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Analyzing Nitrogen Dioxide (NO_2) Dispersion Patterns Using the Distribution Lag Model (DLM) in Urban Environments

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Abstract

Recent research into deteriorating air quality and its related dangers has revealed a notable connection between the expanding pace of urban development and the rising presence of automobiles on our roadways. Additionally, it is noteworthy that the escalating emissions of pollutants from vehicular operations, including nitrogen dioxide, carry detrimental effects on both individuals and the environment. The objective of this investigation is to scrutinize the influence of certain identified factors on the spread of nitrogen dioxide utilizing the Distribution Lag Model (DLM). Data collection was conducted at seven chosen locations, namely the University of Benin Main Gate, Ekosodin junction, Ageri Junction, Super D junction, Nitel junction, Okhunmwun junction, and Oluku Market junction. The monitoring of pollutants from vehicular emissions, such as nitrogen dioxide, was carried out in both morning and evening periods over a span of 35 days, from the 7th of July to the 12th of August 2020. This was facilitated using the Aeroqual multi-parameter environmental monitor (series 500) and radiation alert meters. Additionally, other parameters of interest, including maximum temperature and wind speed, were measured using infra-red thermometers and the Sky master thermo anemometer (SM-28). Diagnostic statistics, such as autocorrelation tests, heteroscedasticity assessments, variance inflation factor analysis, and tests of reliability, were conducted to evaluate the quality of the data for regression analysis. The distribution lag model was then employed to explore potential collinearity among the regressor variables and to assess the significant effects of each independent variable on the dependent variable. The study findings indicated elevated levels of nitrogen dioxide (NO_2) in the vicinity of Ugbowo main gate and the Okhunmwun community, particularly during peak traffic hours (4-6 pm) when vehicular activity is highest. Moreover, the results from the distribution lag model revealed a potential correlation between sampling distance and wind speed. Consequently, it was deduced that both sampling distance and wind speed significantly influenced the variation in NO_2 concentration within the study area. Furthermore, based on a computed p-value of 0.0340, it was concluded that temperature has a noteworthy impact on NO_2 dispersion, reaching statistical significance at the 5% confidence level.

1.0.Introduction

Transportation stands as a significant contributor to air pollution in numerous nations, primarily due to the proliferation of vehicles on roadways, a trend propelled by population growth and increased purchasing power [1]. Among the primary outdoor sources of nitrogen dioxide (NO_2) are emissions from transportation, primarily from motor vehicles, and combustion of fuels [2]. NO_2 pollution arises during the combustion of fuel at high temperatures, resulting in the conversion of nitrogen in the dilution air within combustion chambers into nitrogen oxides (NOx). While many nitrogen oxides remain colourless and odourless, one prevalent NOx, nitrogen dioxide (NO_2), coupled with airborne particles, often manifests as a reddish-brown layer above urban regions. Notably, NO_2 serves as a key component in the creation of ground-level ozone, a pollutant known to exacerbate respiratory ailments significantly. Moreover, it reacts to produce nitrate particles and acidic aerosols, contributing to the formation of acid rain. Particulate nitrates stemming from NO_2 are implicated in the formation of fine atmospheric particles that can impair visibility. Furthermore, NOx gases play a role in the global warming phenomenon [2, 3]. According to the World Health Organization (WHO), pollutants released by vehicles are linked to heightened risks of stroke, lung cancer, chronic and acute respiratory ailments such as asthma, heart disease, birth defects, and eye irritation [3, 4].

Moreover, prolonged exposure to high levels of NO_2 can lead to pulmonary edema and diffuse lung injury, while chronic exposure may contribute to the development of acute or chronic bronchitis [5]. A comprehensive review of relevant literature underscores the risks associated with vehicular emissions, as pollutants and particulate matter emitted by vehicles can accumulate in soil and surface waters, eventually entering the food chain and posing threats to various physiological systems in animals [6]. Furthermore, a study by [7] emphasizes the prevalence of internal combustion engines in modern vehicles, which primarily burn gasoline or petroleum products, resulting in the emission of harmful gases such as NO_2, profoundly impacting the surrounding environment. The interaction between nitrogen and oxygen to produce nitrogen oxides (NOx) is a fundamental aspect of vehicular emissions and air pollution. In the presence of sunlight, NOx can react with hydrocarbon fumes to form a photochemical smog, with ozone serving as a key component [8]. This smog, when combined with particulate matter in the air, can create haze, leading to respiratory issues. Recognizing the importance of real-time air quality information, [9, 10] argue that such data is crucial not only for immediate responses to current conditions and safeguarding public health but also for raising awareness and mobilizing action to combat air pollution in the long run.

Furthermore, the dispersion of air pollutants, whether horizontally or vertically, is subject to various influencing factors, including wind speed and direction, ambient temperature, distance, aerodynamics, and the presence of structures such as buildings. This research aims to explore the impact of specific variables, namely; distance, ambient temperature, and wind speed on the dispersion of nitrogen dioxide (NO_2) within the designated study area. The novelty of this study lies in its comprehensive investigation into the influence of selected factors, namely distance, prevailing environmental temperature, and wind speed, on the dispersion of nitrogen dioxide (NO_2) within the study area. By addressing these variables, the study contributes to a deeper understanding of the complex dynamics of air pollutant dispersion, shedding light on critical factors that may affect the distribution and concentration of NO_2 in urban environments. This research not only advances scientific knowledge but also provides valuable insights that can inform the development of effective strategies for mitigating air pollution and protecting public health in densely populated areas.

2.0 Research Methodology

2.1 Description of study area

The study area is limited to some parts of Ovia North East Local Government Area of Edo State particularly Ugbowo and environs where serious traffic jam is experienced on daily bases. The selected location falls within the administrative area of the State. From the onset and even now, Benin City remains the principal administrative and socio-economic center of Edo State in Nigeria. Benin City is a humid tropical urban settlement which comprises three Local Government Areas namely Egor, Ikpoba Okha and Oredo. It is located within latitudes $6^{0}20'$N and $6^{0}58'$N and longitudes $5^{0}35'$E and $5^{0}41'$E. It broadly occupies an area of approximately 112.552 sq km. This extensive coverage suggests spatial variability of weather and climatic elements. Benin City lies visibly in the southern most corner of a dissected margin: a prominent topographical unit which lies north of the Niger Delta, west of the lower Niger Valley, and south of the Western Plain [11]. The specific locations employed for data collection are presented in Figure 1a.

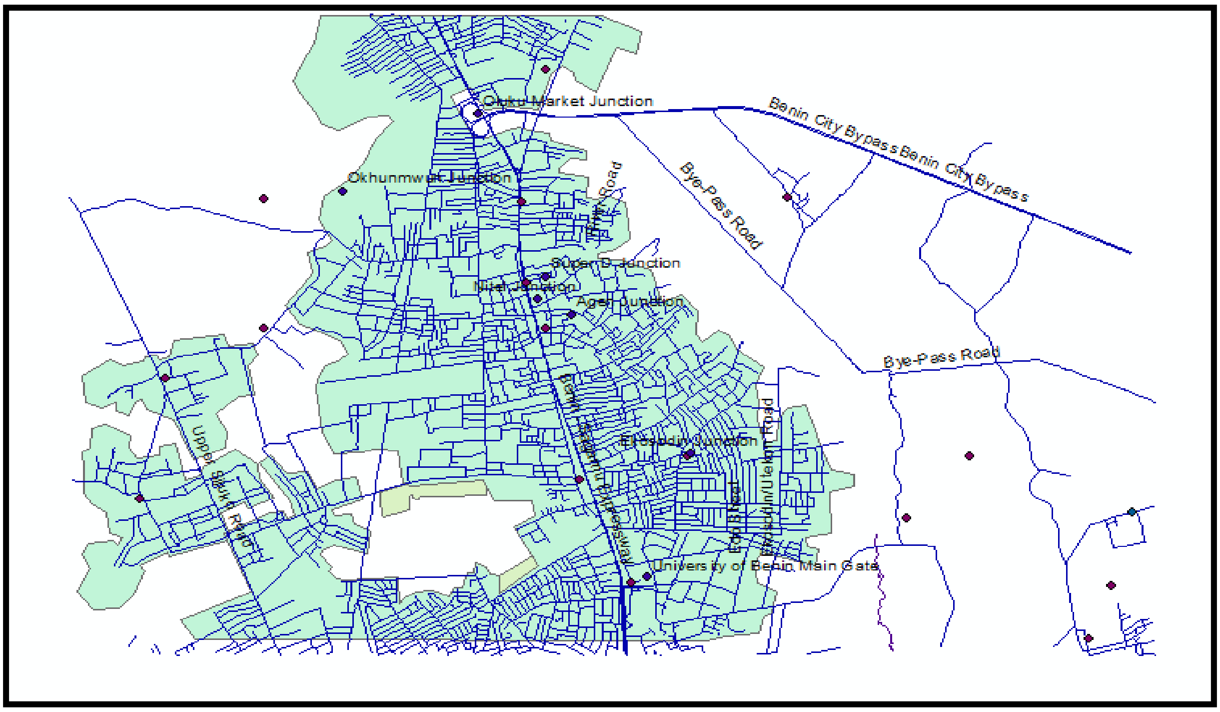

Figure 1a: Map of study area (Google map)

The study area selection is based on several key factors essential for ensuring the relevance and effectiveness of the research. Firstly, the chosen area likely experiences localized air quality issues associated with nitrogen dioxide (NO_2) pollution, making it a pertinent focus for investigation. Additionally, the availability of comprehensive data specific to the selected area enables robust analysis and validation of findings.

2.2 Data collection

Seven (7) selected locations, namely; University of Benin Main Gate, Ekosodin junction, Agen Junction, Super D junction, Nitel junction, Okhunmwun junction and Oluku Market junction were used for data collection. Pollutant from vehicular emission such as nitrogen dioxide (NO_2) was monitored in the morning and evening for a period of 35 days (7th July to 12th August 2020) with the aid of Aeroqual multi-parameter environmental monitor (series 500) and radiation alert meter. Other parameters of interest which were also measured include; maximum temperature and wind speed using infra-red thermometers and Sky master thermo anemometer (SM-28). The duration of measurement, including the calibrated unit of the gas detector is presented in Table 1a.

Table 1a: Measurement procedures and equipment used

S/N	Pollutant	Daily duration of Exposure (hrs)	Equipment	Unit
1	NO_2	1hr (9am to 10am) 1hr (5pm to 6pm)	Aeroqual multi-parameter environmental monitor (series 500)	ppm

The Global Positioning System (GPS) receiver and point positioning techniques were used to obtain the geographical coordinates at each monitoring location in the study area. The coordinates were converted to decimal degrees' format using the Universal Traverse Mercator (UTM) software version 1.0. The maximum concentration of each monitored pollutant during the monitoring period was selected and recorded for data processing.

2.3 Data Analysis
2.3.1 Regression Analysis Approach
One dependent and three independent variables were employed for this analysis. The selected dependent and independent variables are presented in Table 1b.

Table 1b: Selected dependent and independent variables

S/No	Variables	Variable Type	Symbol
1	Nitrogen Dioxide (ppm)	Dependent	NO_2
2	Sampling distance (m)	Independent	SD
3	Temperature (^{0}C)	Independent	Temp
4	Wind speed (m/s)	Independent	WS

The dependence of the dependent variable on the selected independent variables was evaluated using the coded least square regression equation presented as follows;

$$(NO_2) = C * SD * Temp * WS \quad (1)$$

It is pertinent to note that standard error estimation and computation of t-statistics are appropriate in calculating the probability (p-value) by which you test the significance of the regression model. In the presence of heteroskedasticity, it is assumed that the overall standard error of regression and the t-statistics computed for each independent variable may not be completely adequate to estimate the resulting probability (p-value) of regression. In addition, the presence of serial correlation can lead to a number of issues, namely;

i. Make reported standard error and t-statistics to be invalid
ii. Coefficient may be biased, though not necessarily inconsistent

Based on this argument, selected diagnostic statistics were conducted to verify the statistical properties of the overall regression model. The selected diagnostic statistics include;

i. Heteroskedasticity test using Breusch-Pagan Godfrey
ii. Serial Correlation test using Breusch Godfrey
iii. Variance Inflation Factor (VIF)

Heteroskedasticity is a diagnostic test statistic use to diagnose the adequacy of the probability (p-value) calculated for each individual variable. Hence it is important to know whether there is or there isn't heteroskedasticity in our data. The null and alternate hypothesis of heteroskedasticity was formulated as follows;

For p-value < 0.05 reject H0

H0 = Presence of homoscedasticity

H1 = Absence of heteroskedasticity

For p-value > 0.05 accept H0
H0 = Absence of homoscedasticity
H1 = Presence of heteroskedasticity
Serial correlation is a common occurrence in time series data because the data is ordered (overtime). It is therefore not surprising that neighbouring error terms turn out to be correlated. Serial correlation violates the standard assumption of regression theory that error terms are uncorrelated. The null and alternate hypothesis of serial correlation was formulated as follows;
H0 = Absence of serial correlation
H1 = Presence of serial correlation
Variance inflation factor (VIF) measures the correlation of the dependent variable with the independent variables. Ideal VIF is 1; VIF greater than 10 is cause for alarm showing the variables are uncorrelated due to multicollinearity.

2.3.2 Distribution Lag Model Procedures

Distribution lag model methodology is presented in Figure 1b.

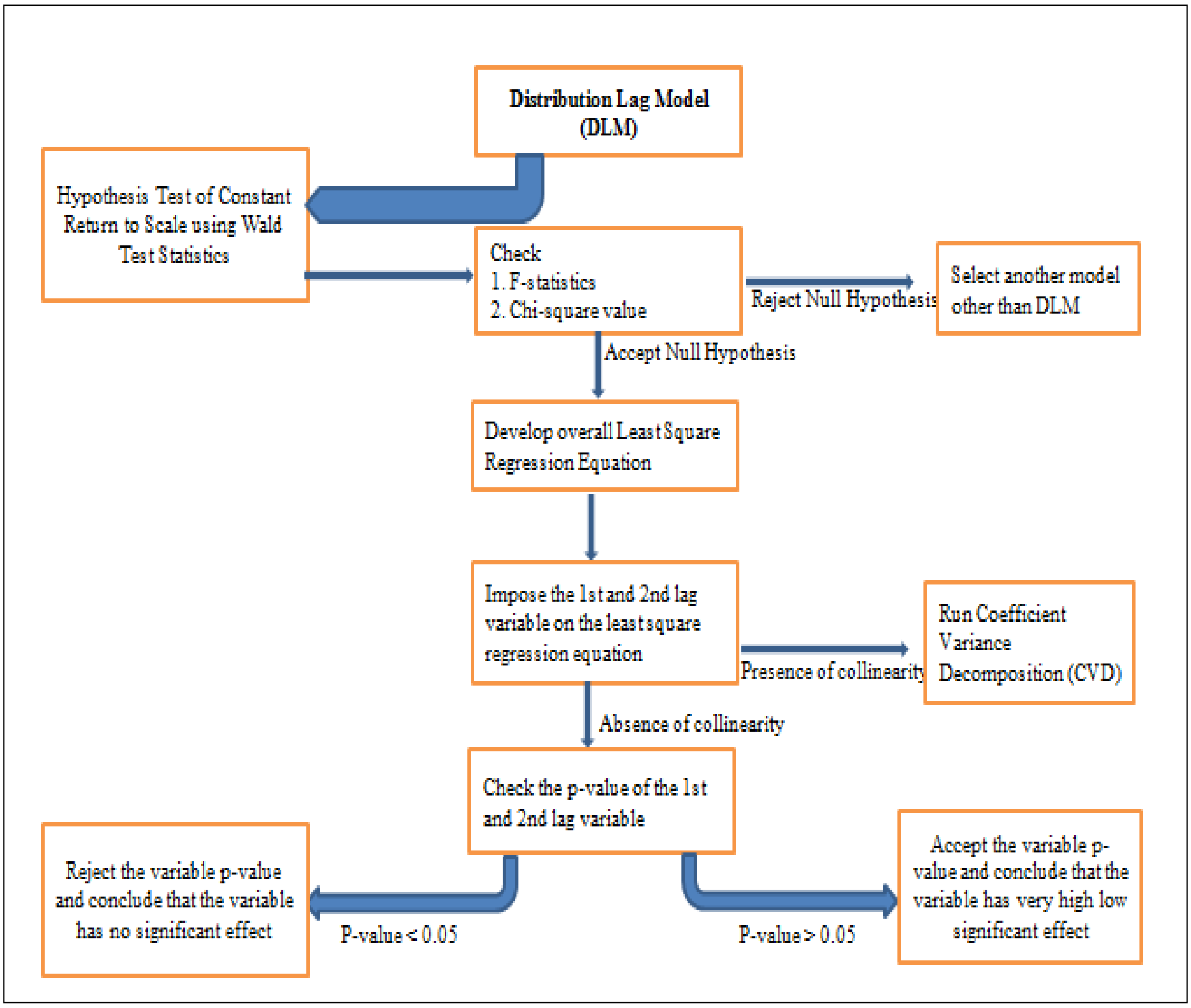

Figure 1b: Distribution lag model methodology

3.0 Results and Discussion

3.1 Result of Descriptive Statistics

The descriptive statistics of the data collected during the period of investigation which comprises of the mean, maximum and minimum values including the variance and standard deviation is presented in Table 1.

Table 1: Descriptive Statistics of data collected

	N	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance
NO_2 (ppm)	245	.01	.05	5.11	.0209	.00990	.000
Temp. (^{0}C)	245	27.4	32.6	7484.6	30.549	1.3716	1.881
Wind Speed (m/s)	245	2.301	2.545	593.635	2.42300	.070870	.005
Sampling Distance (m)	245	10	1534	164325	670.71	448.961	2.016E5
Valid N (listwise)	245						

No standard has been agreed upon for nitrogen dioxides in indoor air. The USEPA National Ambient Air Quality Standards list 0.053 ppm as the average 24-hour limit for NO_2 in outdoor air. Although, the outcome of Table 1 revealed that the maximum concentration of NO_2 stands at 0.050ppm within the period of investigation, it is important that factors that are capable of increasing this concentration are quickly identified and appropriate measure taken to forestall further increase. On whether the concentration of NO_2 and other variables within the study location follows a normal probability distribution, the Jarque-Bera test statistics was employed and result obtained is presented in Figures 2, 3 and 4 respectively.

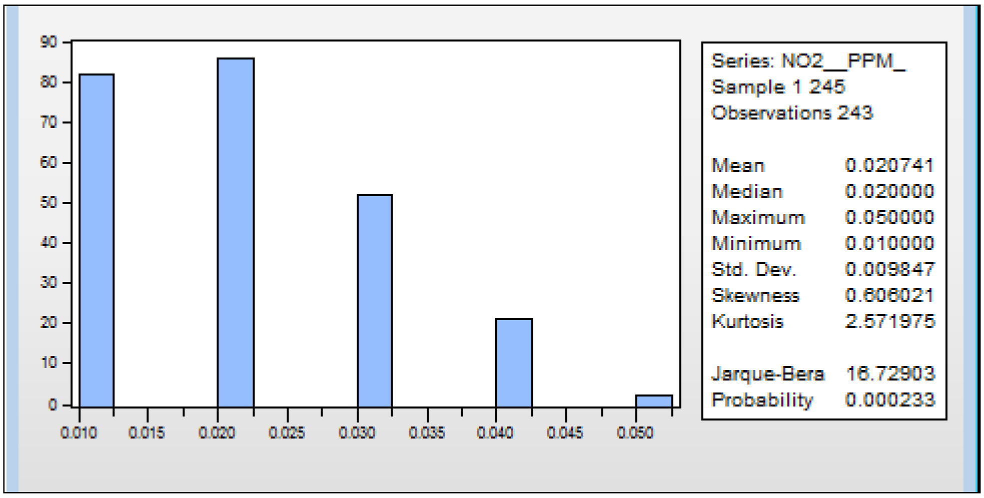

Figure 2: Normality test of NO_2 data

Jarque-Bera test value of 16.72903 and a probability (p-value) of 0.000233% as observed in Figure 2 indicates that the NO_2 data is not normally distributed. A value of JB greater than 10 means that the null hypothesis has been rejected at the 5% significance level. In other words, the data do not come from a normal distribution.

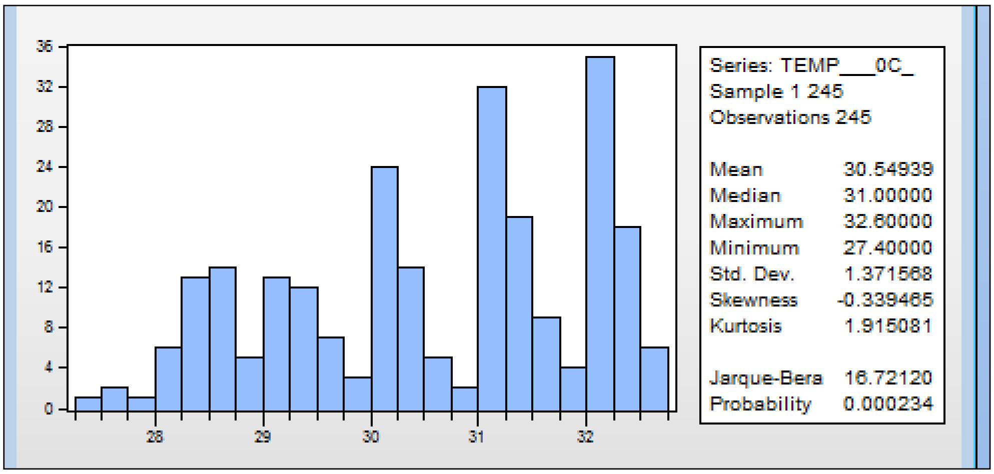

Figure 3: Normality test of temperature data

Jarque-Bera test value of 16.72120 and a probability (p-value) of 0.000234% as observed in Figure 3 indicates that the temperature data is not normally distributed. A value of JB greater than 10 means that the null hypothesis has been rejected at the 5% significance level. In other words, the data do not come from a normal distribution.

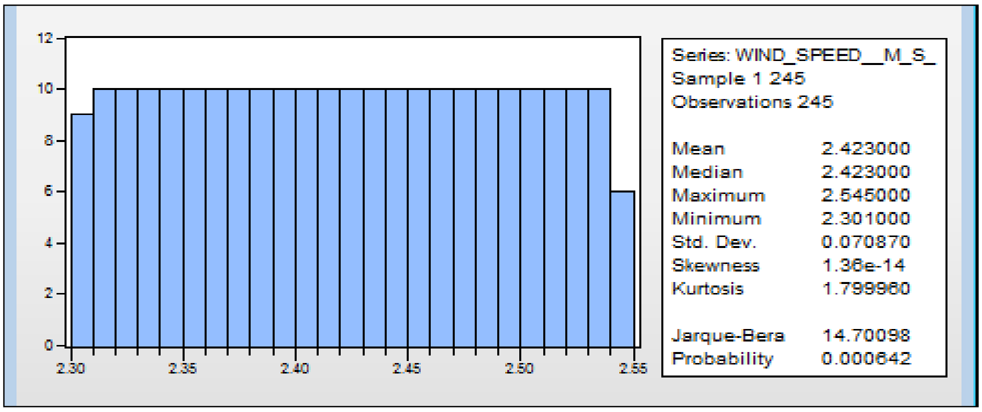

Figure 4: Normality test of wind speed data

Jarque-Bera test value of 14.70098 and a probability (p-value) of 0.000642% as observed in Figure 4 indicates that the wind speed data is not normally distributed. A value of JB greater than 10 means that the null hypothesis has been rejected at the 5% significance level. In other words, the data do not come from a normal distribution.

3.2 Result of Diagnostic Statistics

Results of the diagnostic statistics which were employed to diagnose the statistical properties of the data for use in regression analysis is presented in Tables 3, 4 and 5 representing the results of heteroskedasticity, autocorrelation and variance inflation factor.

Table 3: Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.583099	Prob. F (3,239)	0.6266
Obs*R-squared	1.765652	Prob. Chi-Square (3)	0.6224
Scaled explained SS	1.320212	Prob. Chi-Square (3)	0.7243

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001234	0.001113	1.108669	0.2687
SAMPLING_DISTANCE	9.36E-08	7.79E-08	1.201751	0.2306
TEMP___0C_	4.21E-06	5.77E-06	0.728948	0.4667
WIND_SPEED__M_S_	-0.000549	0.000497	-1.105157	0.2702

R-squared	0.007266	Mean dependent var	9.39E-05
Adjusted R-squared	-0.005195	S.D. dependent var	0.000117
S.E. of regression	0.000117	Akaike info criterion	-15.24769
Sum squared resid	3.29E-06	Schwarz criterion	-15.19019
Log likelihood	1856.594	Hannan-Quinn criter.	-15.22453
F-statistic	0.583099	Durbin-Watson stat	2.116735
Prob(F-statistic)	0.626631		

Table 4: Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.927983	Prob. F (2,237)	0.0210
Obs*R-squared	7.796419	Prob. Chi-Square (2)	0.0203

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.013263	0.091776	-0.144517	0.8852
SAMPLING_DISTANCE__M_	-1.05E-06	6.43E-06	-0.163117	0.8706
TEMP___0C_	-6.45E-05	0.000476	-0.135467	0.8924
WIND_SPEED__M_S_	0.006568	0.041017	0.160136	0.8729
RESID (-1)	-0.177365	0.065930	-2.690217	0.0076
RESID (-2)	-0.054300	0.065477	-0.829298	0.4078

R-squared	0.032084	Mean dependent var	-7.57E-18
Adjusted R-squared	0.011664	S.D. dependent var	0.009710
S.E. of regression	0.009653	Akaike info criterion	-6.418756
Sum squared resid	0.022083	Schwarz criterion	-6.332508
Log likelihood	785.8789	Hannan-Quinn criter.	-6.384016
F-statistic	1.571193	Durbin-Watson stat	1.965911
Prob(F-statistic)	0.168948		

Table 5: Variance Inflation Factors

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.008593	21874.61	NA
SAMPLING_DISTANCE__M_	4.21E-11	69.89555	21.57172
TEMP___0C_	2.31E-07	550.6631	1.106153
WIND_SPEED__M_S_	0.001715	25654.01	21.86343

From the result of Table 3, it was observed that;

i. The calculated (p-value) based on F-statistics is 0.6266
ii. The calculated (p-value) based on langrange multiplier (LM) is 0.6224

Since the computed (p-value) based on F-statistics and langrange multiplier is greater than 0.05 ($P > 0.05$), we rejected the null hypothesis of homoskedasticity and conclude that there is heteroskedasticity in the data. From the result of Table 4, it was observed that;

i. The calculated (p-value) based on the F-statistics is 0.0210
ii. The calculated (p-value) based on langrange multiplier (LM) is 0.0203

Since the computed (p-value) based on F-statistics and langrange multiplier is less than 0.05 ($P < 0.05$), the null hypothesis of serial correlation was accepted and it was concluded that; there is no serial correlation in the data. Since the computed variance inflation factors (centered VIF) for the selected independent variables as observed in Table 5 is less than 10, it was concluded that the variables are well correlated with the dependent variable, hence absence of multicollinearity. To determine the variable that mostly influenced the dispersion of NO_2 around the study area, distribution lag model was employed.

3.3 Distribution Lag Model

In this model, one or more independent variables affect the dependent variable with a lag. Suppose we want to determine how each of the independent variables affects the dependent variable then we need to first test if the difference between the coefficient estimates of the independent variables is statistically significant using the hypothesis test of constant return to scale. To test the hypothesis of constant return to scale, a restriction equation of three independent variables was written as follows;

$$C(2) + C(3) + C(4) = 1 \quad (2)$$

Result obtained is presented in Table 6

Table 6: Result of Wald Test

Test Statistic	Value	df	Probability
t-statistic	-26.30865	239	0.0000
F-statistic	692.1452	(1, 239)	0.0000
Chi-square	692.1452	1	0.0000

Null Hypothesis: C(2)+C(3)+C(4)= 1
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
-1 + C(2) + C(3) + C(4)	1.085598	0.041264

F-statistical value of 0.0000 and chi-square value of 0.0000 shows a strong similarity between both of them. In addition, standard error value of 0.041264 and a p-value greater than 0.05 shows that we decisively accept the null hypothesis of constant return to scale and conclude that the restrictions are linear in coefficient. Using the distribution lag model, an overall regression equation was developed in syntax form and presented as follows;

LS NO2__PPM_ C SAMPLING_DISTANCE__M_ TEMP___0C_ WIND_SPEED__M_S_ (3)

Estimation Equation:
=========================
NO2__PPM_ = C(1) + C(2)*SAMPLING_DISTANCE__M_ + C(3)*TEMP___0C_ + C(4)*WIND_SPEED__M_S_
(4)

Forecasting Equation:
=========================
NO2__PPM_ = C(1) + C(2)*SAMPLING_DISTANCE__M_ + C(3)*TEMP___0C_ + C(4)*WIND_SPEED__M_S_
(5)

Substituted Coefficients:
=========================
NO2__PPM_ = 0.191617948648 + 1.25629468641e-05*SAMPLING_DISTANCE__M_ + 0.00100022166099*TEMP___0C_ - 0.0866107870409*WIND_SPEED__M_S_
(6)

To evaluate the effect of each independent variable on the dependent variable, first and second lag variable were imposed on the least square regression equation as follows;

LS NO2__PPM_ C SAMPLING_DISTANCE__M_ TEMP___0C_ WIND_SPEED__M_S_ (SAMPLING_DISTANCE__M_ (-1)) (SAMPLING_DISTANCE__M_ (-2))
(7)

LS NO2__PPM_ C SAMPLING_DISTANCE__M_ TEMP___0C_ WIND_SPEED__M_S_ (TEMP___0C_ (-1)) (TEMP___0C_ (-2))
(8)

LS NO2__PPM_ C SAMPLING_DISTANCE__M_ TEMP___0C_ WIND_SPEED__M_S_ (WIND_SPEED__M_S_ (-1)) (WIND_SPEED__M_S_ (-2))
(9)

Equation 6, 7 and 8 were employed to study the effects of sampling distance, temperature and wind speed on the dispersion of NO_2 around the study area. Result of the effect of sampling distance on the dispersion of NO_2 using equation 6 is presented in Table 7.

Table 7: Effect of Sampling distance on NO_2 dispersion

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.184570	0.095296	1.936812	0.0040
SAMPLING_DISTANCE__M_	1.22E-06	2.09E-05	0.058698	0.0032
TEMP___0C_	0.001039	0.000491	2.117495	0.0053
WIND_SPEED__M_S_	-0.084130	0.042323	-1.987806	0.0080
SAMPLING_DISTANCE__M_(-1)	2.67E-05	2.87E-05	0.932865	0.0018
SAMPLING_DISTANCE__M_(-2)	-1.57E-05	2.09E-05	-0.752300	0.0026

R-squared	0.930506	Mean dependent var	0.020705
Adjusted R-squared	0.987800	S.D. dependent var	0.009870
S.E. of regression	0.009821	Akaike info criterion	-6.383979
Sum squared resid	0.022667	Schwarz criterion	-6.297220
Log likelihood	775.2694	Hannan-Quinn criter.	-6.349025
F-statistic	1.478873	Durbin-Watson stat	2.312897
Prob(F-statistic)	0.197458		

Result of the distribution lag model shows an improvement in the R-squared value and the Adjusted R-squared value. In addition, since the p-value of the first and second lag variable is less than 0.05, it was concluded that the lag variables are not significant hence the p-value of 0.0032 for sampling distance is valid. Based on the computed p-value of 0.0032, it was concluded that; the impact of sampling distance on the dispersion of NO_2 is highly significant at the 5% confidence interval. Distribution lag result on the effect of temperature on the dispersion of NO_2 is presented in Table 8.

Table 8: Effect of temperature on NO_2 dispersion

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.183772	0.093663	1.962058	0.0509
SAMPLING_DISTANCE__M_	1.20E-05	6.57E-06	1.833612	0.0680
TEMP___0C_	0.001323	0.000621	2.132302	0.0640
WIND_SPEED__M_S_	-0.082640	0.042077	-1.964031	0.0507
TEMP___0C_(-1)	-0.000869	0.000703	-1.235807	0.2178
TEMP___0C_(-2)	0.000499	0.000612	0.815567	0.4156

R-squared	0.933250	Mean dependent var	0.020705
Adjusted R-squared	0.927580	S.D. dependent var	0.009870
S.E. of regression	0.009807	Akaike info criterion	-6.386891
Sum squared resid	0.022601	Schwarz criterion	-6.300133
Log likelihood	775.6204	Hannan-Quinn criter.	-6.351938
F-statistic	1.620291	Durbin-Watson stat	2.308314
Prob(F-statistic)	0.155383		

Result of the distribution lag model also shows an improvement in the R-squared value and the Adjusted R-squared value. In addition, since the p-value of the first and second lag variable (0.2178 and 0.4156) is greater than 0.05, it was concluded that the lag variables are significant hence the p-value of 0.0640 for temperature is invalid. Based on the computed p-value of 0.0640, it was concluded that; the impact of temperature on the dispersion of NO_2 is not significant at the 5% confidence interval.
The distribution lag result of the effect of wind speed shows a different trend from that of sampling distance and temperature. A more formal approach to investigate the relationship among regressor variables was to conduct coefficient variance decomposition analysis.
Coefficient variance decomposition view of an equation provides information on the eigenvector decomposition of the coefficient covariance matrix. This decomposition is a useful tool to help diagnose potential collinearity problems among the regressor which the simple correlation matrix may fail to detect. That is;

$$X_1 = X_2 + 3X_3 \quad (10)$$

In the case of a simple linear least square regression, the coefficient variance covariance matrix can be decomposed as follows;

$$Var(\beta) = \sigma^2 (X^1 X)^{-1} = \sigma^2 V S^{-1} V^1 \quad (11)$$

Where;
S is a diagonal matrix containing the eigenvalues of X^1X and
V is a matrix whose columns are equal to the corresponding eigenvector
Result of the coefficient variance decomposition employed to test potential collinearity among the regressor is presented in Table 9.

Table 9: Coefficient Variance Decomposition

Eigenvalues	0.01027 6	3.29E-05	1.36E-09	6.02E-13
Condition	5.86E11	1.83E-08	0.000443	1.000000

Variance Decomposition Proportions

	Associated Eigenvalue			
Variable	1	2	3	4
C	0.999376	0.000624	1.68E-10	7.43E-17
SAMPLING_DISTANCE__M_	0.008278	0.015131	0.032313	0.014278
TEMP___0C_	0.712709	0.961460	0.005831	2.59E-09
WIND_SPEED__M_S_	0.004095	0.015905	4.52E-09	2.27E-15

Eigenvectors

	Associated Eigenvalue			
Variable	1	2	3	4
C	-0.914192	-0.403972	-0.032550	0.001030
SAMPLING_DISTANCE__M_	-6.20E-05	0.000139	0.031639	0.999499
TEMP___0C_	-0.000858	0.082284	-0.996110	0.031520
WIND_SPEED__M_S_	0.405281	-0.911063	-0.075527	0.002543

From the result of Table 9, the conditional number was observed to be 5.86E11. Conditional number greater than 0.001 as observed in Table 9 signifies total absence of collinearity among the regressor. From the result of variance decomposition proportion, it was observed that sampling distance and wind speed had associated eigenvalues of 0.008278 and 0.004095 which is less than 0.05. This indicates that; there is no aorta of collinearity between these variables. By implication therefore, sampling distance and wind speed contributes immensely to change in the concentration of NO_2 around the study area.

4.0. Conclusion

In this study, we conducted a comprehensive investigation into the efficacy of the distribution lag model (DLM) in identifying potential collinearity among regressor variables. Through rigorous analysis, we found no evidence of collinearity between sampling distance and wind speed, indicating that these factors act independently in influencing the concentration of nitrogen dioxide (NO_2) within our study area. Our findings strongly suggest that both sampling distance and wind speed significantly contribute to variations in NO_2 concentration, highlighting their crucial roles in the dispersion of air pollutants. Moreover, our analysis yielded a computed p-value of 0.0640 for the impact of temperature on NO_2 dispersion. While this value falls slightly above the conventional threshold for statistical significance at the 5% confidence level, it is essential to interpret this result cautiously. Despite not meeting strict significance criteria, the observed trend suggests a potential influence of temperature on NO_2

dispersion, albeit to a lesser extent compared to other factors examined in our study. Overall, these findings deepen our understanding of the intricate dynamics underlying air pollutant dispersion and provide valuable insights for policymakers and urban planners seeking to develop effective strategies for mitigating air pollution in densely populated areas.

The study's conclusion underscores the independent influence of factors such as sampling distance and wind speed on nitrogen dioxide (NO_2) concentration, highlighting their pivotal roles in air pollutant dispersion. Although the significance of temperature's impact on NO_2 dispersion was inconclusive, its observed trend suggests potential relevance, necessitating further exploration. To address air quality challenges effectively, integrating advanced monitoring techniques and modeling approaches is crucial. Policymakers and urban planners should consider implementing strategies such as zoning regulations, green infrastructure development, and transportation planning, which account for the unique contributions of sampling distance, wind speed, and temperature to NO_2 dispersion, ultimately aiming for comprehensive urban planning approaches that mitigate air pollution in densely populated areas.

4.1. Limitation/Recommendation

While the study provides valuable insights into nitrogen dioxide (NO_2) dispersion dynamics, several limitations and potential sources of uncertainty warrant consideration. Firstly, the study's focus on a specific geographical area may limit the generalizability of its findings to other regions with different environmental characteristics. Additionally, the analysis did not account for potential interactions between NO_2 and other pollutants, which could influence dispersion patterns. Future research could address these limitations by conducting multi-site studies encompassing diverse environmental conditions and incorporating comprehensive analyses of pollutant interactions.

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