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Influence of Meteorological Parameters on Air Pollution Propagation in an Active Dumpsite in Abeokuta, Nigeria

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ABSTRACT

Air pollution from dumpsites is a growing concern due to its detrimental effects on both human health and the environment. This study examines the influence of meteorological parameters on the propagation of air pollution from a dumpsite, focusing on the Saje dumpsite in Abeokuta, Nigeria. The concentration of the air pollutants; particulate matters ($PM_{2.5}$, PM_{10}), formaldehyde (HCHO), total volatile organic compound (TVOC), carbon monoxide (CO), oxygen (O_2) and selected meteorological factors (wind speed, wind direction, temperature and humidity) were measured using portable handheld gas detectors. Multiple linear regression (MLR) and multiple nonlinear regression (MNLR) models were employed to predict the relationship between the meteorological parameters and the air pollutants using XLSTAT® 2018 modelling software. Regression analysis showed that, the coefficient of determination (R^2) ranged from 0.114 – 0.157 (dry season sampling) and 0.006 – 0.319 (wet season sampling) for MLR and 0.466 – 0.673 (dry season sampling) and 0.390 – 0.671 (wet season sampling) for MNLR models. The MNLR model is best used in predicting the air pollutants concentration propagation using meteorological parameters as predictors. This finding emphasizes the significant role of meteorological parameters in influencing air pollution dynamics. As such, the study recommends the adoption of MNLR models for more accurate predictors and effective management of air pollution from dumpsites.

Keywords: Air pollution, Meteorological parameters, Propagation, Regression models.

INTRODUCTION

Air pollution is a pervasive environmental challenge in developing countries with significant implications for public health and the overall balance of ecosystems. Various human activities, such as the combustion of fossil fuels like natural gas, coal, and oil for industrial processes, transportation, brick making, and other industrial operations, are the principal source of pollutants responsible for deteriorating air quality (Begum *et al*., 2008). Furthermore, the rapid growth of urban populations and changes in land use due to urban expansion are significant factors contributing to declining air quality in developing nations (Mayer, 1999). Consequently, both indoor and outdoor air quality in urban areas is straying from acceptable standards, leading to a continuous exposure of a large number of urban residents to harmful air pollutants and associated health risks (Kayes *et al*., 2019).

The intricate interplay between the air quality and meteorological parameters has prompted extensive research aimed at understanding and modeling the complex relationships governing pollutant concentrations (Opkala, and Yorkor, 2013). Meteorological elements are crucial factors influencing air quality (Antai *et al*., 2018; Manju *et al*., 2018). Among these, wind speed and direction, relative humidity, air pressure, and temperature are particularly noteworthy as they can impact the dispersion process, mechanisms for pollutant removal, and the formation of atmospheric particles (Zhang *et al*., 2015). Consequently, they play a substantial role in regulating air pollutant concentrations. Additionally, rainfall can also have varying effects on pollutant concentrations through the elimination of gaseous pollutants and the deposition of particulate matter through atmospheric chemical processes (Shukla *et al*., 2008; Kayes *et al*., 2019).

In recent years, statistical modeling techniques, particularly multiple linear regression (Antai *et al*., 2018) and multiple nonlinear regression (Kayes *et al*., 2019), have emerged as powerful tools for investigating the complex connections between meteorological elements and air pollution. These techniques enable researchers to analyze the impact of various meteorological elements on pollutant concentrations and provide valuable insights into the underlying dynamics of pollution sources and transport mechanisms. The aim of this study is to model the relationship between air pollutants concentrations propagation and the meteorological parameters at Saje Dumpsite, Abeokuta, Nigeria.

MATERIALS AND METHODS

Study Area

Abeokuta, the capital of Ogun State in southwest Nigeria, spans an area of approximately 879 km^2 and is positioned between latitude 7º 9' 39'' N and longitude 3º 20'54''E. The city is situated in Nigeria's rainforest region and benefits from its strategic location, providing easy access to Lagos, Nigeria's commercial capital, as well as to industrial areas and the main seaport (Ufoegbune *et al*., 2008). Abeokuta is situated on a basement complex of igneous and metamorphic origins. The study area which is the Saje dumpsite and the adjoining residential areas is located between 7°°10'30" and 7°12'0"N and between 3°21'0" and 3°22'30"E in the humid tropical region in Abeokuta, Nigeria. The dumpsite was created in 2006 in order to reclaim the site as it was previously a quarry site occupied by Associated Granite Industry (AGI) Quarry (Afu *et al*., 2015).

Data Collection

Air pollutants concentrations data of particulate matters ($PM_{2.5}$, PM_{10}), formaldehyde (HCHO), total volatile organic compound (TVOC), carbon monoxide (CO), oxygen (O_2) and meteorological factors such as wind speed, wind direction, humidity and temperature were determined using handheld gas detectors (Multifunctional gas detector and professional air tester). A total of forty data were collected on the dumpsite and the adjoining residential area towards the four paths of propagation (North, South, East and Western transverse) as shown in figure 1 for a period of six (6) month (February to July 2023). The February to April sampling were classified as the dry season sampling and May to July sampling as the wet season sampling.

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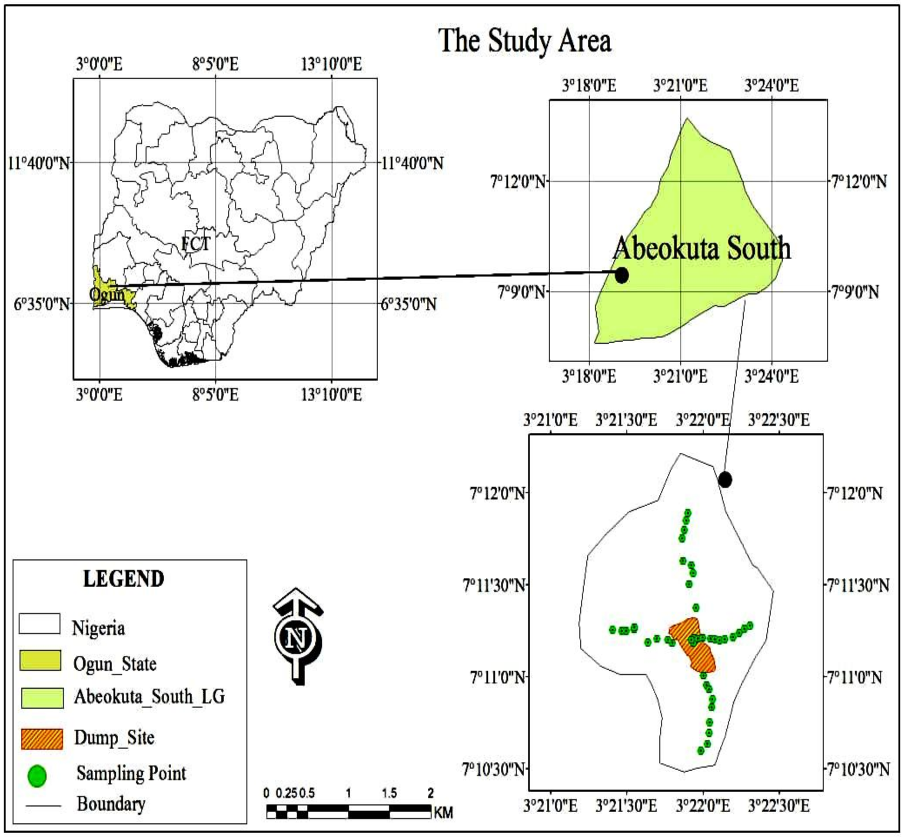

Figure 1: Study area map

Model Development

The regression models in predicting the air pollutants propagation with meteorological parameters were determined using multiple linear regression (Antai *et al*., 2018) and multiple nonlinear regression (Kayes *et al*., 2019). The meteorological parameters such as wind speed (Ws), wind direction (Wd), Temperature (Temp) and relative humidity (RH) were used as the predictors. The models of each air pollutants were generated using XLSTAT 2018 software for both multiple linear regression (MLR) and multiple nonlinear regression (MNLR). A polynomial model of third order was employed to build a models using the MNLR techniques. The modelling of the MLR and MNLR were based on the fundamental approaches in Equation 1 – 5.

$$\text{Outcome}_i = (\text{model}) + \text{error}_i \quad (1)$$

$$Y_i = (b_0 + b_i X_{i1} + b_2 X_{i2} + \ldots\ldots + b_n X_n) + \varepsilon_i \quad (2)$$

$$Y_i = \beta_0 + \sum_{i=1}^{n} \beta ixi + \varepsilon i \quad (3)$$

$$Y_i = \beta_o + \beta_i X + \beta X^2 + \ldots. + \beta_h X^h + \varepsilon_i \quad (4)$$

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \beta_3 x_i^3 + \varepsilon_i \quad (5)$$

Where, Y_i and y_i are models outcome.
$X_1, X_2 \ldots\ldots\ldots X_n$ are predictor variables.
$b_0, b_1, b_2 \ldots\ldots\ldots \beta n$ are regression coefficient
h is called the degree of the polynomial and
ε_i is the error factor called residual.

Model Validation

Several statistical metrics, including mean square error (MSE) and root mean square error (RMSE), were employed to evaluate and validate the accuracy of the prediction models. Additionally, the coefficient of determination, known as R-squared (R^2), was used to evaluate the extent to which the model equations accounted for the total variability in the dependent variables. The mean square error (MSE) was calculated as the average difference between the predicted and observed values using Equation (6), while the root mean square error was determined using Equation (7).

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(Ypred,i - Xmeas,i) \quad (6)$$

$$RMSE = [\frac{1}{N}\sum_{i=1}^{n}(Ypred,i - Xmeas,i)^2]^{1/2} \quad (7)$$

Where, N represents the total number of measured data points or observation

Sum of square error (SSE) was be computed using Equation (8)

$$SSE = \sum(Xmeas,i - Xm,i)^2 \quad (8)$$

The sum of squares of the regression model (SS_M) was calculated using Equation (9).

$$SS_M = \sum_i(Ypred,i - Xmeas,i)^2 \quad (9)$$

Coefficient of determination (R^2)

The coefficient of determination (R^2) value represents the proportion of variation in the sample that is accounted for by the regression models, indicating the degree to which the models accurately fit the data. Equation (10) was used to compute the coefficient of determination.

$$R^2 = \frac{Explained\ Varaition}{Total\ variation} = \frac{SSM}{SST} = \frac{\sum_i(Ypred,i - Xm)^2}{\sum_i(Xmeas,i - Xm)^2} \quad (10)$$

Where Ypred,i represents the predicted pollutant concentration,
Xmeas,i denotes the individual measured air pollutant concentration, and
Xm is the mean measured pollutant concentration.

RESULTS AND DISCUSSION

Variation of air Pollutants Concentration with Meteorological Parameters in the Dry Season

A model equations generated using multiple linear regression model (MLR) and multiple nonlinear regression model (MNLR) are presented in equation 11 to 16 and 17 to 22 respectively. The equations were used to predict the concentrations of each pollutants in the sampling area during the dry season. Table 1 and 2 shows the goodness of fit statistics for multiple linear regression (MLR) and multiple nonlinear regression (MNLR) model during the dry season sampling.

The model equations generated using multiple linear regression (MLR) to predict dry season sampling are presented below:

$$PM_{2.5} = 73 - 3.5Ws + 1.45Wd - 13.5Temp + 0.76Rh \quad (11)$$

$$PM_{10} = 117 - 6.6Ws + 1.53Wd - 14.6Temp + 0.72Rh \quad (12)$$

$$HCHO = - 0.14 - 0.0154Ws + 0.00697Wd - 0.0549Temp + 0.00442Rh \quad (13)$$

$$TVOC = - 2.29 + 0.338Ws + 0.0343Wd - 0.273Temp + 0.0302Rh \quad (14)$$

$$CO = 4.8 + 0.193Ws + 0.0499Wd - 0.554Temp + 0.0077Rh \quad (15)$$

$$O_2 = 23.5 - 0.402Ws - 0.00810Wd + 0.0261Temp - 0.0116Rh \quad (16)$$

The model equations generated using multiple nonlinear regression (MNLR) to predict dry season sampling are presented below:

$$PM_{2.5} = 99556.221 - 105.176*Ws + 132.597*Wd - 11636.591*Temp + 340.052*Rh - 0.476*Wd^2 + 374.830*Temp^2 - 4.773*Rh^2 + 5.849E\text{-}04*Wd^3 - 4.001*Temp^3 + 2.224E\text{-}02*Rh^3 \quad (17)$$

$$PM_{10} = 113179.401 - 108.869*Ws + 315.246*Wd - 14561.006*Temp + 370.553*Rh - 1.178*Wd^2 + 469.\ *Temp^2 - 5.204*Rh^2 + 1.477E\text{-}03*Wd^3 - 5.009*Temp^3 + 2.427E\text{-}02*Rh^3 \quad (18)$$

$$HCHO = 363.321-0.503*Ws + 3.222*Wd - 65.649*Temp + 1.287*Rh - 1.212E\text{-}02*Wd^2 + 2.108*Temp^2 - 1.756E\text{-}02*Rh^2 + 1.512E\text{-}05*Wd^3 - 2.240E\text{-}02*Temp^3 + 7.982E\text{-}05*Rh^3 \quad (19)$$

$$TVOC = 635.035-2.667*Ws + 18.209*Wd - 231.877*Temp + 5.829*Rh - 6.799E\text{-}02*Wd^2 + 7.456*Temp^2 - 7.921E\text{-}02*Rh^2 + 8.407E\text{-}05*Wd^3 - 7.923E\text{-}02*Temp^3 + 3.601E\text{-}04*Rh^3 \quad (20)$$

$$CO = 2991.012-5.089*Ws - 7.902*Wd - 280.286*Temp + 22.608*Rh + 3.307E\text{-}02*Wd^2 + 9.070*Temp^2 - 0.339*Rh^2 - 4.388E\text{-}05*Wd^3 - 0.098*Temp^3 + 1.67E\text{-}03*Rh^3 \quad (21)$$

$$O_2 = -251.260 + 0.396*Ws + 11.452*Wd - 67.954*Temp - 1.310*Rh - 4.405E\text{-}02*Wd^2 + 2.235*Temp^2 + 1.800E\text{-}02*Rh^2 + 5.573E\text{-}05*Wd^3 - 2.418E\text{-}02*Temp^3 - 7.780E\text{-}05*Rh^3 \quad (22)$$

Table 1: Goodness of fit statistics for multiple linear regression (MLR) model during the dry season sampling

S/N	Pollutants	Observation	DF	SSE	MSE	RMSE	R^2	P-value
1	$PM_{2.5}$	80	75	49652	12413	111.4136	0.157	0.012
2	PM_{10}	80	75	58175	14544	120.5985	0.152	0.014
3	HCHO	80	75	0.94632	0.23658	0.486395	0.12	0.045
4	TVOC	80	75	22.363	5.591	2.36453	0.205	0.002
5	CO	80	75	56.073	14.018	3.744062	0.114	0.057
6	O_2	80	75	2.2164	0.5541	0.744379	0.181	0.004

Table 2: Goodness of fit statistics for multiple nonlinear regression (MNLR) model during the dry season sampling

S/N	Pollutants	Observation (N)	DF	SSE	MSE	RMSE	R^2	P-value
1	$PM_{2.5}$	80	67.00	135350.087	2020.151	44.946	0.573	0.000
2	PM_{10}	80	67.00	159822.783	2385.415	48.841	0.581	0.000
3	HCHO	80	67.00	3.897	0.058	0.241	0.504	0.000
4	TVOC	80	67.00	35.683	0.533	0.730	0.673	0.000
5	CO	80	67.00	223.312	3.333	1.826	0.546	0.000
6	O_2	80	67.00	6.515	0.097	0.312	0.466	0.034

The sum of square error (SSE), mean square error (MSE), and root mean square error (RMSE) for the model generated for each air pollutants ($PM_{2.5}$, PM_{10}, HCHO, TVOC, CO and O_2) for dry season sampling model using multiple linear regression model (MLR) and multiple nonlinear regression model (MNLR) are presented in table 1 and 2 respectively. The results shows that, the meteorological factors significantly influence (p-value < 0.05)

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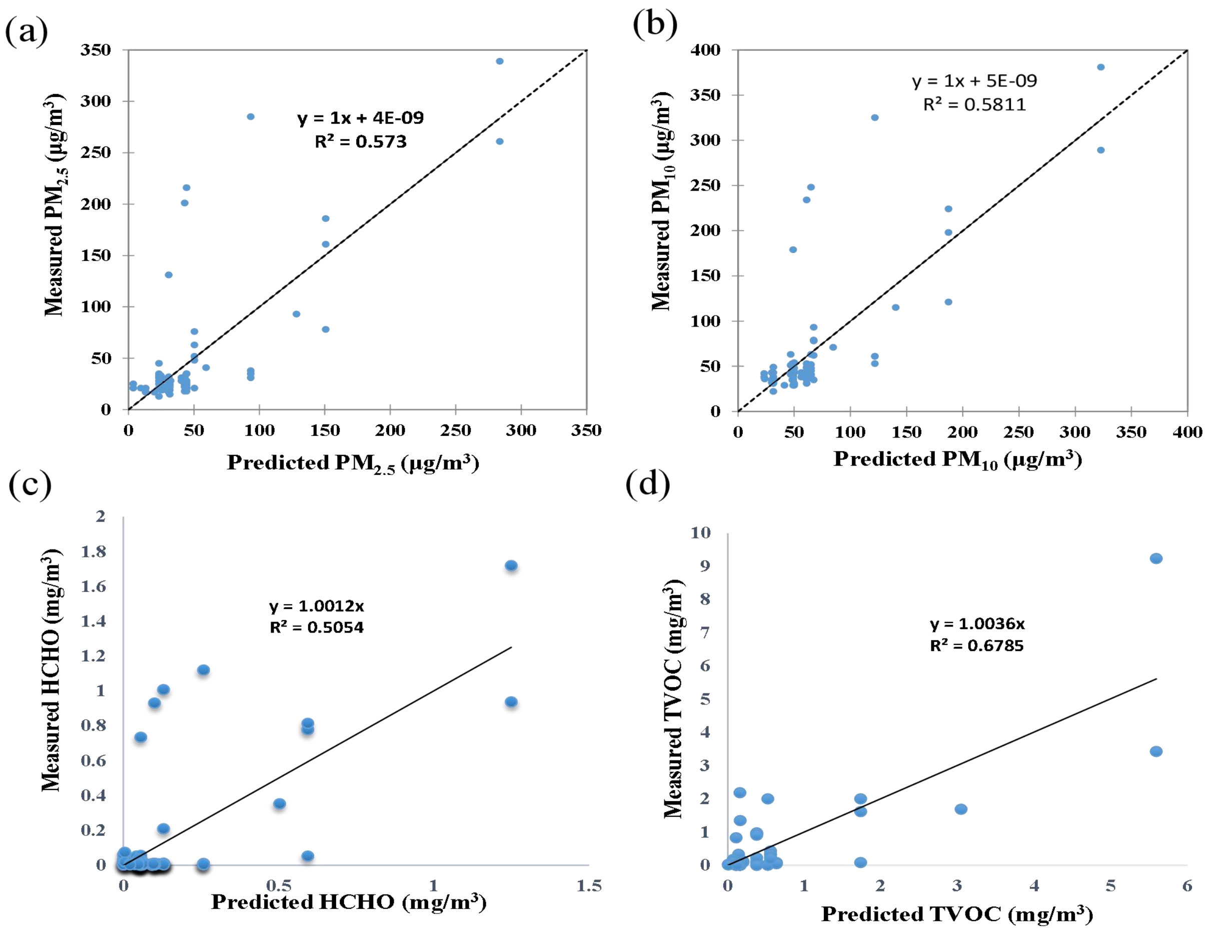
the propagation of the concentrations of the air pollutants when both MNLR and MLR are used to predict except for CO that is not significantly influence (p-value > 0.05) the propagation of CO by meteorological parameters.

The goodness of fit of the various air pollutants when MLR is used to predict shows that, the meteorological parameters accounted for 0.157, 0.152, 0.120, 0.205, 0.114, and 0.181 of the coefficient of determination (R^2) of $PM_{2.5}$, PM_{10}, HCHO, TVOC, CO and O_2 respectively. This is similar to what is reported by Antai *et al*., (2018) with a coefficient of determination of 0.048, 0125 and 0.125 for VOC, CO and $PM_{2.5}$ during the dry sampling respectively. Also, the goodness of fit of the various air pollutants when MNLR is used to predict shows that, the meteorological parameters accounted for 0.573, 0.581, 0.504, 0.673, 0.546, and 0.466 of the coefficient of determination (R^2) of $PM_{2.5}$, PM_{10}, HCHO, TVOC, CO and O_2 respectively in the study area. The relationship between the predicted and measured of each air pollutants are presented in figure (2) for dry season air pollutants sampling.



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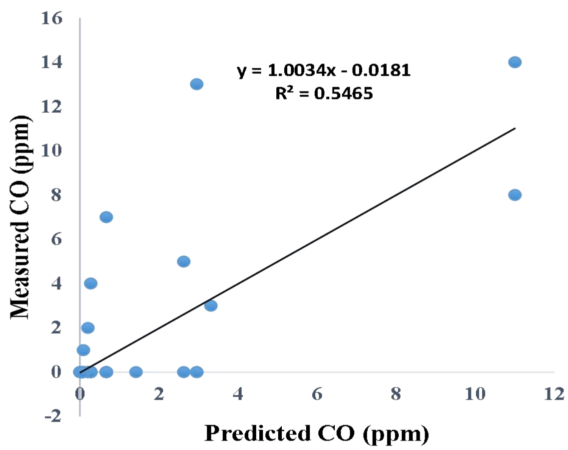

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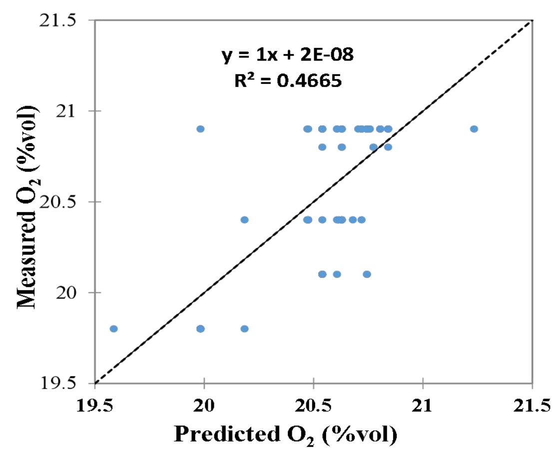

Figure 2: Relationship between predicted and measured (a) $PM_{2.5}$ (b) PM_{10} (c) HCHO (d) TVOC (e) CO (f) O_2 during the dry season.

Variation of air pollutants concentration with meteorological parameters in the wet season

A model equations generated using multiple linear regression model (MLR) and multiple nonlinear regression model (MNLR) are presented in equation 23 to 28 and 29 to 34 respectively. The equations were used to predict the concentrations of each pollutants in the sampling area during the wet season. Table 3 and 4 shows the goodness of fit statistics for multiple linear regression (MLR) and multiple nonlinear regression (MNLR) model during the wet season sampling.

The model equations generated using multiple linear regression (MLR) to predict wet season sampling are presented below:

$$PM_{2.5} = - 58 - 4.01Ws - 0.240Wd + 2.28Temp + 1.02Rh \quad (23)$$
$$PM_{10} = - 60 - 3.78Ws - 0.249Wd + 2.43Temp + 1.04Rh \quad (24)$$
$$HCHO = - 0.201 + 0.00024Ws - 0.000048Wd + 0.00472Temp + 0.00116Rh \quad (25)$$
$$TVOC = - 0.412 + 0.00220Ws - 0.000049Wd + 0.0096Temp + 0.00231Rh \quad (26)$$
$$CO = - 0.25 + 0.0208Ws + 0.000086Wd + 0.0002Temp + 0.0026Rh \quad (27)$$
$$O_2 = 17.3 + 0.0715Ws + 0.00167Wd + 0.0770Temp + 0.0120Rh \quad (28)$$

The model equations generated using multiple nonlinear regression (MNLR) to predict wet season sampling are presented below:

$$PM_{2.5} = 9868.277 - 66.794*Ws + 231.145*Wd - 3392.115*Temp + 273.656*Rh - 0.879*Wd^2 + 107.221*Temp^2 - 4.169*Rh^2 + 1.103E-03*Wd^3 -1.123*Temp^3 + 2.060E-02*Rh^3 \quad (29)$$

$$PM_{10} = 8164.657 - 64.662*Ws + 244.3985*Wd - 3331.443*Temp + 269.057*Rh -0.928*Wd^2 + 105.287*Temp^2 - 4.108*Rh^2 + 1.164E-03*Wd^3 - 1.102*Temp^3 + 2.034E-02*Rh^3 \quad (30)$$

$$HCHO = -3.980 - 3.210E-02*Ws + 0.290*Wd - 2.380*Temp + 0.157*Rh - 1.086E-03*Wd^2 + 0.0755*Temp^2 - 2.473E-03*Rh^2 + 1.343E-06*Wd^3 - 7.937E-04*Temp^3 + 1.271E-05*Rh^3 \quad (31)$$

$TVOC = -40.895 - 2.679E\text{-}02*Ws + 0.613*Wd - 1.715*Temp + 0.190*Rh - 2.260E\text{-}03*Wd^2 + 0.05466*Temp^2 - 3.159E\text{-}03*Rh^2 + 2.760E\text{-}06*Wd^3 - 5.762E\text{-}04*Temp^3 + 1.719E\text{-}05*Rh^3$ (32)

$CO = 7050.499 - 1.529*Ws - 4.286E\text{-}02*Wd - 672.979*Temp + 8.919*Rh + 2.702E\text{-}02*Ws^2 + 2.121E\text{-}04*Wd^2 + 20.490*Temp^2 - 9.342E\text{-}02*Rh^2 - 0.206*Temp^3 + 2.627E\text{-}04*Rh^3$ (33)

$O_2 = -339.295 + 0.400*Ws + 3.505*Wd + 10.208*Temp - 1.877*Rh - 1.302E\text{-}02*Wd^2 - 0.372*Temp^2 + 0.027*Rh^2 + 1.578E\text{-}05*Wd^3 + 4.463E\text{-}03*Temp^3 - 1.302E\text{-}04*Rh^3$ (34)

Table 3: Goodness of fit statistics for multiple linear regression (MLR) model during the wet season sampling

S/N	Pollutants	Observation	DF	SSE	MSE	RMSE	R^2	P-value
1	$PM_{2.5}$	80	75	8740.3	2185.1	46.74505	0.319	0.000
2	PM_{10}	80	75	9490	2372.6	48.70934	0.312	0.000
3	HCHO	80	75	0.001297	0.000324	0.018008	0.061	0.309
4	TVOC	80	75	0.003672	0.000918	0.030299	0.034	0.618
5	CO	80	75	0.02989	0.00747	0.086429	0.006	0.977
6	O_2	80	75	0.26905	0.06726	0.259345	0.07	0.238

Table 4: Goodness of fit statistics for multiple nonlinear regression (MNLR) model during the wet season sampling

S/N	Pollutants	Observation (N)	DF	SSE	MSE	RMSE	R^2	P-value
1	$PM_{2.5}$	80	67.00	9023.045	134.672	11.605	0.671	0.000
2	PM_{10}	80	67.00	10893.060	162.583	12.751	0.642	0.000
3	HCHO	80	67.00	0.008	0.000121	0.011	0.622	0.000
4	TVOC	80	67.00	0.043	0.001	0.025	0.601	0.000
5	CO	80	67.00	300.123	4.479	2.116	0.390	0.040
6	O_2	80	67.00	9.302	0.139	0.373	0.615	0.000

The sum of square error (SSE), mean square error (MSE), and root mean square error (RMSE) for the model generated for each air pollutants ($PM_{2.5}$, PM_{10}, HCHO, TVOC, CO and O_2) for wet season sampling model using multiple linear regression model (MLR) and multiple nonlinear regression model (MNLR) are presented in table 3 and 4 respectively. The results shows that, the meteorological factors significantly influence (p-value < 0.05) the propagation of the concentrations of the air pollutants when a multiple nonlinear regression (MNLR) is used to predict the pollutants. The meteorological parameters did not significantly influence (p-value > 0.05) the propagation of the air pollutants when a multiple linear regression (MLR) is used except for $PM_{2.5}$ and PM_{10} which are significantly influence (p-value < 0.05).

The goodness of fit of the various air pollutants when MLR is used to predict shows that, the meteorological parameters accounted for 0.319, 0.312, 0.061, 0.034, 0.006, and 0.07 of the coefficient of determination (R^2) of $PM_{2.5}$, PM_{10}, HCHO, TVOC, CO and O_2 respectively. Also, the goodness of fit of the various air pollutants when MNLR is used to predict shows that, the meteorological parameters accounted for 0.671, 0.642, 0.622, 0.601, 0.390, and 0.615 of the coefficient of determination (R^2) of $PM_{2.5}$, PM_{10}, HCHO, TVOC, CO and O_2 respectively in the study area. The variations of CO concentration was

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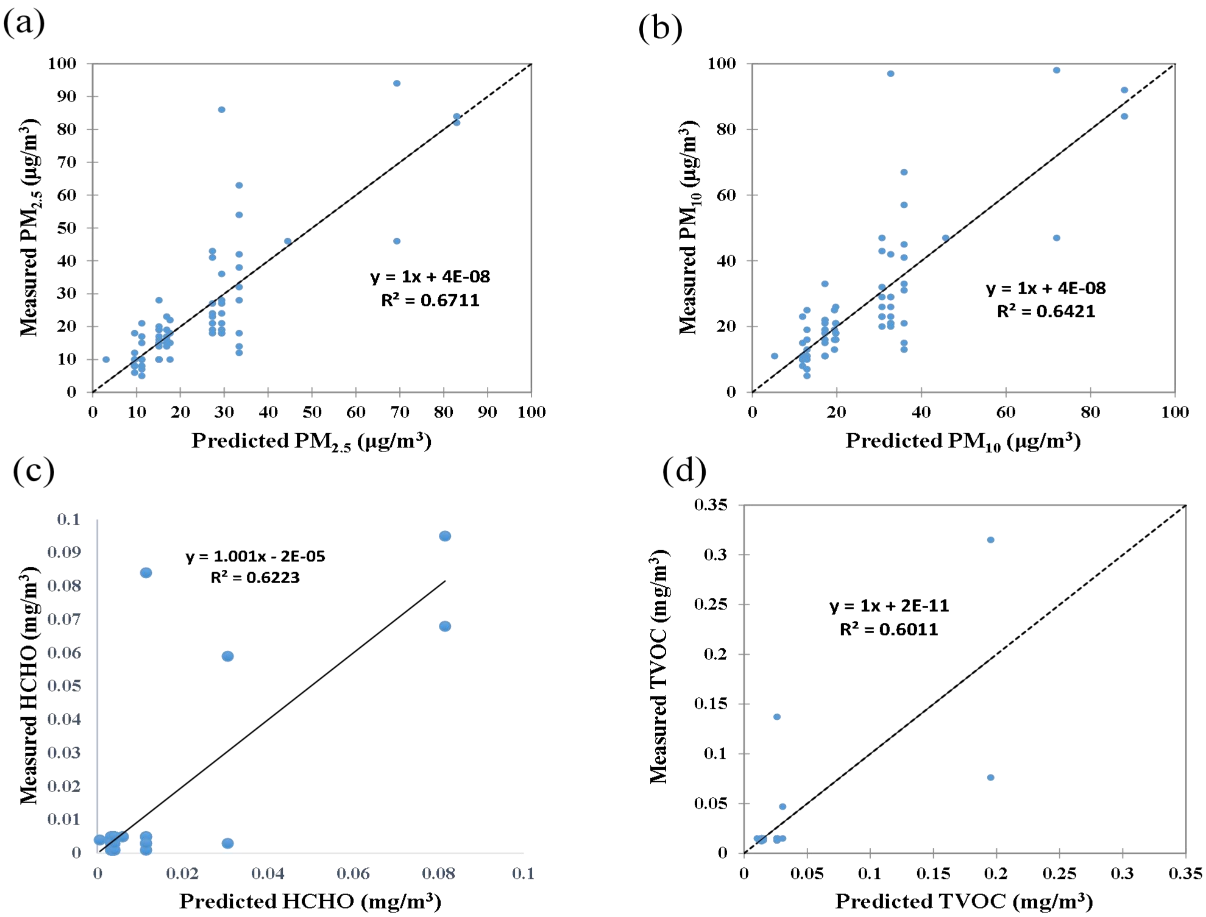
least explained by the meteorological parameters.

The coefficient of determination (R^2) of this study were similar to what was reported by Kayes *et al*., (2019) in the relationship between $PM_{2.5}$ and PM_{10} with meteorological parameters. Kayes *et al*., (2019) noted that, the coefficient of determination of CO, $PM_{2.5}$, PM_{10} were 0.1494, 0.7027, 0.6167 and 0.19, 0.72 and 0.63 using multiple linear regression (MLR) and multiple nonlinear regression (MNLR) respectively. Comparison of the models show MNLR model performed better than the linear model (MLR). Yi *et al*., (2016) also documented that MNLR models exhibited superior performance in elucidating the relationship between $PM_{2.5}$ concentration and meteorological factors in China. The relationship between the predicted and measured of each air pollutants are presented in figure (3) for wet season air pollutants sampling.



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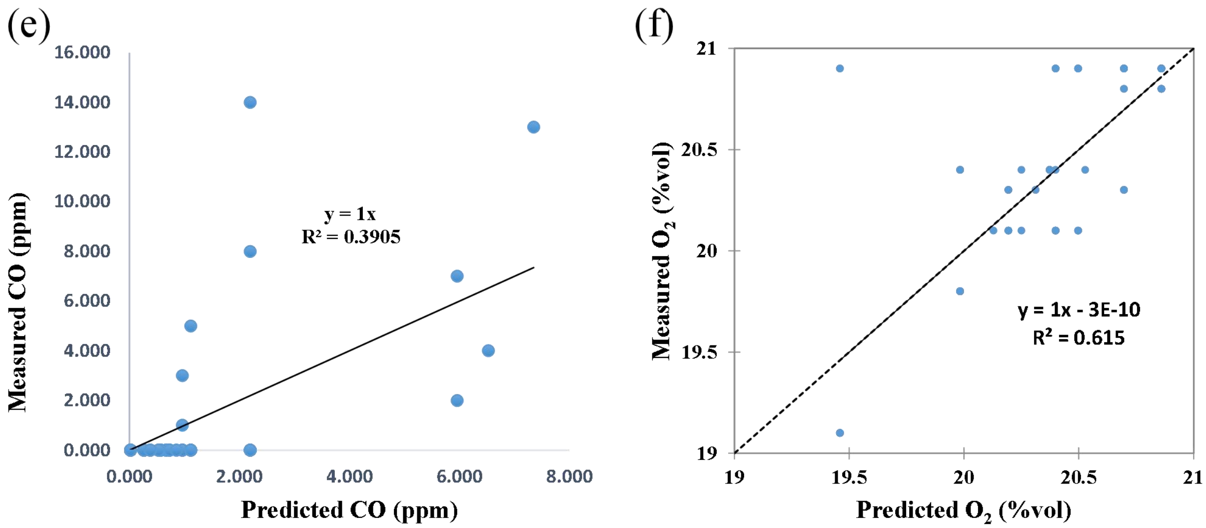

Figure 3: Relationship between predicted and measured (a) $PM_{2.5}$ (b) PM_{10} (c) HCHO (d) TVOC (e) CO (f) O_2 during the wet season.

CONCLUSION AND RECOMMENDATION

The results of the multiple linear regressions and the multiple nonlinear regressions in the study area revealed that, the meteorological parameters induced the propagation of the air pollutants concentrations in the study area. The MNLR model performed better in predicting the concentration propagation than the MLR. The findings underscore the significance of embracing MNLR as a preferred modelling approach when addressing air pollution scenarios characterized by intricate and non-linear dependencies on meteorological parameters. As we strive for more effective pollution management and targeted mitigation strategies, the adoption of MNLR contributes to a more comprehensive and accurate assessment of the interaction between meteorological parameters and air quality, ultimately advancing our capacity to address and ameliorate the impacts of air pollution on public health and environmental well-being.

Given the superior performance of multiple nonlinear regression (MNLR) models in predicting air pollutant concentration propagation, future research and environmental monitoring efforts should prioritize the use of MNLR models for more accurate assessments. There is a need to enhance the monitoring of meteorological factors such as wind speed, wind direction, temperature, and humidity. This will improve the understanding and prediction of air pollution dynamics. Targeted mitigation measures should be implemented to address the specific meteorological conditions that contribute to increased air pollution levels. For example, measures to control emissions during periods of low wind speed or unfavorable wind direction could be implemented.

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