels and maintenance systems, and insufficient transportation management are the main causes of excessive vehicular emissions. These factors are visible in Effurun. Daily fluctuations in air pollutant emission patterns are possible, especially near highways or roadsides. Based on the foregoing and other potential factors, it is necessary to examine the levels of some parameters such as NO_2 and CO in Effurun and its environs in Delta State, to see if these parameters are increasing as a result of anthropogenic activities such as industrial and vehicular emissions within the study area. As a result, the environment has a significant impact on one's quality of life. Examining the problem of air pollution from the standpoint of public health appears appropriate and appropriate. Air Pollution Modelling. Air pollution models are frequently used to assess air quality in rural regions, but a mix of monitoring and modeling can aid air quality predictions in heavily traveled metropolitan areas (Frank et al., 2011). Numeric techniques which include Statistical modeling like regression techniques are used to simulate physical and chemical processes with an aim of predicting atmospheric pollutant dispersion, distribution, and concentration in the atmosphere (Conti et al, 2017).

Geo-statistics for Air Pollution Modelling

One of the most important approaches to statistical modeling of air pollution prediction is regression modeling, which is a machine learning process suitable for predictive modeling. Regression is a statistical approach for establishing the link between independent variables or features and a dependent variable or result, and it is commonly used in supervised machine learning processes as a way for predictive modeling. (Buskirk et al 2018). It is a method of modeling output using equations when the correlation coefficient between variables shows a substantial relationship. The availability of independent variables, derived intercept and defined slope can be used to model a resultant effect known as the dependent variable. This has been extensively used to model air pollution. Environmental determinants of pollution, such as rainfall, wind direction, speed, and air temperature, are considered by most air pollution models in their pollutant distribution simulations. Integrating these models with GIS gives air quality data a geographic dimension by linking actual pollution concentrations to plant and human life in each region, which can show the link between prevailing air quality and environmental health using its numerous analysis algorithms (Yerramilli et al., 2011).

The inverse Distance Weighted approach is a geostatistical approach based on the assumption that the amount of impact in proximity sample points should be greater than the effect of more distant sample points (Ouabo et al., 2020). Each input point has a local impact that declines with distance, according to the Inverse Distance Weighting interpolator. It gives more weight to points that are closer to the processing cell than to those that are farther away. This approach presupposes that the effect of the variable being mapped diminishes with distance from the sampled site and is suitable for interpolating air pollution concentration to show spatial attributes.

MATERIALS AND METHODS

Study Area

The scope of the study is limited to select points along the east-west road in Effurun City, Delta State. Effurun is located between latitude 5° 33' 0" North and longitude 5° 47' 0" East. The city is a major economic hub and the place with the most residents, industries and important government infrastructures in Delta State.

Climate

The climatic condition of Uvwie LGA experiences moderate rainfall and moderate humidity for most part of the year. The climate is equatorial and is marked by two distinct seasons: the dry season and the rainy season. The weather in Effurun is tropical monsoon with an annual average temperature of 28.08 degree centigrade and an annual rainfall of 236.82mm (Historical Weather Data, 2022). Tropical rain forest and swamps are the major native flora in the area which creates lumbering activities, palm harvesting activities in the area.

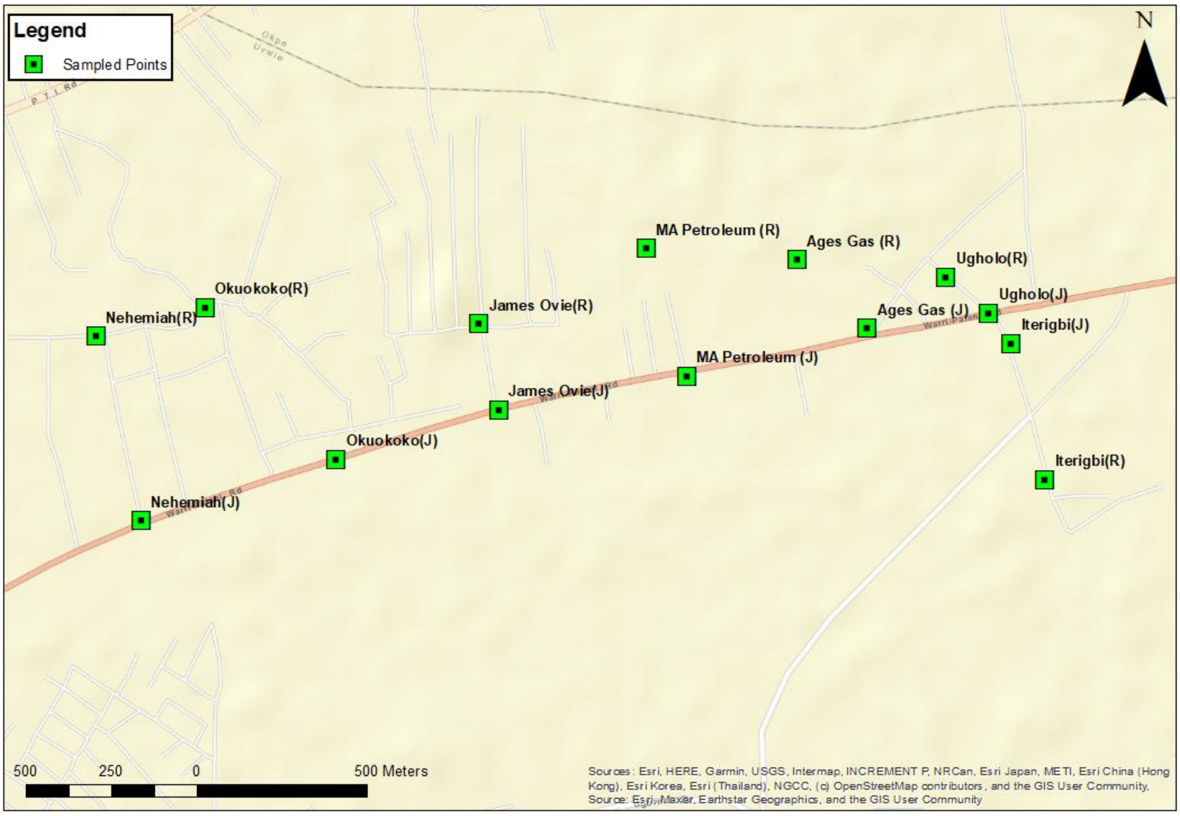

Fig 1 Map of Study Area

Materials

For this research work, the air pollution measurements will be carried out using direct reading, automatic in situ gas monitors. The Series 300 monitor from Aeroqual is a versatile monitor with the ability to accurately measure multiple target gases at different concentrations in indoor and outdoor applications. For this project, the instrument was used to measure concentration levels for VOC, NO2 and CO. R studio software was used to execute correlation and simple linear regression analysis with climatic and vehicular load data.

Data Collection

Sampling was done on the first and second week of the month of October, at selected locations which are either residential or by the roadside along the East-West Road leading to Ughelli-PortHarcourt. Sampling involved open air sampling on the pavements in closest proximity to the roads and at a height of 1m. Measurements will be taken after steadying the equipment for at least 15 minutes before readings are taken in order to provide real time reading of parameters of interest.

Data Analysis

The generation of air pollutants and changes in pollutant concentration are significantly impacted by meteorological conditions. The prerequisite and foundation for scientifically developing air pollution prevention and control plans is a comprehensive study of the link between air pollutant concentration and meteorological conditions (Liu et al., 2020). Although existing studies have attempted to explore the relationship between air pollution and meteorological conditions at a few sites or typical areas, very few have tried modelling future air pollution dynamics especially in the Niger Delta where air pollution monitoring is almost inexistent.

During field campaigns, data on three pollutants were gathered in three phases. These pollutants were primarily determined by a combination of weather conditions and vehicle load (the beginning of the month, mid-month and end of the month). This was done to obtain a trend which would be used to extract variation patterns, observe relationships, establish degree of relationships and generate linear regression models that will be used to model past and futuristic air pollutant concentrations as defined. The three pollutants of importance for the study were VOC, CO and NO_2. Also, rainfall data was collected from an online weather platform. For our research, Vehicle Count which was obtained from real time count every 5 mins and recorded points where pollutant concentration was measured. Vehicle load was then defined as a function of holidays which determines peak and mid-peak and off-peak periods, with weighted values of 1, 0.7 and 0.5 respectively. Mean values for concentration of each of the parameters was calculated for repeated measurements and as well as to obtain a representative discrete value. Graphs was generated with the data and used to compare side by side, the concentrations of the different parameters for the different sampling locations on the various sampling periods. Rainfall and vehicle count were labelled independent variables, while air pollutant concentration was labelled dependent variable to be determined by changes as they occur on the independent variables. The data was analyzed using R Studio software. Linear regression was used to obtain the model which was then applied to predict past pollution concentration. This same approach can also be used to determine future pollution concentrations.

Interpolation Methods Using GIS

GIS technology is becoming essential tool to combine various maps and remote sensing information to generate various models, which are used in real time environment. (Van Westen, 2013). Interpolation is a geostatistical process used for predicting values for cells in a raster from a limited number of sample data points. Inverse distance weight is a type of interpolation in geostatistics used to predict the values for unknown locations and creating continuous raster surface using known value (Belief, 2018). It has been applied to forecast unknown values for geographic point data, such as elevation, precipitation, chemical concentrations, and noise levels. (Samanta et al., 2012). The IDW which was preferred for this project uses a method of interpolation that estimates cell values by averaging the values of sample data points about each processing cell. The closer a point is to the center of the cell being estimated, the more influence or weight it has in the averaging process and has been used in several instances to interpolate the air pollutant concentrations.

DISCUSSION OF RESULTS

Linear regression which is simple and accommodates a lot of predictors was chosen as the apported tool to model a cause-effect relationship which performed excellently well and gave significant results that gave us insight about trends and behavior of pollutants aggravated by climatic variables and vehicular concentration in a locality. Data from in-situ measurements were collected and used for linear regression to model past pollution concentration trend. Values for VOC, CO and NO_2 were taken for fourteen locations around Uvwie, seven of which were residential and seven were points by the roadside. These locations were selected at random with no actual criteria sited behind their selection. This is because air pollution can occur anywhere including indoors, which is seen as more dangerous than outdoor air pollution. However, outdoor air quality can also affect indoor air quality hence the need to measure, monitor and model air pollutant concentration. At first, areas close to the junction were sampled. All the areas close to junctions along the East – West Road were busy point with high concentration of human activities, vehicular movement and some economic activities.

The tables below show the only climatic variable which correlated with air pollution concentration for the points sampled, vehicular load which are both independent variables and determinant of the air pollutant concentration for our study. Values were modelled for October to May. Values obtained showed a particular trend where pollutant concentration was a determinant rate of rainfall. It was observed that pollutant concentration increases as a result of an increase in rainfall intensity. This has been supported by several literatures. Tables below shows data modelled using linear regression model in SPSS for VOC, CO and NO_2, for residential areas and roadsides. Findings as observed from the tables showed a significant cause-effect relationship between the climatic variables and air pollutant concentration. The modelled results showed this trend and is deemed useful for future pollution studies. The concentration in pollutants varied spatially as determined by vehicular load, peak, mid-peak and off-peak period across each month.

Climatic Variables

Climatic factors varied with season. Rainfall was more between October and November and between April and August. It was low between mid-November and mid-March. These variations in precipitation affected pollutant concentration across all locations when modelled. Wind speed was low between the last week of October and first week of February. Then it peaked again between February and remained at its high till august, which signifies high dispersion rate between these periods. Temperature between these periods modelled was almost even as variations were not significant, hence it was less effective in determining pollutant concentration for this study. Rainfall and wind speed were considered the major climatic variables that were affecting air pollution concentration in locations observed.

Vehicular Load

The pollutants selected to be modelled were those produced from combustion engines. This implies that their availability in a location would be largely dependent on number of machineries powered by combustion engines. During this study, the selected locations had various types of machineries around but vehicles, tricycles and motorbikes were predominant hence vehicle count was used to determine vehicular load, a key variable for our model. The vehicle count obtained for each of the locations were shown on Table 1.

Table 1. Vehicle Count

Location	Residential	Junction
Ugholo	4	46
Nehemiah	4	16
James Ovie	6	33
Ages Gas	4	24
Iterigbi	6	13
MA Petroleum	3	18
Okuokoko	8	27

On the other hand, since we were not able to get the exact vehicular load for all the period to be modelled, we used modulation of human activities across for each month to determine period when vehicles will be high, medium and low, which was labelled as Peak, mid-peak and off peak. A coefficient was selected for each of the period which was used to multiply the number of vehicles observed at each sample point for a period of two minutes.

Results from Statistical Modelling.

Tables below shows summary and mean concentration for air pollutant concentration modelled in residential areas and junctions where samples were taken.

Table 2 Modelled Mean Concentration for Air Pollutants at Junctions

Location	Latitude	Longitude	VOC (ppm)	NO_2(ppm)	CO (ppm)
Ugholo	5.581484	5.840047	2645.39	0.048	4.96
Nehemiah	5.576	5.81763	1528.13	0.048	1.78
James Ovie	5.57893	5.82709	1915.67	0.016	3.73
Ages Gas	5.581094	5.836842	1335.04	0.052	3.47
Iterigbi	5.580686	5.840631	4993.89	0.033	3.54
MA Petroleum	5.579817	5.832058	883.95	0.028	1.42
Okuokoko	5.57762	5.8228	2012.59	0.026	6.66

Table 3 Modelled Mean Concentration for Air Pollutants at Residential Areas

Location	Latitude	Longitude	VOC (ppm)	NO2(ppm)	CO (ppm)
Ugholo	5.582449	5.838928	1548.21	0.034	1.60
Nehemiah	5.58088	5.81644	902.78	0.034	2.55
James Ovie	5.58121	5.82658	1602.60	0.022	2.52
Ages Gas	5.582905	5.834983	1515.04	0.022	1.40
Iterigbi	5.577085	5.841523	3411.91	0.063	3.32
MA Petroleum	5.5832	5.831	1412.30	0.025	1.01
Okuokoko	5.58164	5.81933	497.130	0.073	2.56

Junctions

From the results at junctions, it was observed that Iterigbi Junction has the highest mean concentration of 4993.89ppm, Ugholo at 2645.39ppm, 2012.59ppm at Okuokoko, 1915.67ppm at James Ovie, 1528.13ppm at Nehemiah, 1335.04 at Ages Gas and 883.95ppm at MA Petroleum. From the mean values computed and graphs plotted for NO_2, it was observed that Ages Gas Junction has the highest mean concentration of 0.052ppm, 0.048ppm at Ugholo and Nehemiah respectively, 0.033ppm at Iterigbi, 0.028ppm at Okuokoko and 0.016ppm at James Ovie. From the mean values computed and graphs plotted for CO at junctions sampled, it was observed that Okuokoko Junction has the highest mean concentration with 6.66ppm, 4.96ppm at Ugholo, 3.73ppm at James Ovie, 3.54ppm at Iterigbi, 3.47ppm at Age Gas,1.78ppm at Nehemiah and 1.42ppm at MA Petroleum.

Residentials Areas

From the mean values computed and graphs plotted for VOC, it was observed that Iterigbi had the highest mean concentration of 3,411.91ppm, James Ovie with 1,602.60ppm at James Ovie, 5,548.21ppm at Ugholo,1,515.04ppm at ages Gas, 1,412.30ppm at MA Petroleum, 902.78ppm at Nehemiah and 497.13ppm at Okuokoko with the lowest concentration. For NO_2, it was observed that Okuokoko had the highest mean concentration of 0.073ppm, 0.063ppm at Iterigbi, 0.034ppm at Ugholo and Nehemiah respectively, 0.025ppm at MA Petroleum and 0.002ppm at James Ovie and Ages Gas respectively with the least concentration. For CO, Iterigbi had the highest mean concentration of 3.32ppm, 2.56ppm at Okuokoko, 2.55ppm at Nehemiah, 2.52ppm at James Ovie, 1.60ppm at Ugholo, 1.40ppm at ages Gas and 1.01ppm at MA Petroleum.

Results from GIS Analysis

The IDW-Geostatistical approach was used to combine various maps and spreadsheet information relating to air pollution concentration and its locational attribute to generate continuous surfaces of influence around the sampled areas at junctions and residential areas along the east west road. The results are shown on maps from Fig 2 to Fig 7.

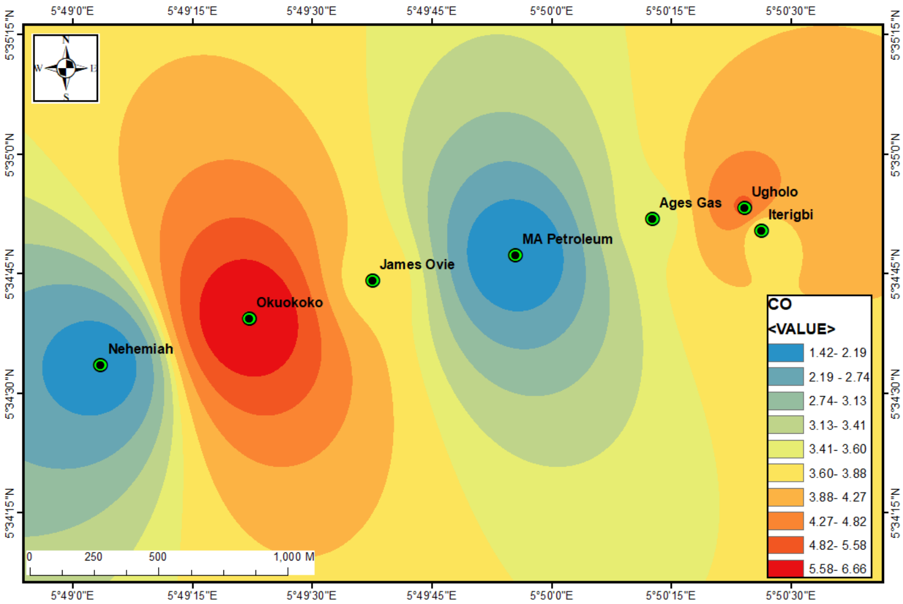

Fig 2 Map of CO concentration at Junctions

From the concentration maps showing influence for CO, it was observed that Okuokoko has the highest values with corresponding high influence around it. It was followed by Ugolo Iterigbi, Ages gas, James Ovie, Nehemiah and M.A. Petroleum with the lowest values with corresponding low influence around it.

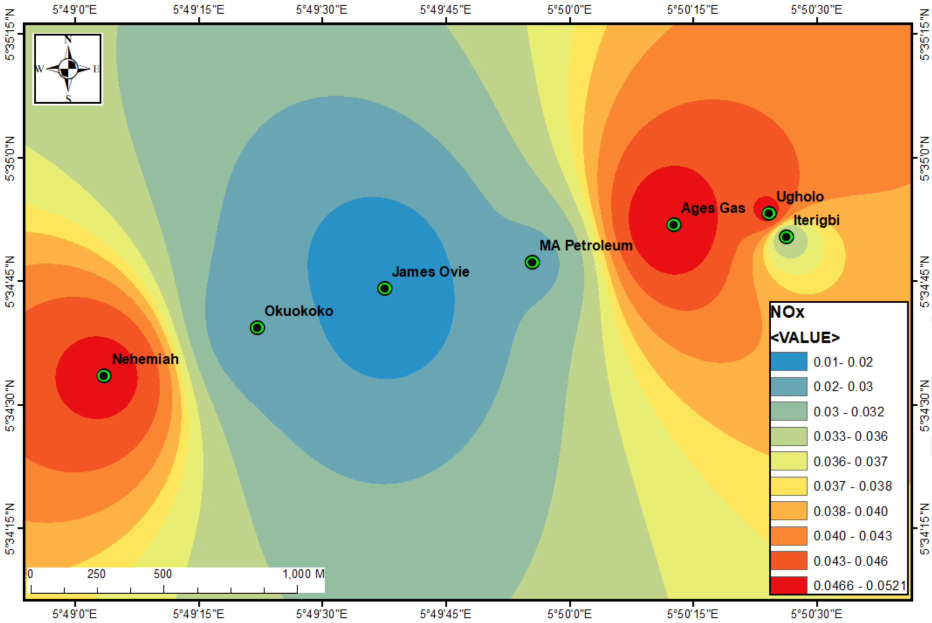

Fig 3 Map of NO_2 at Junctions

From the concentration map showing areas of influence for NO_2, it was observed that Ages gas has the highest values with corresponding high influence around it. This was followed by Nehemiah, followed by Ugolo, followed by Iterigbi, followed by M.A. Petroleum, followed by Okuokoko and James Ovie which has the lowest values with corresponding low influence around it.

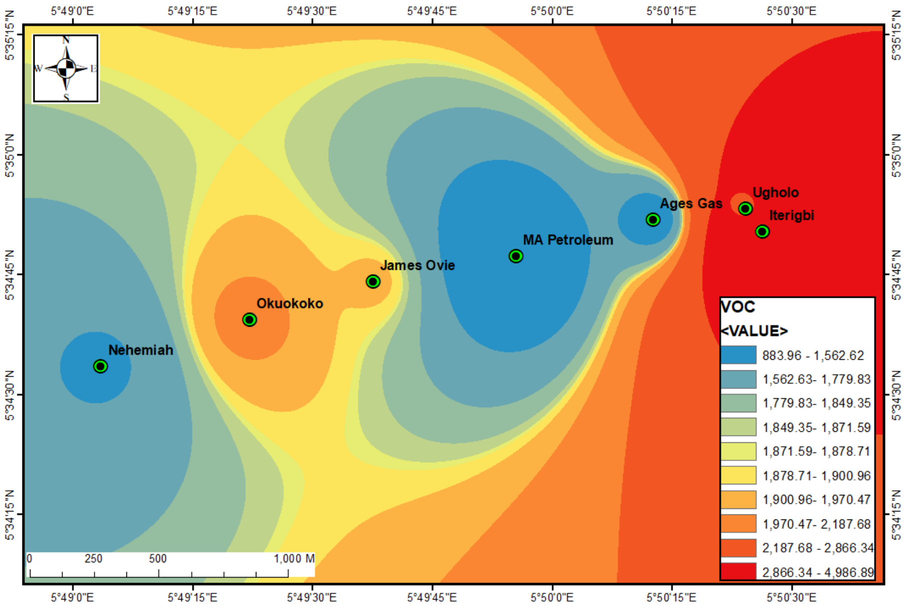

Fig 4 Map of VOC at Junctions. From the concentration map showing areas of influence for VOC, it was observed that Iterigbi has the highest values with corresponding high influence around it. It was

followed by Ugolo which is next highest to iterigbi, followed by Okuokoko, James Ovie, Ages gas, Nehemiah and M.A Petroleum with the lowest values with corresponding low influence around it.

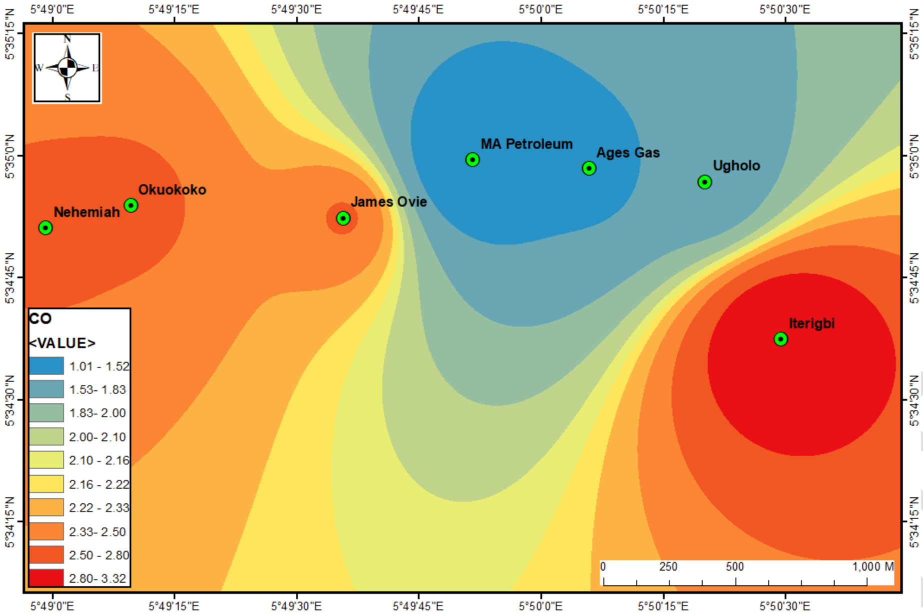

Fig 5 Map of CO at Residential Areas. From the concentration map showing areas of influence for CO, it was observed that Iterigbi has the highest value with corresponding high influence around it. It was followed by Okuokoko and Nehemiah, James Ovie, Ugolo, Ages gas and M.A Petroleum has the lowest values with corresponding low influence around it.

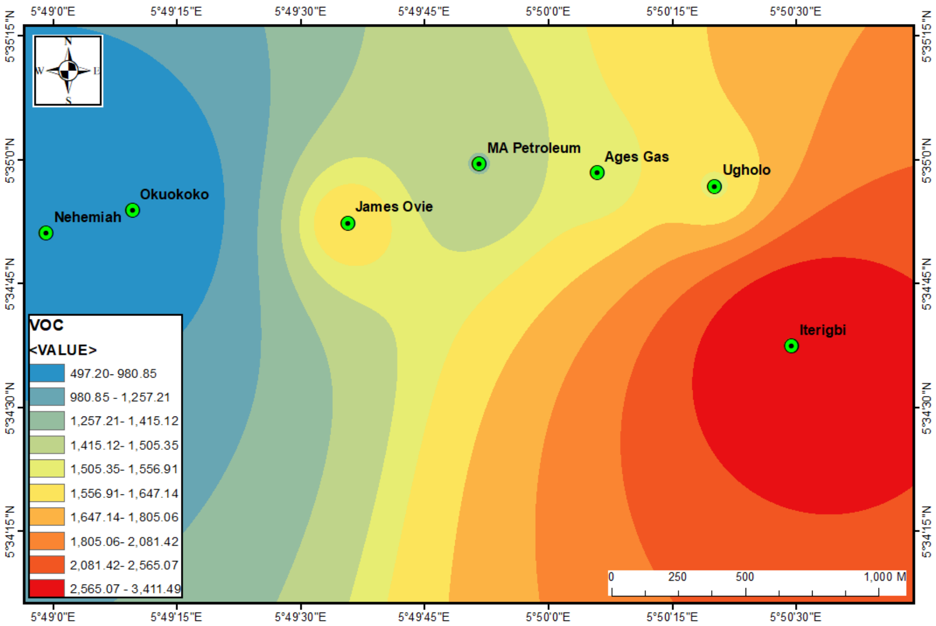

Fig 6 Map of VOC at Residential Areas. From the concentration map showing areas of influence for VOC, it was observed that Iterigbi has the highest values with corresponding high influence around it. Followed by Ugolo, James Ovie, Ages Gas and M.A Petroleum, followed by Nehemiah and Okuokoko the least values and low corresponding influence around it.

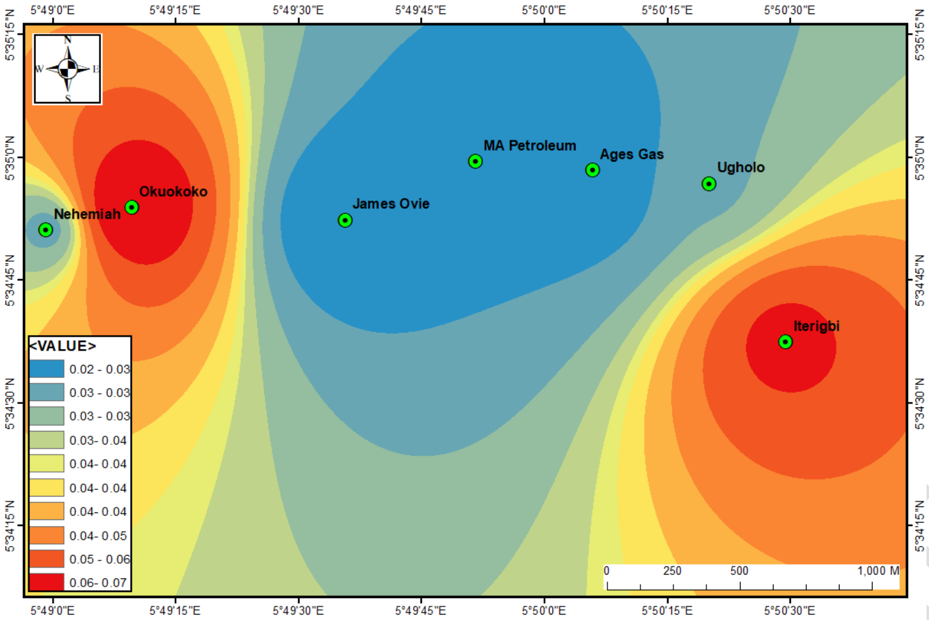

Fig 7 Map of NO_2 at Residential Areas. From the concentration map showing areas of influence for Nox, it was observed that okuokoko has the highest values with corresponding high influence around it. This was followed by Iterigbi, followed by Ugolo, Nehemiah, Ages gas, James Ovie and M.A Petroleum with the least values with corresponding low influence around it.

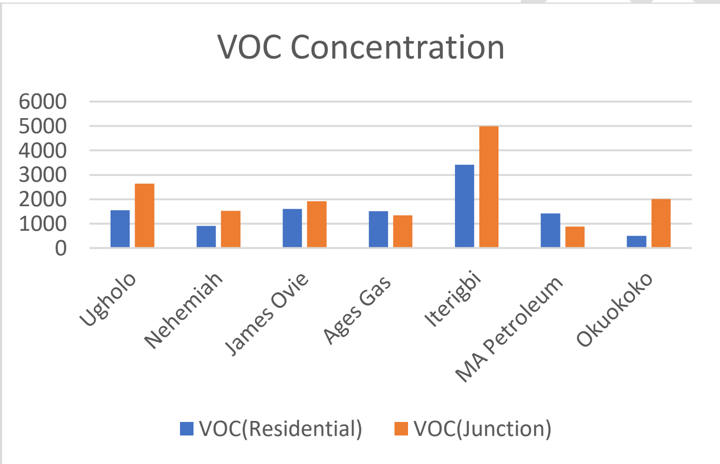

Figure 8 Graph of mean concentration of VOC in Residential areas and Junctions

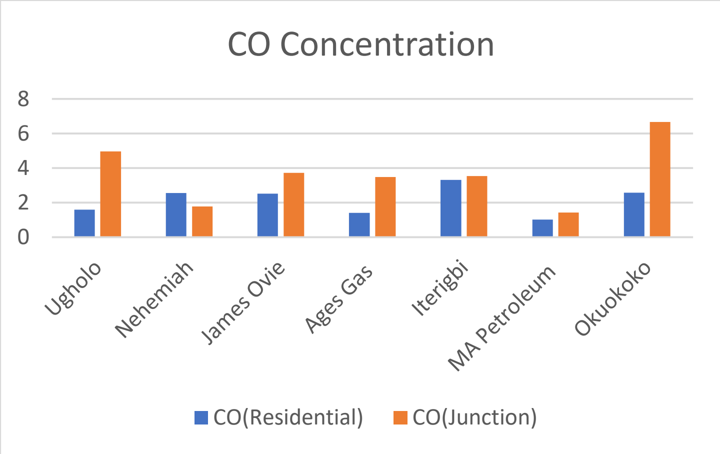

Figure 9 Graph of mean concentration of CO in Residential areas and Junctions

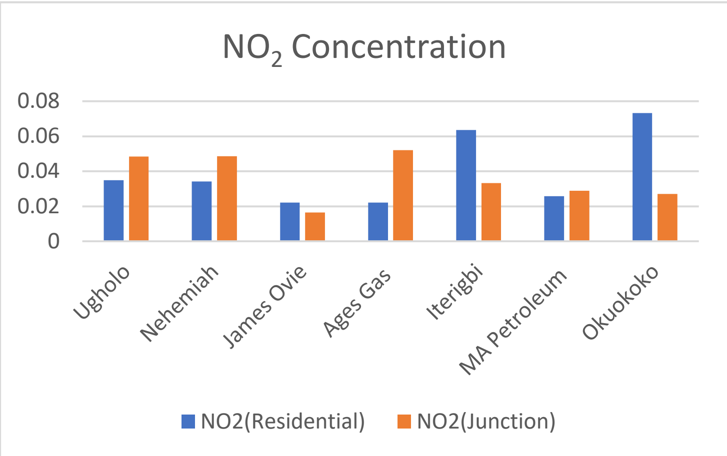

Figure 10 Graph of mean concentration of NO_2 in Residential areas and Junction

CONCLUSION AND RECOMMENDATION

Conclusion

Modeling air pollution levels is an important part of assessing environmental quality and managing natural assets. Increase in concentrations of contaminants may exceed acceptable levels and would have a negative impact on human health. Trends and patterns are vital for forecasting how pollutant concentration levels have been in the past and how they will be in the future, which is why modelling is so important. Since scientists discovered that climatic factors may totally control air pollution concentration trends, global warming and the greenhouse effect, which modifies climate patterns, have been a source of concern, which is why this study is so important. The study found that climatic conditions had a significant impact on air pollution concentration levels. Rain fall intensity identified as a key determinant of air pollutant concentration.

Given that vehicle load is a crucial predictor, holidays and weekends both had a significant influence, since traffic-related emissions are lower during holidays due to less traffic. The data will be extremely useful to policymakers in refining environmental policies relating to air quality and human health. Another major contribution was that the research showed how GIS suited with customized algorithms used for geospatial analysis can be used to model influence of incidents with weights assigned to each point where they occur. For this research IDW which is a type of interpolation approach was used to model and show the area of influence of each pollutant where they were sampled.

Recommendations

Regulators, environmental experts and key stakeholders should translate simple but useful environmental models into practicable procedures by harnessing important trends and patterns of air pollutant concentration towards reducing activities that aggravate pollution load. Feasible mitigative measures should employed by tackling the sources of pollutants that have been identified through the simple linear regression cause-effect approach. Busy round-abouts and bus stops like the junctions identified should be decongested by remodeling and re-routing vehicles to other road available in the study area. A similar approach used in the study can be used to model future pollution concentration on weekly or even daily basis where climatic data is readily available real-time. The information will be very helpful for decision makers in polishing environmental policy related to air quality and human's health. The approach can also be used for water and soil pollution concentration modelling.

REFERENCES

Belief, E. (2018). GIS based spatial modeling to mapping and estimation relative risk of different diseases using inverse distance weighting (IDW) interpolation algorithm and evidential belief function (EBF)(Case study: Minor Part of Kirkuk City, Iraq). Int J Eng Technol, 7(4.37), 185-91.

Bernstein, J. A., Alexis, N., Barnes, C., Bernstein, I. L., Nel, A., Peden, D., ... & Williams, P. B. (2004). Health effects of air pollution. Journal of allergy and clinical immunology, 114(5), 1116-1123.Buskirk, T. D., Kirchner, A., Eck, A., & Signorino, C. S. (2018). An introduction to machine learning methods for survey researchers. Survey Practice, 11(1)

Dey, S., & Mehta, N. S. (2020). Automobile pollution control using catalysis. Resources, Environment and Sustainability, 2, 100006

Frank J. Kelly, Gary W. Fuller, Heather A. Walton and Julia C. Fussell (2011). Monitoring air pollution: Use of early warning systems for public health. Respirology (2012) 17, 7-19.

Najeeba S, Saleem M (1997). "Air pollution by motor vehicle emission at Murree Highway". J. Rawal. Med. Coll. 1(2): 75-78.

Historical Weather Data. (2022). Effurun, Delta, NG Climate Zone, Monthly Averages, Retrieved 15 October 2022, from https://tcktcktck.org/nigeria/delta/effurun

Liu, Y., Zhou, Y., & Lu, J. (2020). Exploring the relationship between air pollution and meteorological conditions in China under environmental governance. Scientific reports, 10(1), 1-11.

Oladimeji T, Sonibare J, Odunfa M, Ayeni A (2015). Modeling of criteria air pollutant emissions from selected Nigeria petroleum refineries. Journal of Power and Energy Engineering, 3(06):31.

Oliveri Conti, G., Heibati, B., Kloog, I., Fiore, M., & Ferrante, M. (2017). A review of AirQ Models and their applications for forecasting the air pollution health outcomes. Environmental Science and Pollution Research, 24(7), 6426-6445.

Ouabo, R. E., Sangodoyin, A. Y., & Ogundiran, M. B. (2020). Assessment of ordinary Kriging and inverse distance weighting methods for modeling chromium and cadmium soil pollution in E-waste sites in Douala, Cameroon. Journal of Health and Pollution, 10(26).

Pandey, B., Agrawal, M., & Singh, S. (2014). Assessment of air pollution around coal mining area: emphasizing on spatial distributions, seasonal variations and heavy metals, using cluster and principal component analysis. Atmospheric pollution research, 5(1), 79-86.Salami KA(2007). "Emission Control Technology by Automotive Industry: Trends and Challenges", Inaugural Lecture Series 10, Federal University of Technology, Minna. Pp. 8-9.

Samanta, S., Pal, D. K., Lohar, D., & Pal, B. (2012). Interpolation of climate variables and temperature modeling. Theoretical and Applied Climatology, 107(1), 35-45.

Shima, F. K. (2015). Epidemiology of canine parvovirus enteritis among hospitalized dogs in Effurun/Warri Metropolitan Region of Delta State, Nigeria. Open Access Library Journal, 2(01), 1

Van Westen, C. J. (2013). Remote sensing and GIS for natural hazards assessment and disaster risk management. Treatise on geomorphology, 3, 259-298.

Wargo J, Wargo L, Alderman N. The harmful effects of vehicle exhaust: a caseforpolicy change [Internet]. North Haven, CT: Environment and Human Health Inc; 2006 [cited 2018 Jun 18]. 64 p.

Wegesser, T. C., & Last, J. A. (2009). Mouse lung inflammation after instillation of particulate matter collected from a working dairy barn. Toxicology and applied pharmacology, 236(3), 348-357.Wilkinson, P., Smith, K. R., Joffe, M., & Haines, A. (2007). A global perspective on energy: health effects and injustices. The Lancet, 370(9591), 965-978

Zagha, O. and Nwaogazie, I.L. (2015). Roadside Air Pollution Assessment in Port-Harcourt, Nigeria. Standard Scientific Research and Essays Vol 3(3):2-10.

Zhu Y, Hinds WC, Kim S, SioutasC(2002). "Concentration and size distribution of ultrafine particles near a major highway". J. Air Waste Manag. Assoc. 52(9): 1032-1042.