Prediction and Modeling of Dry Seasons Air Pollution Changes Using Multiple Linear Regression Model: A Case Study of Port Harcourt and its Environs, Niger Delta, Nigeria.

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Abstract—The influence of meteorological parameters on air pollutants over Port Harcourt and its environs in the dry season was modeled using multiple linear regressions model. Results indicated that meteorological parameters significantly influenced pollutant concentrations; results also showed poor linear relationships between meteorological parameters and pollutant concentrations, and that meteorological parameters are poor predictor variables of concentrations of air pollutants in the area. Pollution roses of pollutants dispersion pattern in the study area showed that pollutant concentrations increase with increased wind speed. Result also showed that wind speed exerts positive influence on the concentration levels of pollutants in the study area. The yearly prediction of air pollutants was also carried out using a ten-year data from previous studies conducted in the study area. The prediction was done using regression analysis and year as the predictor variable to develop a model. The relationship between air pollutants and year was therefore established for the annual prediction of the future pollutant concentrations in the dry seasons for period of the next fifteen years.
Keywords—Multiple linear Regressions Model, Air Pollution changes, Meteorological variables concentration.

I.   INTRODUCTION

Air quality impacts on the environment can therefore be quantified by simulating environmental conditions using analytical tool known as modeling (Okpala *et al.,* 2013).
The simulating of real-life environmental situations can use the systematic method called modeling. Modeling is a tool by which mathematical equations are used to predict the air pollutants future behaviour.

Modeling assists in studying and predicting the impacts of various environmental components and also viewing the environment as a system by representing simplified variation of environmental system mathematically and also prediction, testing and comparison of reasonable alternative situations (Okpala *et al.,* 2013).

The effective and efficient way to understand the interactions of various air pollution scenarios as relate with meteorology, topography and existing air quality characteristics are air pollution models (Okpala *et al.,* 2013).

The relative high concentration of air pollutants in Port Harcourt can be attributed majorly to industrial activities such as oil and gas related activities and vehicular emissions (Antai, 2016). Geographical and meteorological conditions of the study area can also influence some local background concentration of air pollutants since there is a relationship between air pollution and meteorological variables, thus air pollution modeling is the development of a functional relationship between air pollutions concentration and other control variables.

Most of the conventional models have been proved inaccurate (Esplin, 1995). These models depend basically on detailed knowledge of pollutant sources, topography in the surrounding environment (Elangasinghe *et al*., 2014).

Multiple linear regression (MLR) model was developed and applied to predict the variations of air pollutants concentrations with meteorological parameters of the study area. This study highlights how the relationships between

measured air pollutant concentrations and meteorological parameters were modeled using multiple linear regressions and generalized additive model.

STUDY LOCATION
Description of the Study Area
Location

Port Harcourt metropolis is located between latitudes $4^035'$ and $5^030'$ North and between longitudes $6^054'$ and $7^008'$ East. It covers an estimated area of 1811.6 square kilometer and is the capital of Rivers State. Port Harcourt was established in 1914 by the British colonial administration under Lord Lugard to meet the pressing economic needs of the Europe. Port Harcourt which lies at the heart of the Niger Delta, one of the world's richest wetlands, is bounded on the South by the Atlantic Ocean, to the North by Imo and Abia States to the East by Akwa Ibom State and to the West by Bayelsa and Delta State respectively. Some of the well known residential areas in Port Harcourt and its environs include: Port Harcourt, Obio/Akpor, Eleme, Oyigbo, Ikwerre and Etche Local Government Areas (LGAs) (Awosika, 1995).

II.   METHODOLOGY
METHOD OF DATA ANALYSIS AND MODELING

Mean concentration of air pollutants was computed using equation (1)

$$\overline{X} = \frac{\sum_{i=1}^{n} X_{meas,i}}{N} \tag{1}$$

Standard deviation was computed using equation (2)

$$s = \sqrt{\frac{\sum \left(X_{meas,i} - \overline{X} \right)}{N-1}} \tag{2}$$

Standard error estimate was determined using equation (3)

$$\sigma_X = \frac{s}{\sqrt{N}} \tag{3}$$

where, s is the standards deviation, $X_{meas,i}$ is the measured i^{th} data point, $\overline{X}$ is the mean and N is the total number of data set.

Coefficient of variation of air pollutants

The coefficient of variation of each parameter was computed using Equation (4)

$$\% CV = \frac{S}{\overline{X}} = \frac{\sqrt{\frac{\sum \left(X_{meas,i} - \overline{X} \right)^2}{N-1}}}{\frac{\sum_{i=1}^{N} X_{meas,i}}{N}} \tag{4}$$

Computation of Exceedance Factor (EF)

A factor known as Exceedance Factor (CPCB, 2006) was used to determine pollutants compliance with national and international standards.

The Exceedance Factor (EF) was calculated using equation (5) as follows:

$$\text{Excedence Factor (EF)} = \left(100 \ \frac{C_i}{C_{std}} \right) \tag{5}$$

where C_i is the measured concentration of the ith parameter in the ambient air.

C_{std} is the regulatory standard recommended for the ith parameter.

For EF < 100, the parameter is said to be withing permissible limit, and for EF > 100, the parameter is said to exceed permissible limit. The EF for each pollutant was computed based on the Federal Ministry of Environment (FMEnv) stipulated permissible limit as contained in FEPA (1991, 1992) and National Ambient Air Quality Standards (NAAQS).

Model Development

Multiple linear regression (MLR) models were applied to predict the variations of pollutant concentrations with meteorological parameters. The following steps were applied in the model building process.

i.   Data was collected through field measurement.
ii. Data was prepared and analysed using statistical software.
iii. Appropriate variables were selected as input parameters.
iv. Models were built using the variables.
v.   Models were tested and validated models and

vi.   Pollutants were predicted using built models.

Multiple linear regression (MLR) modeling approach was employed to model the influence of meteorological variations on air pollutants.

Modeling was based on the following fundamental approaches:

$$\text{outcome}_i = (\text{model}) + \text{Error}_i \qquad (6)$$

$$Y_i = (b_o + b_1 X_{i1} + b_2 X_{i2} + ... + b_n X_n) + \varepsilon_i \qquad (7)$$

$$y_i = \beta_o + \sum_{i=1}^{n} \beta_i x_i + \varepsilon_i \qquad (7)$$

Where; Y_i and y_i are model outcomes or outputs,

$X_1, X_2, ..., X_n$ are predictor variables,

b_0, b_1, b_2, ..., b_n are regression coefficients, and

ε_i is the error factor called residual.

Multiple linear regressions (MLR) modeling technique was employed to predict air pollutants concentration in the study area using wind speed (Ws), wind direction (Wd), temperature (Temp), air pressure (Ap) and relative humidity (Rh) as predictor variables. The multiple linear regressions were performed using Statistical Package for the Social Science (SPSS) software, originally developed by International Business Machines (IBM). Stepwise regression approach was used to determine the relationship between air pollutants and individual meteorological parameter. Stepwise regression of independent parameter was performed using Equations (7) and (8).

$$PM_{pred} = f(X_i)$$
$$PM_{pred} = f(Wsp_i, Wd_i, Temp_i, Rh_i) \qquad (8)$$

Model Validation

The model performance was evaluated in consonance with guidelines instituted by EPA (2007). Specific analyses was performed to validate the model outputs against measured data. Both quantitative (statistical) and qualitative (visual) methods were adopted. Measured data was paired against predicted values. Various statistical parameters such as mean square error (MSE) , root mean sqaure error (RMSE) were used to validate and determine the quality of the prediction models. In addition, a measure of goodness of fit known as coefficient of determination, R-sqaure (R^2) was used to determine the total variability in the dependent variables that is accounted for by the model eqautions.

The mean square error (MSE) was computed as the mean difference between predicted and measured values using Equation (9), while the root mean square error was computed using Equation (10).

$$MSE = \frac{1}{N} \sum_{i=1}^{n} (Y_{pred,i} - X_{meas,i}) \qquad (9)$$

$$RMSE = \left[\frac{1}{N} \sum_{i=1}^{n} (Y_{pred,i} - X_{meas,i})^2 \right]^{\frac{1}{2}} \qquad (10)$$

where N is the number of measured data or observations.

Sum of square error (SSE) will be calculated using equation (11)

$$SSE = \sum (X_{meas,i} - \overline{X})^2 \qquad (11)$$

The sum of squares of the regression model (SS_M) was computed using Equation (12).

$$SS_M = \sum_i (Y_{pred,i} - X_{meas,i})^2 \qquad (12)$$

The residual sum of squares (RSS) was computed using Equation (13)

$$RSS = \sum_{i=1}^{n} (\varepsilon_i)^2 = \sum_{i=1}^{n} (y_i - f(x_i))^2 \qquad (13)$$

The residual sum of square error is therefore computed as

The residual sum of squares (SS_R) was computed using Equation (14).

$$SS_R = \sum_i (Y_{pred,i} - \overline{X})^2 \qquad (14)$$

The total sum of squares (SS_T) was computed using Equation (15).

$$SS_T = SS_M + SS_R = \sum_i (X_{meas,i} - \overline{X})^2 \qquad (15)$$

Coefficient of determination R-sqaure (R^2)

The coefficient of determination is the proportion of the total sample variability explained by the regression models and indicates how well the models fit the data. The coefficient of determination was computed using Equation (16).

$$R^2 = \frac{\text{Explained variation}}{\text{Total variation}} = \frac{SS_M}{SS_T} = \frac{\sum_i (Y_{pred,i} - \overline{X})^2}{\sum_i (X_{meas,i} - \overline{X})^2} \qquad (16)$$

where Y_i is the predicted concentration of pollutant, $X_{meas,i}$ is the individual measured concentration of air pollutant and

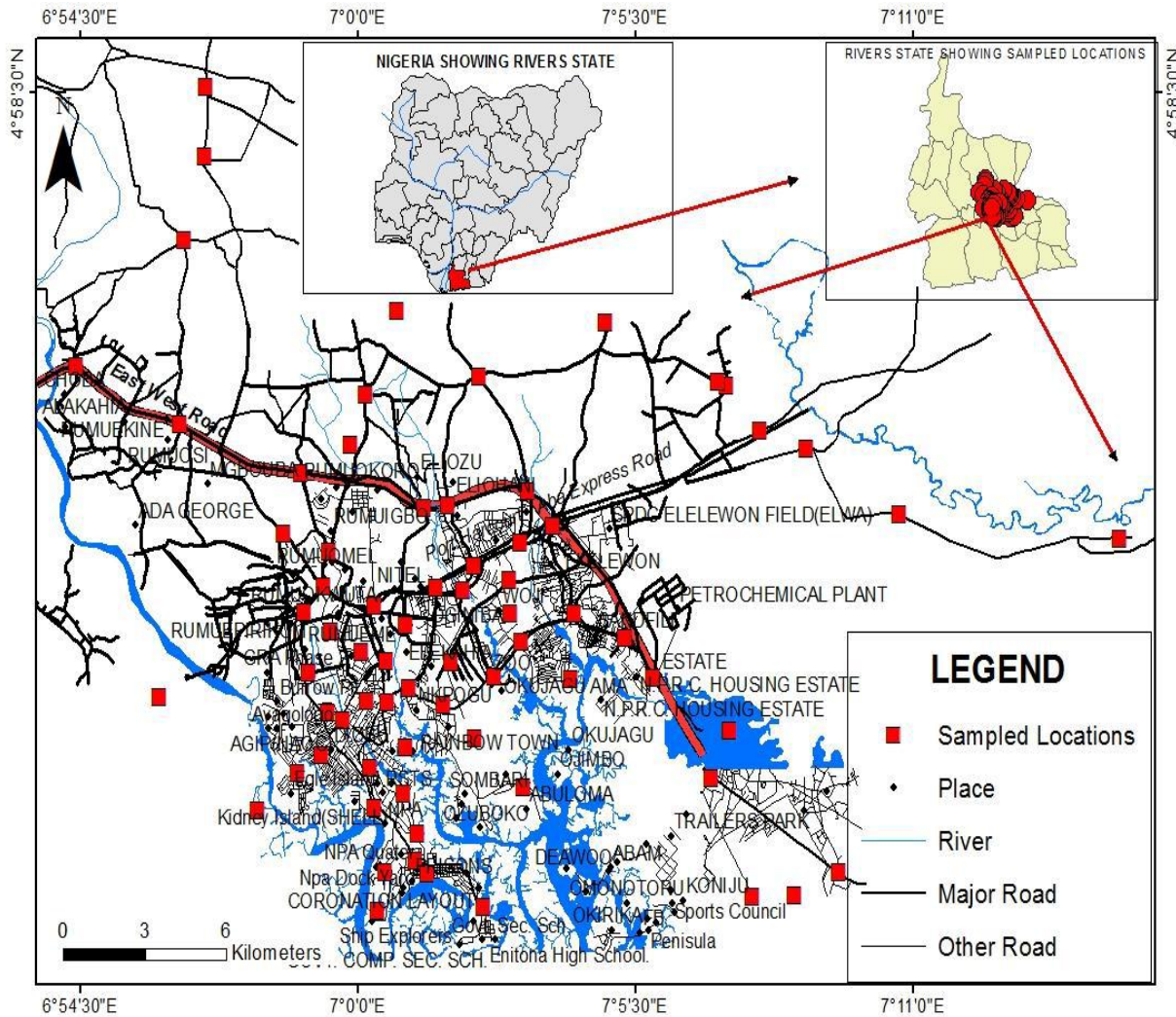$\overline{X}$ is the mean concentration of measured pollutant.

Fig.1: Port Harcourt and its Environs showing Sampling Points for the Study.

III.   PRESENTATION OF RESULT

(i)   Variation of Volatile Organic Compounds (VOCs) with Meteorological Parameters in the Dry Season

The results (shown in Figure 2 (a-e)) indicated that VOCs varied significantly with temperature, and positively correlated with wind speed. The stepwise regression linear models (shown in Table 1) show that the linear relationships between VOCs and wind speed, wind direction, relative humidity and air pressure are not significant at 0.05 confidence levels. However, the relationship between ambient temperature and VOCs concentrations is significant at 0.01 confidence level for a 2-tail test with a coefficient of determination (R^2) of 0.015). This implies that though VOCs varies significantly with temperature, only a fraction of 1.5% of the variation can be explained. Results (Table 1) further indicated that wind speed, wind direction, relative humidity and air pressure respectively accounted for 1.8%, 0.18%, 0.14% and 0.014% of the variation.
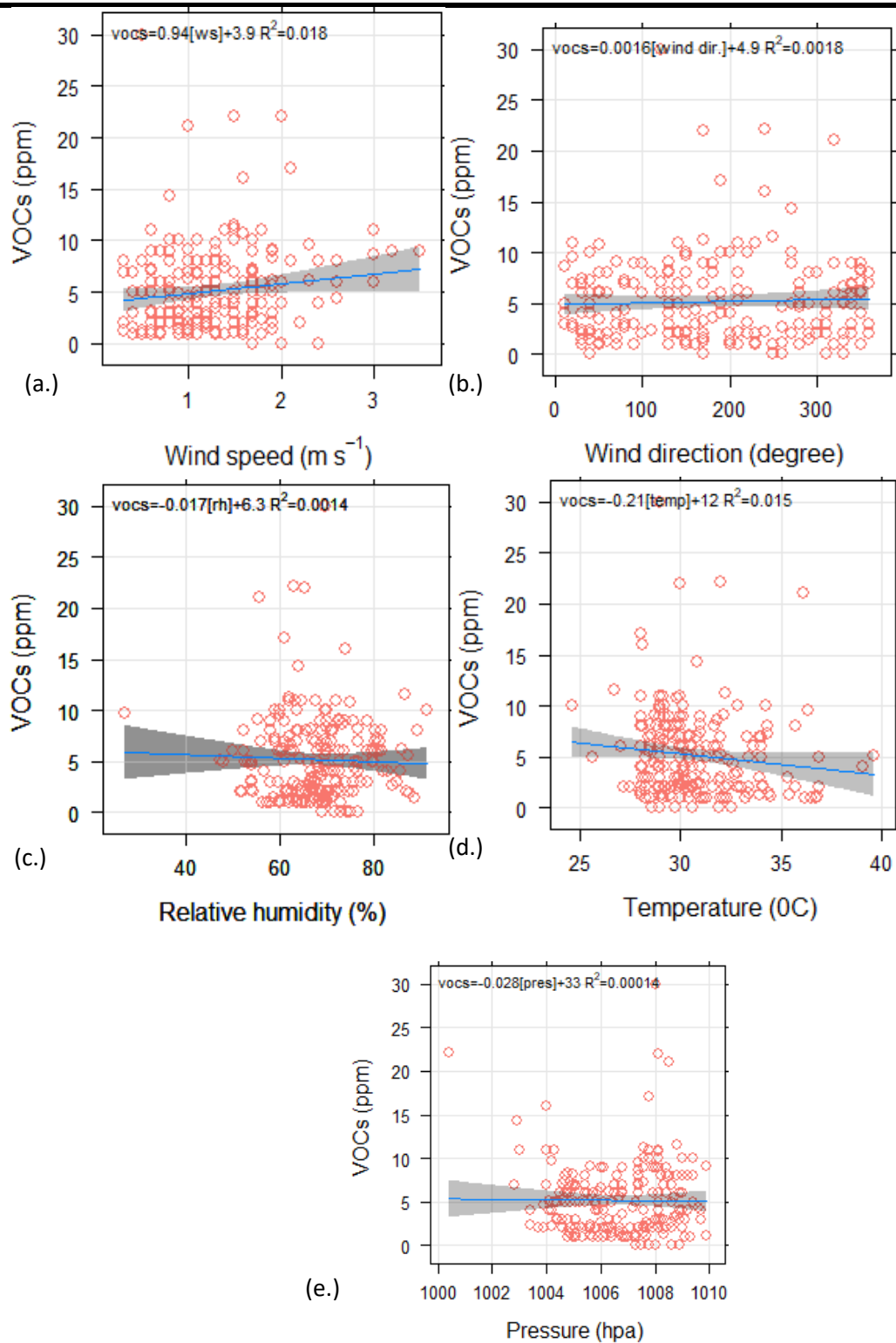
Fig.2 (a-e): Relationship between Predicted VOCs and Meteorological Parameters in the Dry Season

Table.1: Stepwise Linear Models for Dry Season VOCs

Pollutant	Model	R^2	t-statistic	Sig. (2-tailed)
VOCs	= 3.9 + 0.94*Wsp	0.018	1.807	0.072
	= 4.9 + 0.0016*Wd	0.0018	0.294	0.769
	= 6.3 – 0.017*Rh	0.0014	-1.692	0.092
	= 12 – 0.21*Temp	0.015	-2.084	0.038*
	= 33.0 – 0.028*Pres	0.00014	-0.070	0.944

* Correlation is significant at the 0.05 level (2-tailed).

A multiple linear regression model for the prediction of VOCs was developed using all the meteorological parameters as predictor variables. The model for the prediction of VOCs concentrations was therefore derived as shown in Equation (17). The derived Equation (17) was used to predict the concentrations of VOCs in the study area in the dry season.

$$VOCs = 28.755 + 0.901*Wsp + 0.001*Wd - 0.063*Rh - 0.279*Temp - 0.012*Pres \qquad (17)$$

Table.2: Analysis of Variance (ANOVA) for Dry Season VOCs Prediction Model

Model	SSE (ppm)	df	MSE (ppm)	RMSE (ppm)	F	Sig.
Regression (SS_M)	159.996	5	31.999	5.6568	1.857	0.103*
Residual (SS_R)	3567.538	207	17.234			
Total (SS_T)	3727.534	212				

*Not significant at the 0.05 level (2-tailed).

The mean square error (MSE) and the root mean square error were computed to be 31.999ppm and 5.6568ppm respectively. The model sum of squares error (SS_M), residual sum of squares error (SS_R) and total sum of squares error (SS_T) were computed to be 159.996ppm, 3567.538ppm and 3727.534ppm respectively as shown in Table 2. The result (Table 2) showed that meteorological parameters significantly (P-value <0.05) influence the concentrations of VOCs in the area. However, the goodness of fit (Figure 3)

shows a poor linear relationship between VOCs and meteorological parameters with a coefficient of determination (R^2) of 0.043. This implies that meteorological parameters accounted for only 4.3% of the variation of VOCs concentrations in the area. The goodness of fit between predicted and measured concentrations of VOCs is shown in Figure 3, while the predicted values are plotted against measured values as shown in Figure 4.
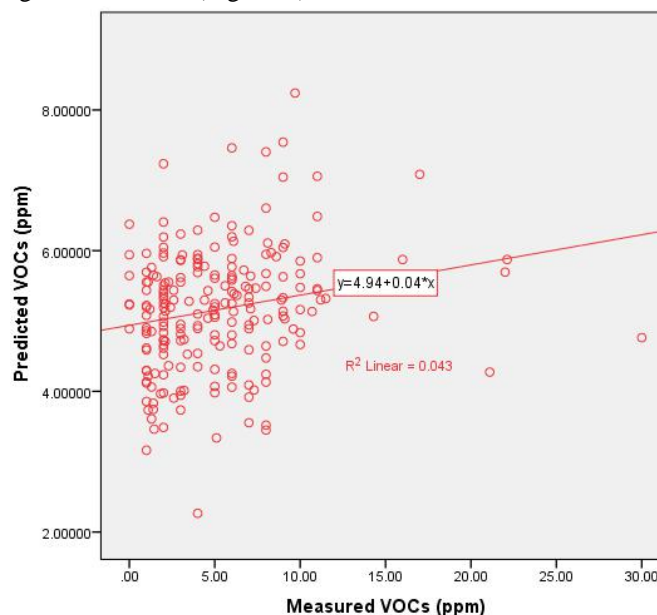

Fig.3: Relationship between Predicted VOCs and Measured VOCs in the Dry Season
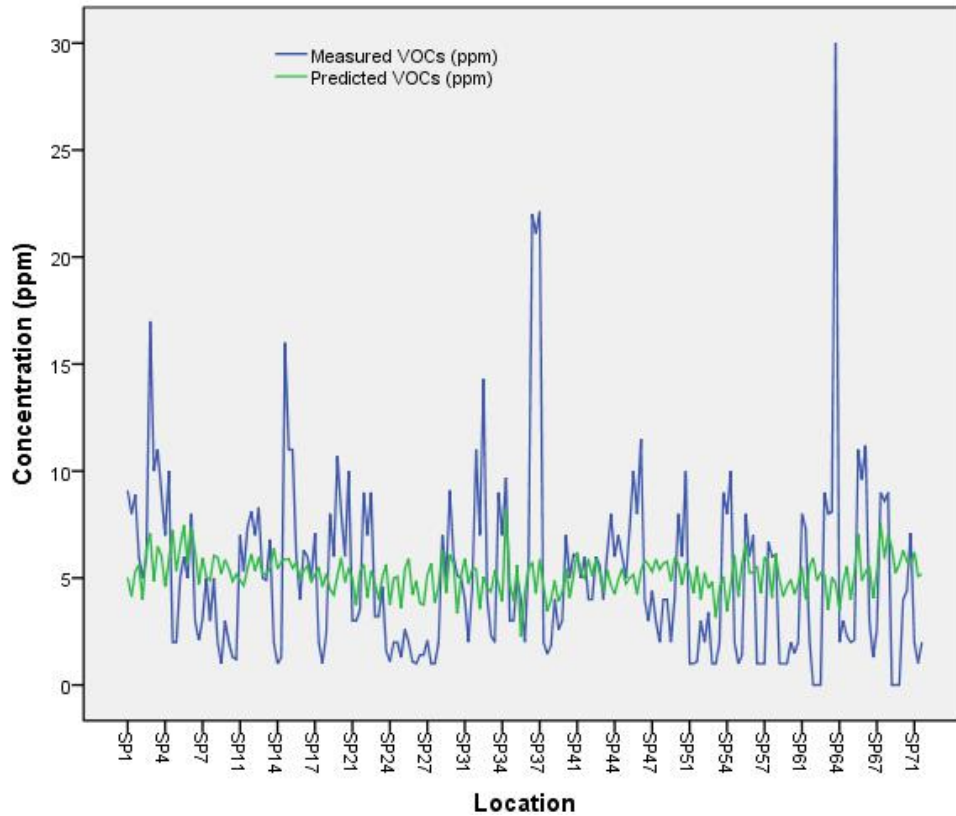
Fig.4: Predicted VOCs versus Measured VOCs in the Dry Season

Variation of Carbon Monoxide (CO) with Meteorological Parameters in the Dry Season

Results (shown in Figure 5 (a-e)) showed that concentrations of CO correlated significantly with wind speed in a positive manner. The stepwise regression linear models (shown in Table 3) show that the linear relationships between concentrations of CO and wind direction, relative humidity, temperature and air pressure are not significant at 0.05 confidence levels. However, the relationship between wind speed and concentrations of CO is highly significant at 0.01 confidence level for a 2-tail test with a coefficient of determination (R^2) of 0.088. This implies that though concentrations of CO vary positively with wind speed, only a fraction of 8.8% of the variation can be explained.
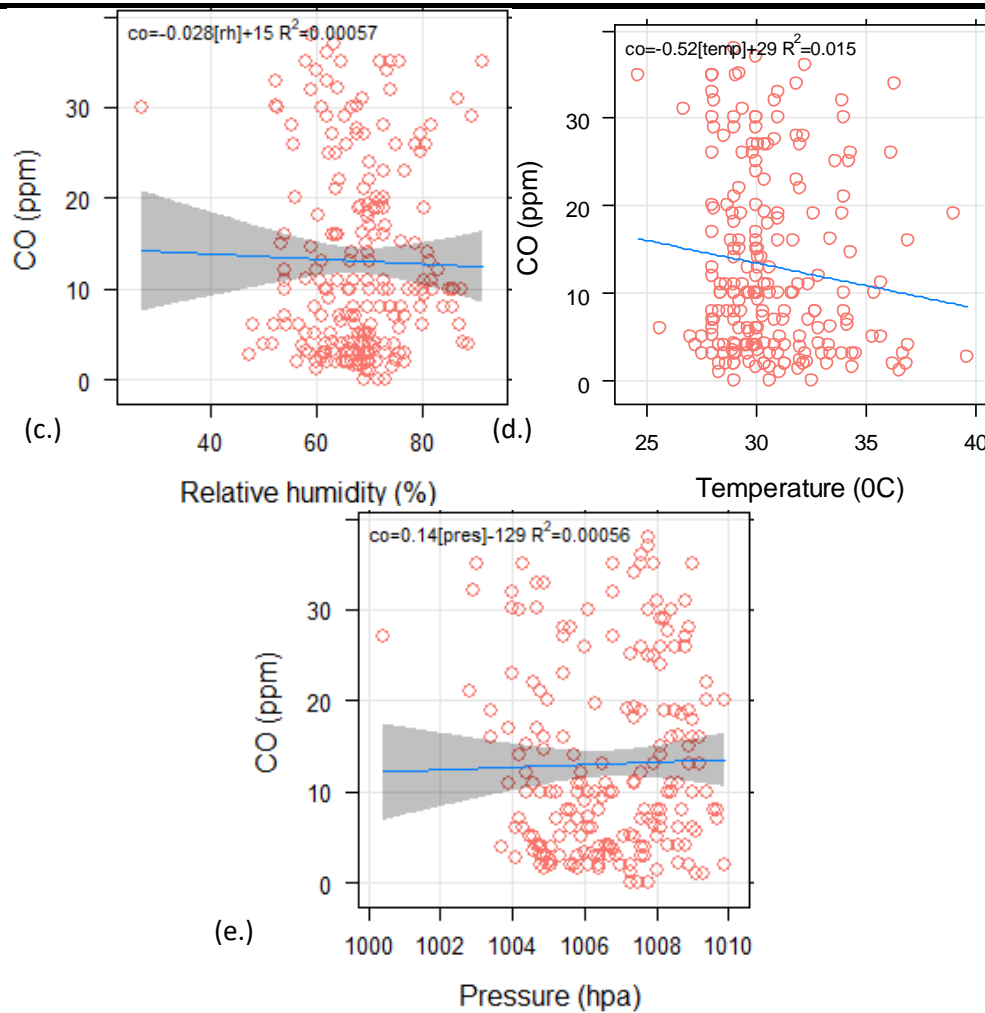

(a.)

(b.)
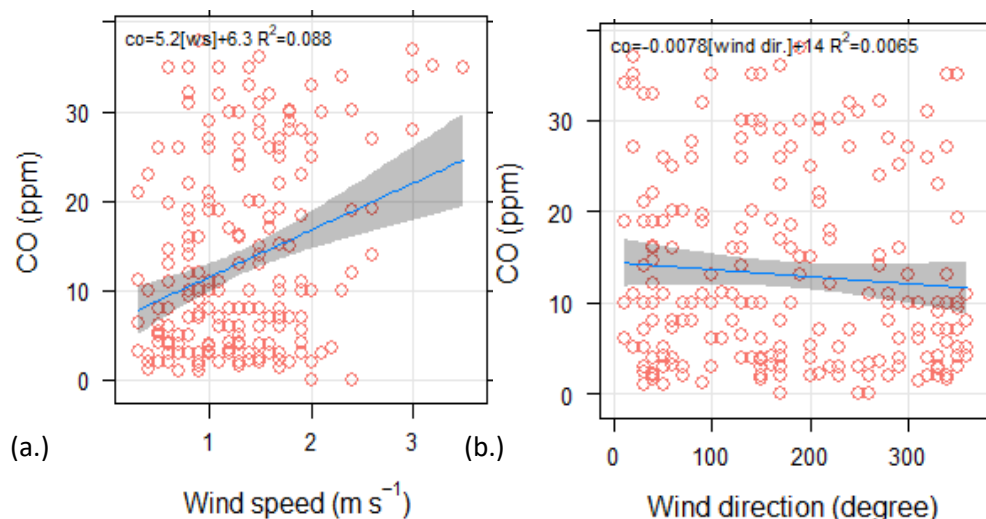
Fig.5 (a-e): Relationship between Predicted CO and Meteorological Parameters in the Dry Season

Table.3: Stepwise Linear Models for Dry Season CO

Pollutant	Model	R^2	t-statistic	Sig. (2-tailed)
CO	= 6.3 + 5.2*Wsp	0.088	4.612	0.000**
	= 14 - 0.0078*Wd	0.0065	-1.665	0.097
	= 15.0 - 0.028*Rh	0.00057	-1.921	0.056
	= 29.0 - 0.52*Temp	0.015	-1.901	0.059
	= − 129.0 + 0.14*Pres	0.00056	0.153	0.878

**Correlation is significant at the 0.05 and 0.01 levels (2-tailed).

A multiple linear regression model for the prediction of CO was developed combining all meteorological parameters as predictor variables. A model for the prediction of CO concentrations was thus derived as shown in Equation (18). The derived Equation (18) was used to predict the concentrations of CO in the study area in the dry season.

$$CO = -24.993 + 5.489*Wsp - 0.011*Wd - 0.171*Rh - 0.608*Temp + 0.063*Pres \qquad (18)$$

Table.4: Analysis of Variance (ANOVA) for Dry Season CO Prediction Model

Model	SSE (ppm)	df	MSE (ppm)	RMSE (ppm)	F	Sig.
Regression (SS$_M$)	2785.668	5	557.134	23.604	5.650	0.000*
Residual (SS$_R$)	20413.113	207	98.614			
Total (SS$_T$)	23198.782	212				

*Significant at the 0.01 level (2-tailed).

The mean square error (MSE) and the root mean square error were computed to be 557.134ppm and 23.604ppm respectively. The model sum of squares error (SS$_M$), residual sum of squares error (SS$_R$) and total sum of squares error (SS$_T$) were computed to be 2785.668ppm, 20413.113ppmand 23198.782ppm respectively as shown in Table 4. The result (Table 4) showed that meteorological parameters significantly (P-value <0.05) influence the concentrations of CO concentration in the area. However, the goodness of fit (Figure 6) between predicted and measured values showed a poor linear relationship between CO concentrations and meteorological parameters with a coefficient of determination (R^2) of 0.120. This implies that meteorological parameters accounted for only 12.0% of the variation of concentrations in the area in the dry season. The goodness of fit between predicted and measured concentrations of CO is shown in Figure 6, while the predicted values are plotted against measured values as shown in Figure 7.
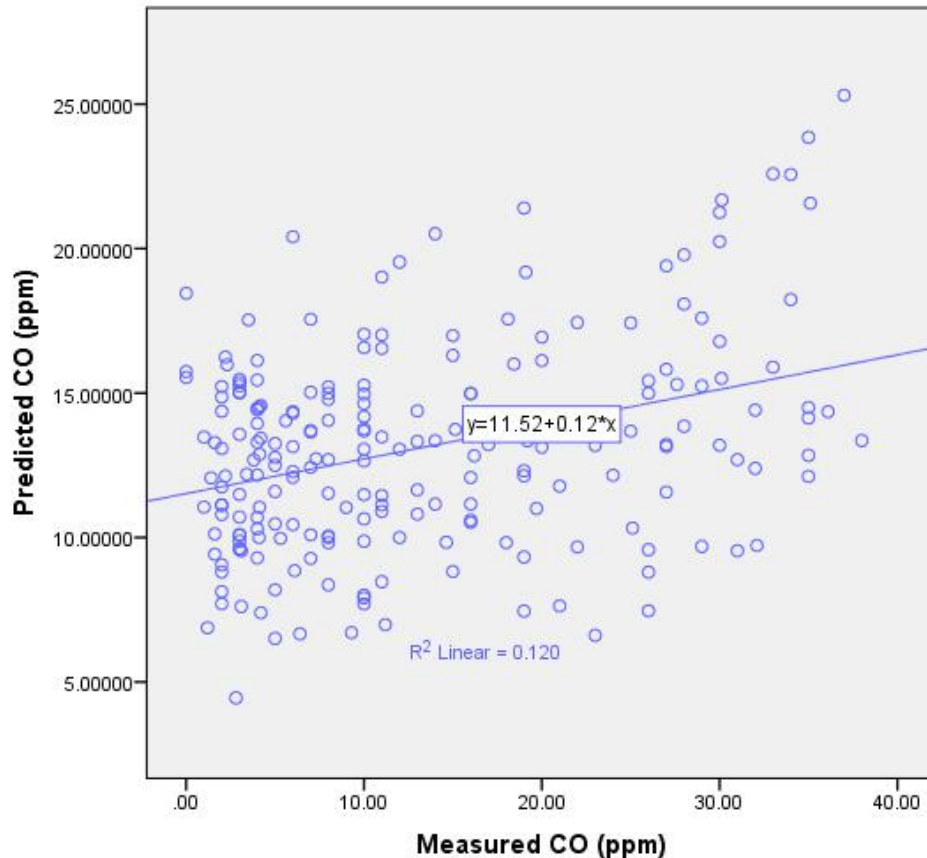

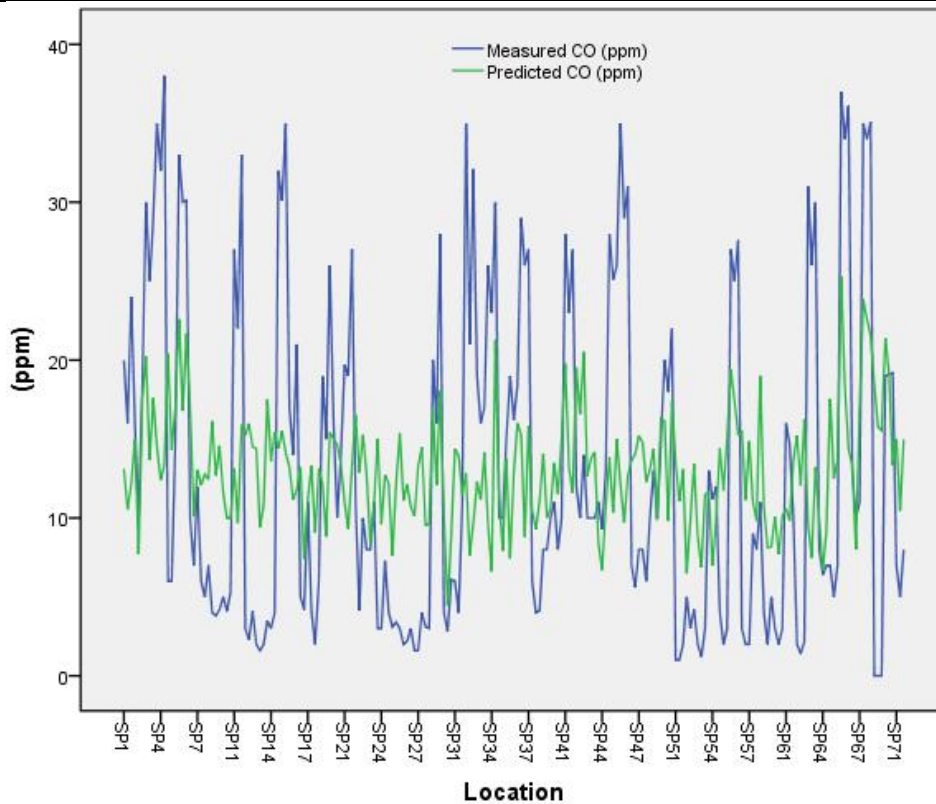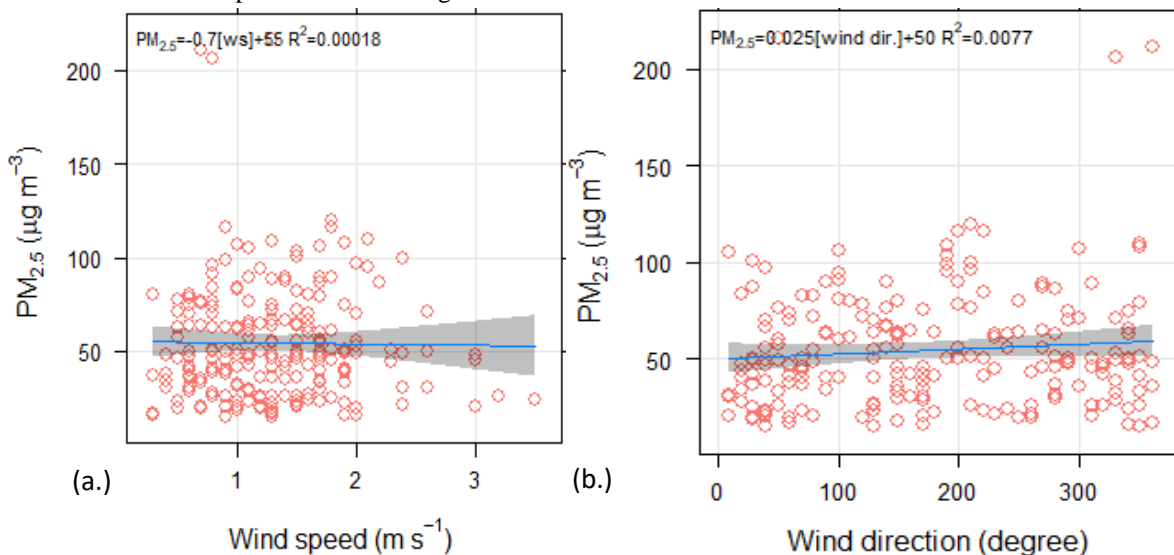*Fig.6: Relationship between Predicted CO and Measured CO in the Dry Season*

Fig.7: Predicted CO versus Measured CO in the Dry Season

Variation of PM$_{2.5}$ Particulate Matter with Meteorological Parameters in the Dry Season

The results (shown in Figure 8 (a-e)) indicated that PM$_{2.5}$ varied significantly with relative humidity and temperature and positively increased with wind speed and air pressure. The stepwise regression linear models (shown in Table 5) show that the linear relationships between PM$_{2.5}$ and wind speed, wind direction and air pressure are not significant at 0.05 confidence levels. However, the relationship between relative humidity and concentrations of PM$_{2.5}$ particulate matter is highly significant at 0.01 confidence level for a 2-tail test with a coefficient of determination (R^2) of 0.047. This implies that though PM$_{2.5}$ varies significantly with relative humidity, only a fraction of 4.7% of the variation can be explained.
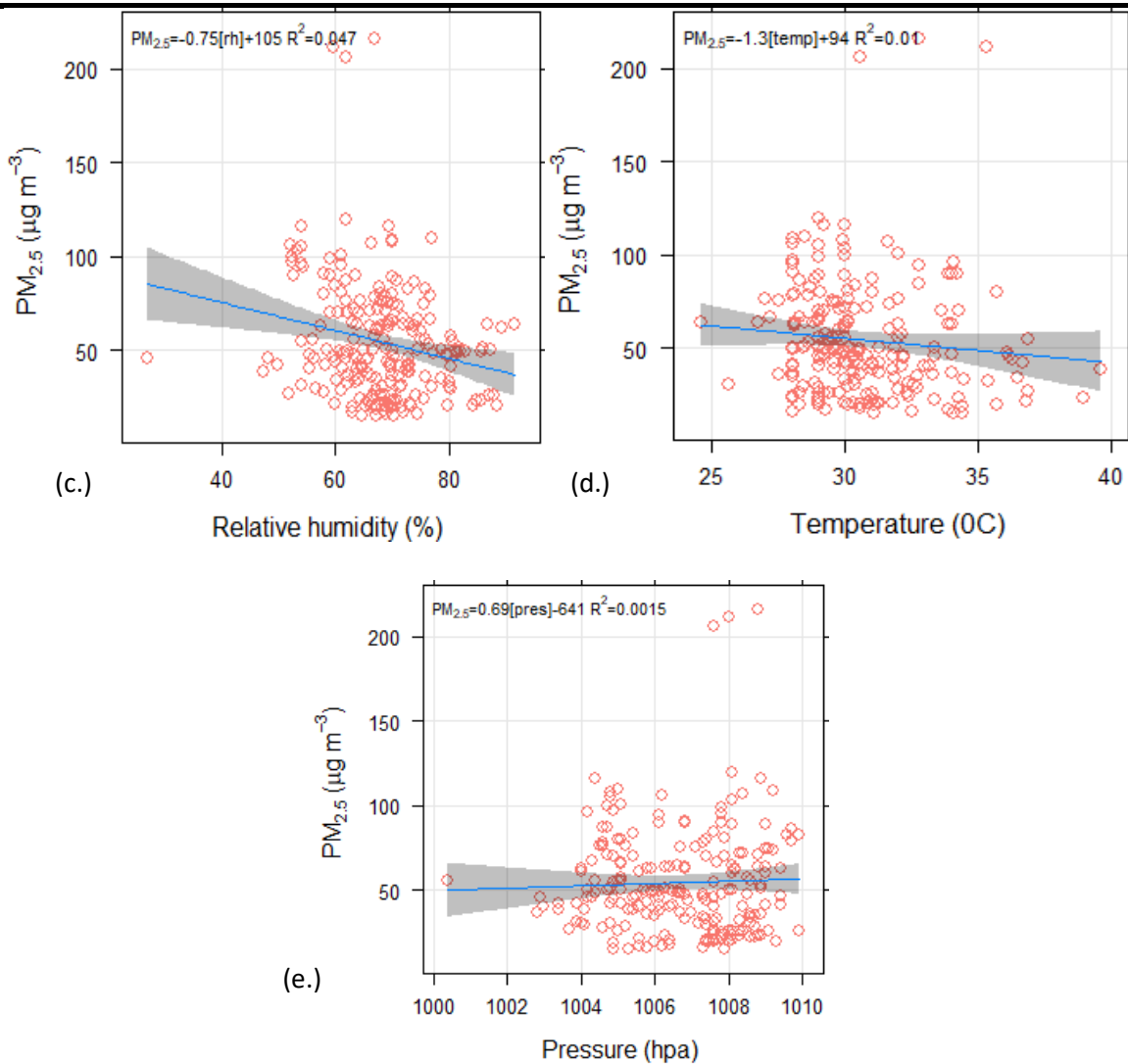
Fig.8 (a-e): *Relationship between Predicted $PM_{2.5}$ and Meteorological Parameters in the Dry Season*

Table.5: *Stepwise Linear Models for $PM_{2.5}$ in the Dry Season*

Pollutant	Model	R^2	t-statistic	Sig. (2-tailed)
$PM_{2.5}$	= 55 – 0.7*Wsp	0.00018	- 0.334	0.739
	= 50 + 0.025*Wd	0.0077	1.637	0.103
	= 105 – 0.75*Rh	0.047	- 4.846	0.000*
	= 94 – 1.3*Temp	0.01	- 3.492	0.001*
	= - 641 + 0.69*Pres	0.0015	1.835	0.068

* Correlation is significant at the 0.05 and 0.01 levels (2-tailed).

A multiple linear regression model for the prediction of $PM_{2.5}$ was developed using a combination of all the meteorological parameters as predictor variables. The following predictive model for concentration of $PM_{2.5}$ particulate was derived as shown in Equation (19).The derived Equation (19) was used to predict the concentrations of $PM_{2.5}$ in the study area in the dry season.

$$PM_{2.5} = -2014.453 - 1.187*Wsp + 0.031*Wd - 1.288*Rh - 3.333*Temp + 2.24*Pres \qquad (19)$$

Table.6: Analysis of Variance (ANOVA) for Dry Season PM$_{2.5}$ Prediction Model

Model	SSE ($\mu g/m^3$)	df	MSE ($\mu g/m^3$)	RMSE ($\mu g/m^3$)	F	Sig.
Regression (SS$_M$)	25849.946	5	5169.989	71.903	5.894	0.000*
Residual (SS$_R$)	181565.412	207	877.128			
Total (SS$_T$)	207415.358	212				

*Significant at the 0.01 level (2-tailed).

The mean square error (MSE) and the root mean square error were computed to be 5169.989$\mu g/m^3$and 71.903$\mu g/m^3$ respectively. The model sum of squares error (SS$_M$), residual sum of squares error (SS$_R$) and total sum of squares error (SS$_T$) were computed to be 25849.946$\mu g/m^3$, 181565.412$\mu g/m^3$and 207415.358$\mu g/m^3$ respectively as shown in Table 6. The result (Table 6) showed that meteorological parameters significantly (P-value <0.05) influence the concentrations of PM$_{2.5}$ in the area. However,

the goodness of fit (Figure 9) shows a poor linear relationship between PM$_{2.5}$ and meteorological parameters with a coefficient of determination (R^2) of 0.125. This implies that only 12.5% of the variation of PM$_{2.5}$ concentrations can be explained by the meteorological parameters. The goodness of fit between predicted and measured concentrations of PM$_{2.5}$ is shown in Figure 9, while the predicted values are plotted against measured values as shown in Figure 10.
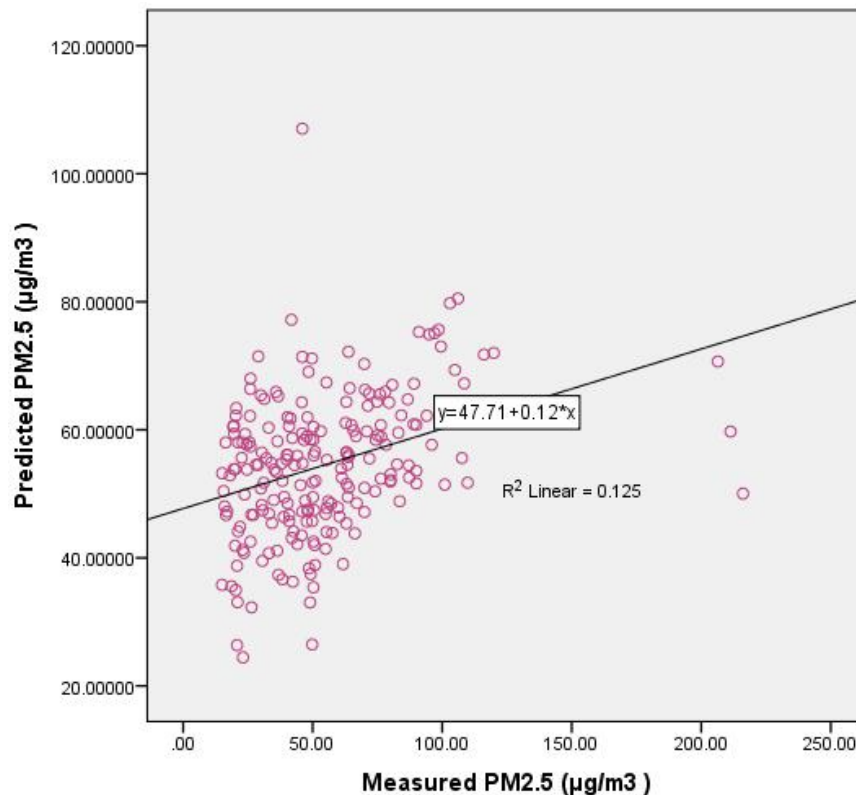

Fig.9: Relationship between Predicted PM$_{2.5}$ and Measured PM$_{2.5}$ in the Dry Season
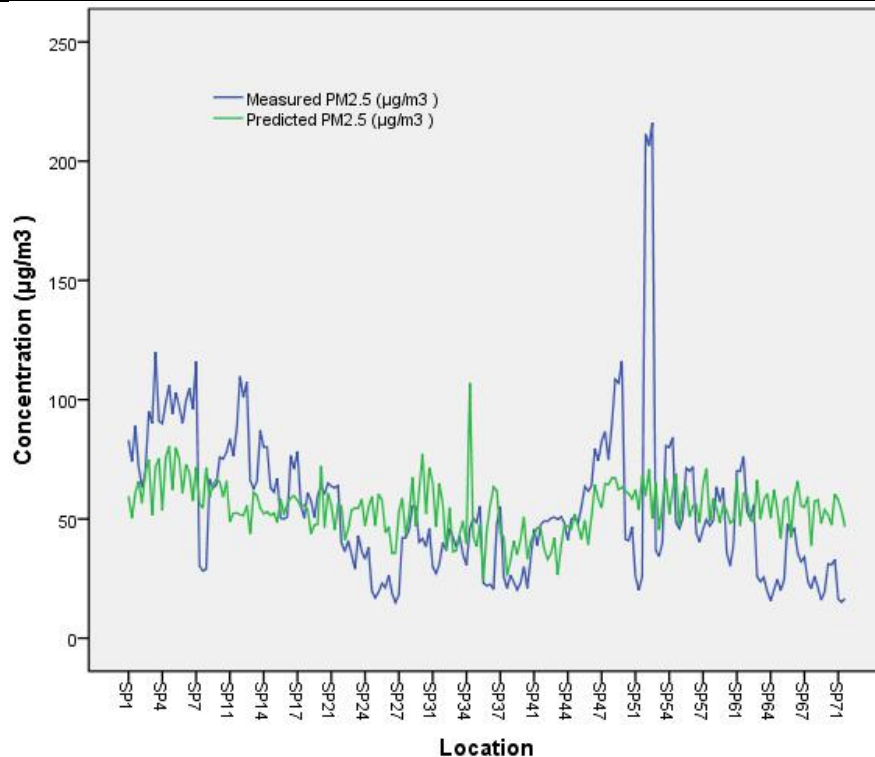
Fig.10: Predicted PM$_{2.5}$ versus Measured PM$_{2.5}$ in the Dry Season

IV. INTERPRETATION AND DISCUSSION MODELING THE RELATIONSHIP BETWEEN AIR POLLUTANTS AND METEOROLOGICAL PARAMETERS IN THE DRY SEASON

(a) Evaluation of Pollutants Dispersion Pattern in the Study Area in the Dry Season

The pollutants dispersion patterns in the study area in the dry season were evaluated with the aid of pollution roses and bivariate polar plots of each pollutant with respect to wind speed and wind direction. The dry season results are presented in Figures 11 (a-c) and 12 (a-c). The pollution roses and polar plots were developed using the mean concentration of each pollutant in different wind speed and percentage frequency count of wind direction categories (Munir, 2016). They were simulated with the aid of Generalized Additive Model (GAM) smoothing techniques Carslaw, (2015) that depict pollutant concentrations as a continuous surface.

Pollution roses (Figure 11 (a-c)) showed that pollutant concentrations increase with increased wind speed. Low concentrations of pollutants were obtained at low wind speed and vice-versa. This implies that wind speed has positive influence on the concentration levels of pollutants in the study area.
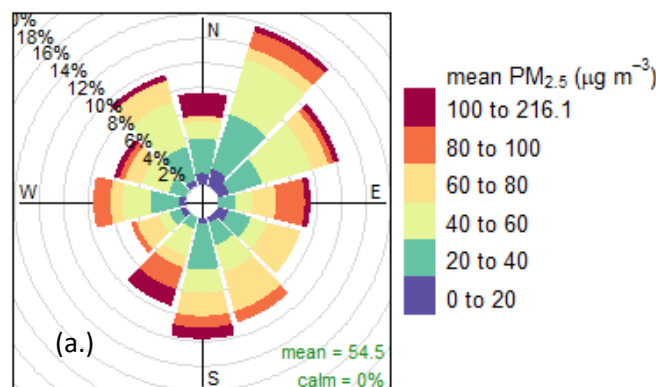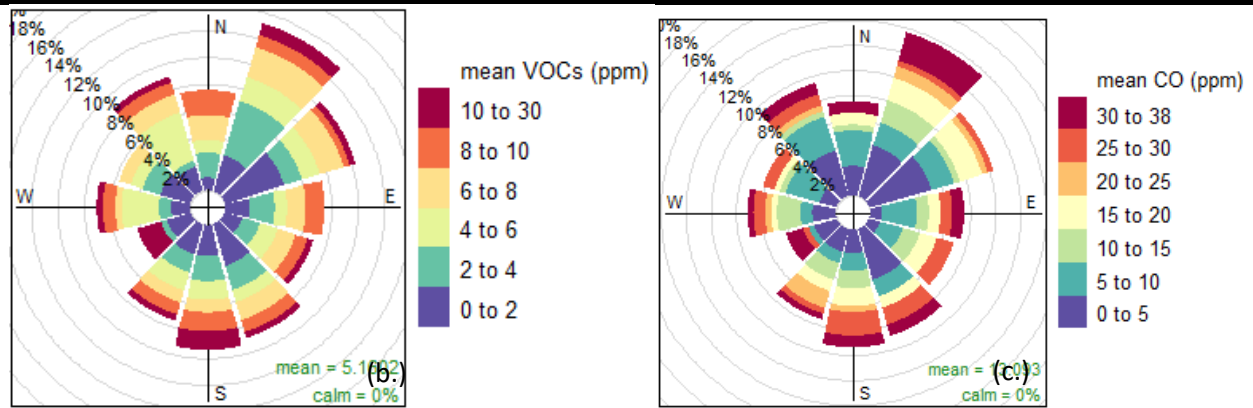
Fig.11 (a-c): Pollution Roses of Pollutants in the Study Area in the Dry Season

The pollutant polar plots (Figure 12 (a-c)) showed that concentrations of pollutants in the area are associated with wind speed up to 3.5m/s. It is also observed from Figure 12 (a-c) that pollutant concentrations increase with increased wind speed (Folorunsho *et al.*, 1995).

Surface polar plots of pollutants concentrations in the study area revealed that high concentrations of SO_2, NO_2, NH_3, H_2S and VOCs are associated with the south-west and south-east directions and are dispersed toward the north-east and north-west directions (Jimmy *et al.,* 2013). This may imply that sources of these pollutants are in the southern part, which is the coastal region of the study area. Industrial activities, especially in Eleme area (refineries, petrochemical company, fertilizer companies, industrial waste management facilities, civil construction, gas flaring, and vehicular movement) and the released of black carbon (black soot) due to illegal refineries in the coastal area may be the sources of these pollutants (Antai, 2017).

The Figure also indicated that concentrations of CO is associated with south-west, south-east and north-east directions and are dispersed toward the north-west directions. This may imply that sources of this pollutant are both in the southern and northern parts, which are the coastal and up-land areas. Industrial activities, vehicular exhaust emissions, gas flaring and oil and gas exploitation in Eleme, Port Harcourt, Obio/Akpor and Etche areas might be the sources of these pollutant (Antai *et al.*, 2016).

Similarly, concentrations of Methane (CH_4) and Particulate Matter (TSP, PM_{10} and $PM_{2.5}$) are associated with both northern and southern directions. This showed that activities in the both the coastal and up-land areas are responsible for the release of these pollutants into the environment (Kochubovski *et al.*, 2012). In other words, industrial activities, vehicular exhaust emissions, civil construction, the released of black carbon (black soot) due to illegal refineries in the coastal area, gas flaring and oil and gas exploitation in Eleme, Port Harcourt, Obio/Akpor, Etche and Ikwerre areas may be the sources of CH_4 and particulate matter in the air environment of the study area in the dry season period (Antai *et al.,* 2017).
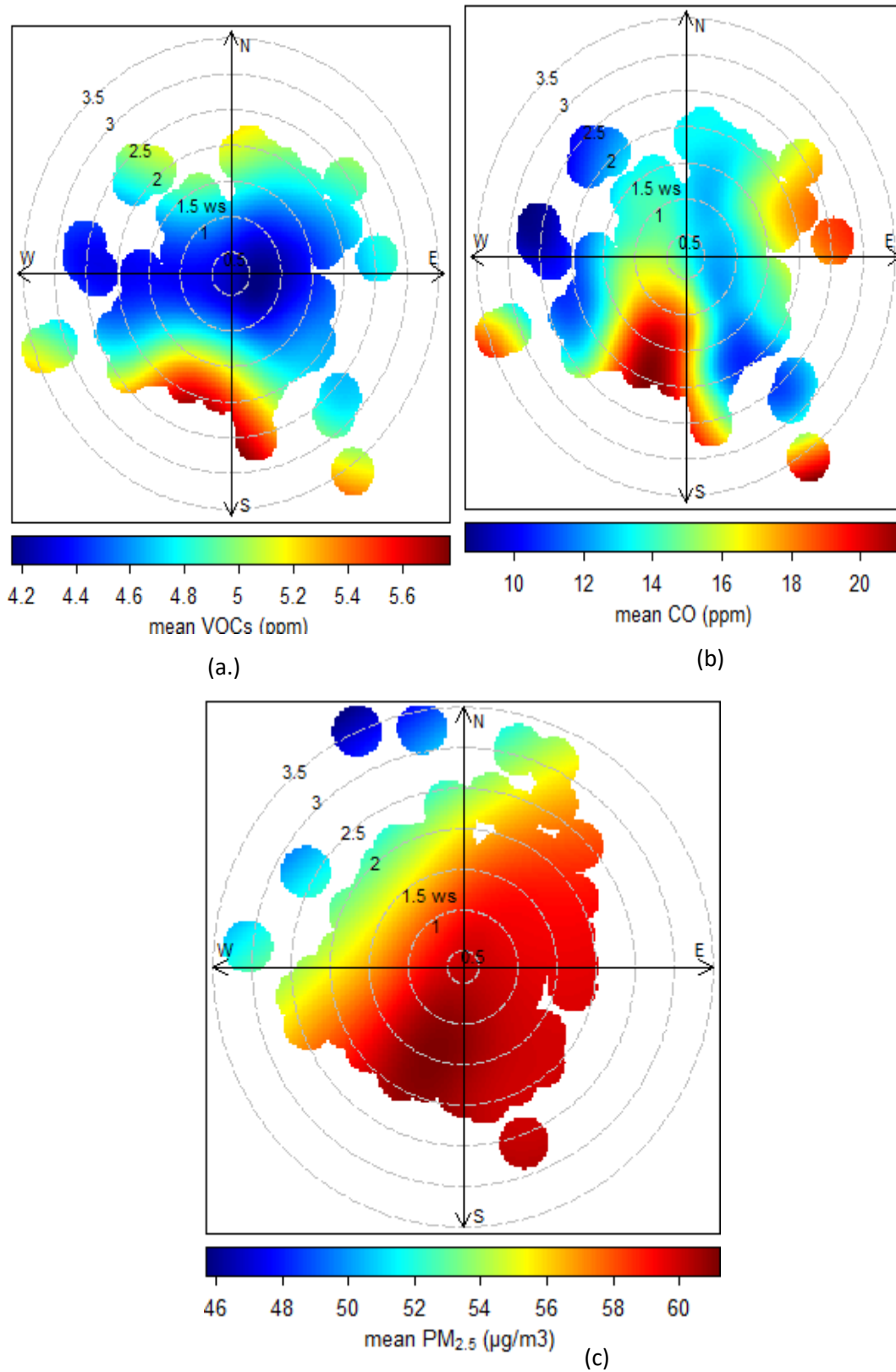
Fig.12 (a-c): Polar Plots of Pollutants in the Study Area in the Dry Season

Yearly Prediction for 15 Years for Dry Seasons

Yearly prediction of air pollutants was carried out using a ten year data from previous studies conducted in the study area.

The prediction was done using regression analysis and year as the predictor variable. The relationship between air pollutants and year was therefore established. The annual prediction of pollutant concentrations was made for the dry seasons. The prediction models for each pollutant in the dry season are presented in Equations (20 to 29).The prediction was made for a period of fifteen years (2017 to 2031) and the results of the annual prediction are presented in Table 7 for the dry seasons.

Dry Season Yearly Prediction

$$TSP = -66243.8 + 33.07812 * Year \tag{20}$$

$$PM_{10} = -5173.13 + 2.603 * Year \tag{21}$$

$$PM_{2.5} = -6343.97 + 3.162 * Year \tag{22}$$

$$SO_2 = -1118.987 + 0.55645 * Year \tag{.23}$$

$$NO_2 = -180.411 + 0.091 * Year \tag{24}$$

$$H_2S = -80.7741 + 0.041 * Year \tag{25}$$

$$VOCs = -1370.99 + 0.6889 * Year \tag{26}$$

$$CO = -716.003 + 0.3594 * Year \tag{27}$$

$$NH_3 = -273.036 + 0.13654 * Year \tag{28}$$

$$CH_4 = -610.2105 + 0.30321 * Year \tag{29}$$

Table.7: Predicted Yearly Dry Seasons Values for 15 Years

Year	TSP	PM$_{10}$	PM$_{2.5}$	SO$_2$	NO$_2$	H$_2$S	VOCs	CO	NH$_3$	CH$_4$
	μg/m^3						ppm			
2017	474.77	77.12	33.78	3.37	3.14	1.92	18.52	8.91	2.37	1.36
2018	507.85	79.72	36.95	3.93	3.23	1.96	19.21	9.27	2.50	1.67
2019	540.92	82.33	40.11	4.49	3.32	2.00	19.90	9.63	2.64	1.97
2020	574.00	84.93	43.27	5.04	3.41	2.05	20.59	9.98	2.77	2.27
2021	607.08	87.53	46.43	5.60	3.50	2.09	21.28	10.34	2.91	2.58
2022	640.16	90.14	49.59	6.15	3.59	2.13	21.97	10.70	3.05	2.88
2023	673.24	92.74	52.76	6.71	3.68	2.17	22.65	11.06	3.18	3.18
2024	706.31	95.34	55.92	7.27	3.77	2.21	23.34	11.42	3.32	3.49
2025	739.39	97.95	59.08	7.82	3.86	2.25	24.03	11.78	3.46	3.79
2026	772.47	100.55	62.24	8.38	3.95	2.29	24.72	12.14	3.59	4.09
2027	805.55	103.15	65.40	8.94	4.05	2.33	25.41	12.50	3.73	4.40
2028	838.63	105.75	68.57	9.49	4.14	2.37	26.10	12.86	3.87	4.70
2029	871.71	108.36	71.73	10.05	4.23	2.41	26.79	13.22	4.00	5.00

| 2030 | 904.78 | 110.96 | 74.89 | 10.61 | 4.32 | 2.46 | 27.48 | 13.58 | 4.14 | 5.31 |
| 2031 | 937.86 | 113.56 | 78.05 | 11.16 | 4.41 | 2.50 | 28.17 | 13.94 | 4.28 | 5.61 |

V. CONCLUSION

The result of multiple linear regressions and generalized additive model in this study revealed that changes in the air pollution of Port Harcourt city and its environs are directly induced and influenced by changes in the meteorological variables in the dry season.

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