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DISPERSION AND ATMOSPHERIC STABILITY SIMULATION OF INDUSTRIAL AMBIENT AIR POLLUTANTS IN KADUNA, NIGERIA USING THE GAUSSIAN PLUME MODEL

Lawal Joseph[a] A. A. Tyovenda[b], T. Igbawua[b]

[a.] Nigerian College of Aviation Technology Zaria, Kuaduna State, Nigeria
[b.] Joseph Sarwuan Tarka University Makurdi, Benue State, Nigeria

Abstract

Industrial air pollution remains a major environmental and public health concern in rapidly urbanizing Nigerian cities. This study applied the Gaussian Plume Model (GPM) to estimate pollutant dispersion from selected industrial stacks in Kaduna metropolis. Emission data for particulate matter ($PM_{2.5}$, PM_{10}, TSP) and gaseous pollutants (CO, SO_2, NO_2, H_2S) were obtained and modeled under different atmospheric stability classes (A–F). The results showed that particulate pollutants dominated industrial emissions, with ground-level concentrations strongly influenced by stability conditions. Under unstable conditions, pollutants dispersed widely with low ground concentrations, whereas under stable conditions, they accumulated near emission sources, resulting in high localized exposure. Model validation using RMSE confirmed strong agreement between predicted and observed concentrations. The findings emphasize the need for stricter particulate control, integration of meteorological forecasts in air quality management, and the application of dispersion modelling as a regulatory tool in Nigeria.

Keywords: Air dispersion simulation; Gaussian Plume Model; Atmospheric stability; Particulate matter; Gaseous pollutants.

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Correspondence:

E-mail:
lawaljoseph1985@gmail.com
Phone:
(+234) 8135087544

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1. Introduction

Air pollution is increasingly recognized as a significant threat to urban environments, particularly in rapidly growing African cities where industrial and transportation activities are expanding without adequate environmental controls (Shiadaa, et al., 2025). The World Health Organization (WHO, 2005) has consistently emphasized the health burden associated with ambient air pollutants such as particulate matter ($PM_{2.5}$, PM_{10}, TSP), gaseous pollutants (nitrogen oxides [NO_x], sulfur dioxide [SO_2], carbon monoxide [CO], and volatile organic compounds [VOCs]. Epidemiological evidence shows strong associations between pollutant exposure and respiratory, cardiovascular, and carcinogenic outcomes (Pope 3rd, et al., 2015; Guo, et al., 2017).

Particulate Matter (PM_x) is a solid matter or liquid droplets. It represents a broad class of chemically and physically diverse substances that exist as discrete particles over a wide range of sizes (Kunt *et al.*, 2021).

In Nigeria, industrial cities such as Kaduna are experiencing deteriorating air quality due to the clustering of factories near residential settlements. Several studies have documented elevated levels of particulate and gaseous pollutants in northern Nigeria. However, while monitoring provides snapshots of concentration levels, dispersion modelling offers predictive insights into pollutant behaviour under different meteorological and topographic conditions.

Both direct air emission and conversion from gaseous precursors (such as ammonia, sulfur dioxide, nitrogen oxides, and non-methane volatile organic compounds) generated from both natural and man-made sources are the two primary processes that give rise to particulate matter (PM). Burning solid fuels (coal, lignite, heavy oil, and biomass), industrial and agricultural operations, and pavement erosion from traffic are only a few examples of the many anthropogenic causes ~~[6]~~. It is well recognized that the effectiveness of PM exposure is greatly influenced by local characteristics such as weather, seasons, geography, particle sources, emission concentrations, and micro-environments. Because PM can quickly enter the bloodstream and travel throughout the body, its effects on human health are much worse

PM pollution has significantly altered the surrounding environment, which has an impact on plant morphology, biochemistry, physiology, and genetic state [8]. Acid rain is created when gases like SO_2 and NO_2 from factories, power plants, and other emission sources enter the atmosphere at high altitudes and mix with moisture, creating acid rain, which is extremely harmful to ecosystems. In fact, some removal mechanisms such as chemical transformation, dry deposition, precipitation scavenging, and tree plantations occur naturally and help remove contaminants from the atmosphere. Precipitation (rain) is intimately related to the formation of cloud droplets in the atmosphere due to cooling water vapor. When certain meteorological conditions are satisfied, cloud droplets change into raindrops, which can then interact with gaseous contaminants and particulate matter in the atmosphere to remove them (absorption, impaction, etc.)

The Gaussian Plume Model (GPM) remains one of the most widely applied tools for predicting pollutant dispersion from point sources such as industrial stacks. It integrates emission characteristics, meteorological conditions, and atmospheric stability to simulate the spatial distribution of pollutants. The GPM has been successfully applied in developed and developing countries. Its application in Nigeria, however, remains limited despite the urgent need for proactive air quality management.

This paper applies the Gaussian Plume Model to selected industries in Kaduna metropolis with the objectives of:

(i) estimating emission rates of particulate and gaseous pollutants.

(ii) simulating pollutant dispersion under different atmospheric stability conditions.

(iii) Validating model predictions against measured air quality data.

(iv) Assessing implications for environmental health and regulatory policy.

2. Materials and Methods

2.1 Study Area

The study was conducted in Kaduna metropolis. Kaduna State is located between latitude 10°38'58" N, longitude 7° 22'14" E and altitude 2,132 feet above sea level, one of Nigeria's largest industrial hubs. The city hosts textile, refinery, and food-processing industries among others, many of which operate with limited emission control technologies. Residential settlements are often located within 2–5 km of industrial estates, raising concerns of chronic exposure.

2.2 Data Collection

Pollutants measured included $PM_{2.5}$, PM_{10}, TSP, CO, SO_2, NO_2, and H_2S from five sampled locations which included Kaduna Refinery, Indomie Factory, Hilkman Gas Plant, PZ Cusson Factory and A. A. rano Diesel Plant. Emission data were obtained from industrial stacks using direct sampling and secondary data from industry records. Meteorological parameters (wind speed, wind direction, temperature, stability class) were obtained from the Nigerian Meteorological Agency.

Data collected for the gaseous pollutants in the five sampled locations in Kaduna are presented in Table 1.

Table 1: Emission rates (Q), correction factor (Ω) and dispersion modelling parameters for gaseous pollutants in the five sampled locations in Kaduna

Location	Emission source	Stack height (m)	CO		NO		NO_2		H_2S		SO_2		NH_3	
			Q (g/s)	Ω	Q (g/s)	Ω	Q (g/s)	Ω	Q (g/s)	Ω	Q (g/s)	Ω	Q (g/s)	Ω

Kaduna Refinery	32 hp diesel engine	5.00	1.55	12.50	0.50	24.50	1.50	6.50	0.28	72.50	0.50	28.50	0.30	78.50
Indomie Factory	28 hp diesel engine	5.00	12.40	2.51	5.00	4.93	15.00	1.645	1.86	7.95	5.10	3.65	4.80	4.60
Hilkman Gas Plant	12 hp diesel engine	2.00	10.50	3.20	3.50	6.98	12.40	1.97	1.25	10.98	2.41	7.60	2.60	8.25
PZ Cusson Factory	12 hp diesel engine	2.00	12.67	2.50	4.80	4.85	12.00	1.75	0.44	20.95	4.20	3.85	3.80	4.55
A. A Rano Diesel Plant	12hp diesel engine	2.00	11.22	3.55	3.86	5.25	12.20	1.55	0.21	38.75	3.42	2.55	2.82	6.35

2.3 Gaussian Plume Model

The Gaussian Plume equation is expressed as:

$$C(x,y,z;H) = \frac{Q}{2\pi u\sigma_y\sigma_z}\left[e^{-\frac{y^2}{2\sigma y^2}}\right]\left[e^{-\frac{(z-H)^2}{2\sigma z^2}} + e^{-\frac{(z+H)^2}{2\sigma z^2}}\right] \quad (1),$$

Here, C is the concentration of pollutants (μg/m^3), Q is the pollutant source emission rate (g/s), u is the wind speed (m/s), x is the downward distance from the emission source (m), y is the crosswind or lateral distance from the plume's centerline (m), z is the vertical distance of the plume's centerline above the ground (m), σ_y *and* σ_z are the plume's diffusion coefficients in the crosswind (y) and vertical (z) directions respectively, H is the effective stack height (m) which is given by Kavishwar, et al. (2014);

$$H = H_s + \Delta h \quad (2),$$

where H_s is the height of stack in meters and Δh is the plume rise which is evaluated from the Holland's model

$$\Delta h = \frac{v_s D}{u}\left[1.5 + 2.68 \times 10^{-3} P \cdot D\left(\frac{T_s - T_a}{T_s}\right)\right] \quad (3),$$

Where v_s is the gas velocity inside the stack in m/s, D is the internal diameter of the stack at exit point in m, u is the wind speed in m/s, P is the atmospheric pressure in millibars (mBar) and T_s *and* T_a are the stack gas temperature and ambient temperature in Kelvin (K).

It is assumed that the pollutant emission from the source is constant and the wind speed is also constant, then the diffusion coefficients $\sigma_y \, and \, \sigma_z$ can be obtained from the Briggs' equations for different stability classes using the downward distance x as follows [14]:

The results of Brigg's equations for Diffusion coefficients for the various stability classes are presented in Table 2.

Table 2: Briggs Equations for Diffusion Coefficients

Stability Classes	$\sigma_y\ (m)$	$\sigma_z\ (m)$
A	$0.22x(1+0.0001x)^{-0.5}$	$0.20x$
B	$0.16x(1+0.0001x)^{-0.5}$	$0.12x$
C	$0.11x(1+0.0001x)^{-0.5}$	$0.08x(1+0.0002x)^{-0.5}$
D	$0.08x(1+0.0001x)^{-0.5}$	$0.06x(1+0.0015x)^{-0.5}$
E	$0.06x(1+0.0001x)^{-0.5}$	$0.03x(1+0.0003x)^{-0.5}$
F	$0.04x(1+0.0001x)^{-0.5}$	$0.016x(1+0.0003x)^{-0.5}$

Source: Holmes, & Morawska (2006)

Results for the emission rates (Q), correction factor (Ω) and dispersion modelling parameters for particulate matter in the five sampled locations in Kaduna are presented in Table 3

Table 3: Emission rates (Q), correction factor (Ω) and dispersion modelling parameters for particulate matter in the five sampled locations in Kaduna

Location	Emission source	Stack height (m)	$PM_{1.0}$		$PM_{2.5}$		PM_{10}	
			Q (g/s)	**Ω**	**Q (g/s)**	**Ω**	**Q (g/s)**	**Ω**
Kaduna Refinery	32 hp diesel engine	5.00	0.10	120.0	0.30	70.00	0.70	18.00
Indomie Factory	28 hp diesel engine	5.00	2.32	8.50	12.3	3.50	32.22	2.50
Hilkman Gas Plant	12 hp diesel engine	2.00	1.39	14.80	11.33	4.80	30.11	2.80
PZ Cusson Factory	12 hp diesel engine	2.00	2.12	11.35	11.84	4.25	33.10	2.45
A. A Rano Diesel Plant	12hp diesel engine	2.00	1.80	12.75	11.13	5.15	31.00	2.95

2.4 Model Validation

Predicted concentrations were validated against observed ambient air quality data using the Root Mean Square Error (RMSE):

Table 4: RMSE values for all the pollutants across the stability classes

Pollutant	A	B	C	D	E	F
Kaduna Refinery (stackheight = 7 m)						
CO	5.420	4.780	3.900	3.940	4.680	8.910
H_2S	3.730	3.380	3.000	2.980	3.610	6.870
PM_1	2.380	1.480	1.060	1.020	1.990	3.780
$PM_{2.5}$	4.100	2.630	2.030	1.990	2.700	4.870
PM_{10}	4.100	2.640	2.040	2.000	2.710	4.870
Indomie Factory (stackheight = 5 m)						
CO	7.231	4.655	1.480	0.532	0.000	7.937
H_2S	0.008	0.006	0.002	0.001	0.000	0.000
PM_1	0.507	0.229	0.069	0.021	0.000	0.000
$PM_{2.5}$	0.729	0.374	0.122	0.040	0.000	0.000
PM_{10}	0.806	0.412	0.134	0.043	0.000	0.000
Hikmann Gas plant (stackheight = 2 m)						
CO	9.964	7.199	6.289	5.796	20.103	20.677
H_2S	4.146	3.756	3.129	2.503	0.973	0.066
PM_1	10.240	10.050	9.560	9.170	11.880	12.400
$PM_{2.5}$	12.950	12.540	11.830	11.310	14.030	14.420
PM_{10}	23.950	23.580	22.720	21.810	25.300	25.650
PZ Cussons Factory (stackheight = 2 m)						
CO	12.151	8.264	6.788	6.362	0.703	0.000
H_2S	5.273	5.785	5.656	3.176	0.000	0.000
PM_1	13.345	10.974	10.291	8.533	0.004	0.000
$PM_{2.5}$`	31.623	30.719	29.900	27.663	0.009	0.000
PM_{10}	41.608	40.634	39.937	37.774	0.012	0.000
A.A Rano Diesel Plant (stackheight = 2 m)						
CO	25.920	27.910	28.230	25.280	24.170	26.620
H_2S	1.540	1.440	1.570	1.680	1.620	1.720
PM_1	20.560	20.950	21.270	20.670	20.870	21.080
$PM_{2.5}$	20.690	21.040	21.300	20.760	21.040	21.160
PM_{10}	29.130	30.040	30.390	29.170	29.640	30.040

3. Results and Discussion

3.1 Emission Characteristics

Emission profiles (Table 5) revealed that particulate pollutants dominated industrial outputs. TSP emissions reached as high as 4.2 g/s, compared to CO levels below 1.0 g/s. This aligns with earlier studies in Nigeria and underscores the particulate-heavy nature of local industries.

Table 5: Emission rates (Q), correction factor (Ω) and dispersion modelling parameters for gaseous pollutants in the five sampled locations in Kaduna

Location	Emission source	Stack height (m)	CO		NO		NO_2		H_2S		SO_2		NH_3	
			Q (g/s)	**Ω**	**Q (g/s)**	**Ω**	**Q (g/s)**	**Ω**	**Q (g/s)**	**Ω**	**Q (g/s)**	**Ω**	**Q (g/s)**	**Ω**
Kaduna Refinery	32 hp diesel engine	5.00	1.55	12.0	0.50	240	1.50	6.0	0.28	72.50	0.50	28.50	0.30	78.50
Indomie Factory	28 hp diesel engine	5.00	12.40	2.51	5.00	4.93	15.00	1.65	1.86	7.95	5.10	3.65	4.80	4.60
Hilkman Gas Plant	12 hp diesel engine	2.00	10.50	3.20	3.50	6.98	12.40	1.97	1.25	10.8	2.41	7.60	2.60	8.25
PZ Cusson Factory	12 hp diesel engine	2.00	12.67	2.50	4.80	4.85	12.00	1.75	0.44	20.5	4.20	3.85	3.80	4.55
A. A Rano Diesel Plant	12hp diesel engine	2.00	11.22	3.55	3.86	5.25	12.20	1.55	0.21	38.5	3.42	2.55	2.82	6.35

3.2 Dispersion Patterns

Simulation outputs (Figures 1–5) showed that stability class significantly influenced pollutant distribution. Under Class A conditions, pollutants dispersed widely with reduced ground concentrations, while under Class E, they remained concentrated within 2–4 km of the stack, creating "hotspots" of exposure

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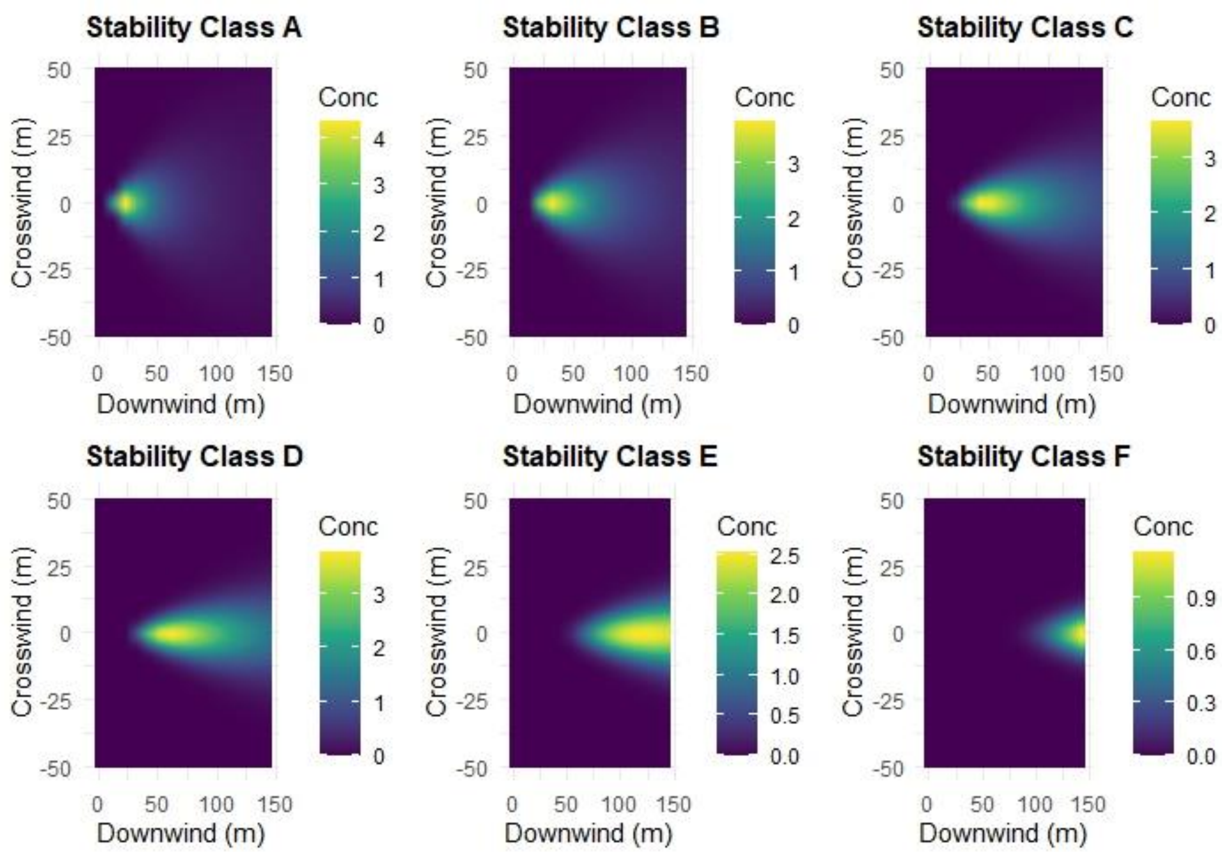

Figure 1: Spatial distribution of PM_{10} concentration using GPM at Indomie Factory across different stability classes

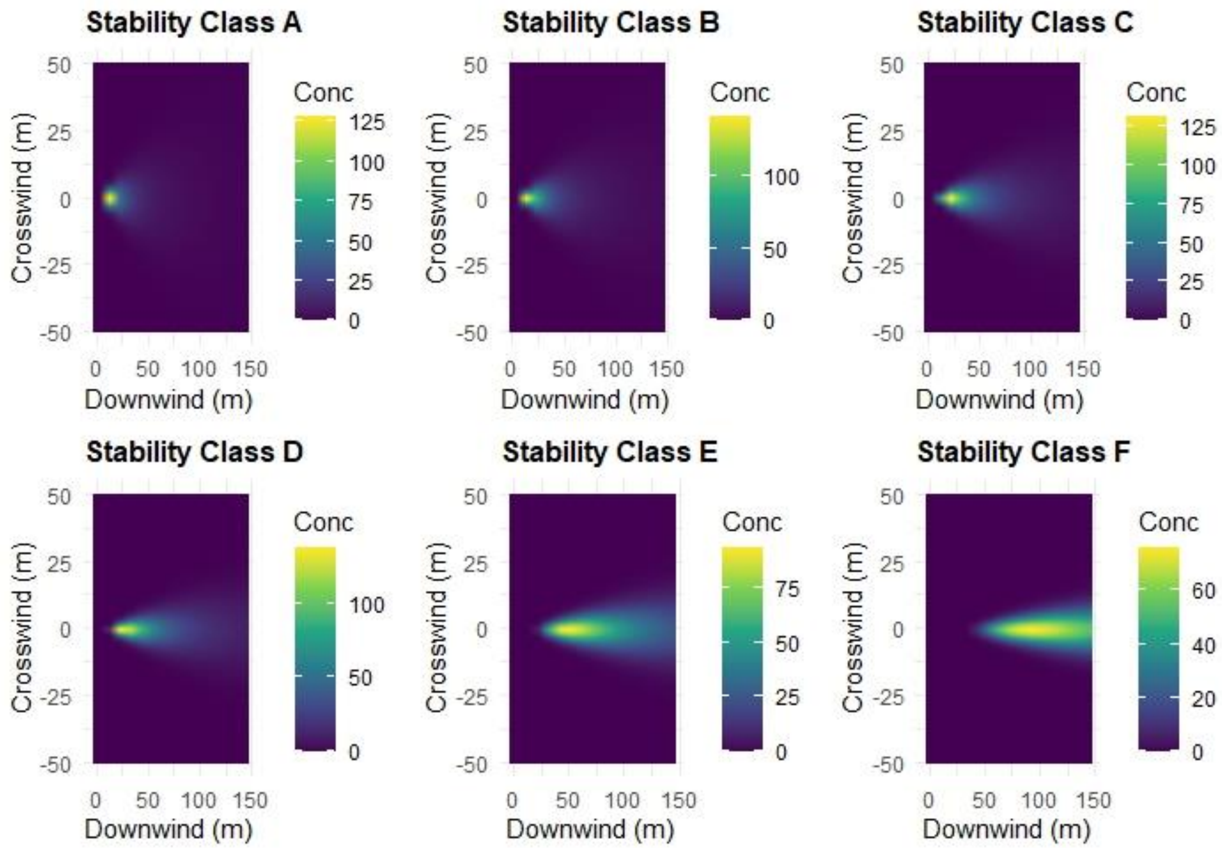

Figure 2: Spatial distribution of CO concentration using GPM at Hikman Gas Plant across different stability classes

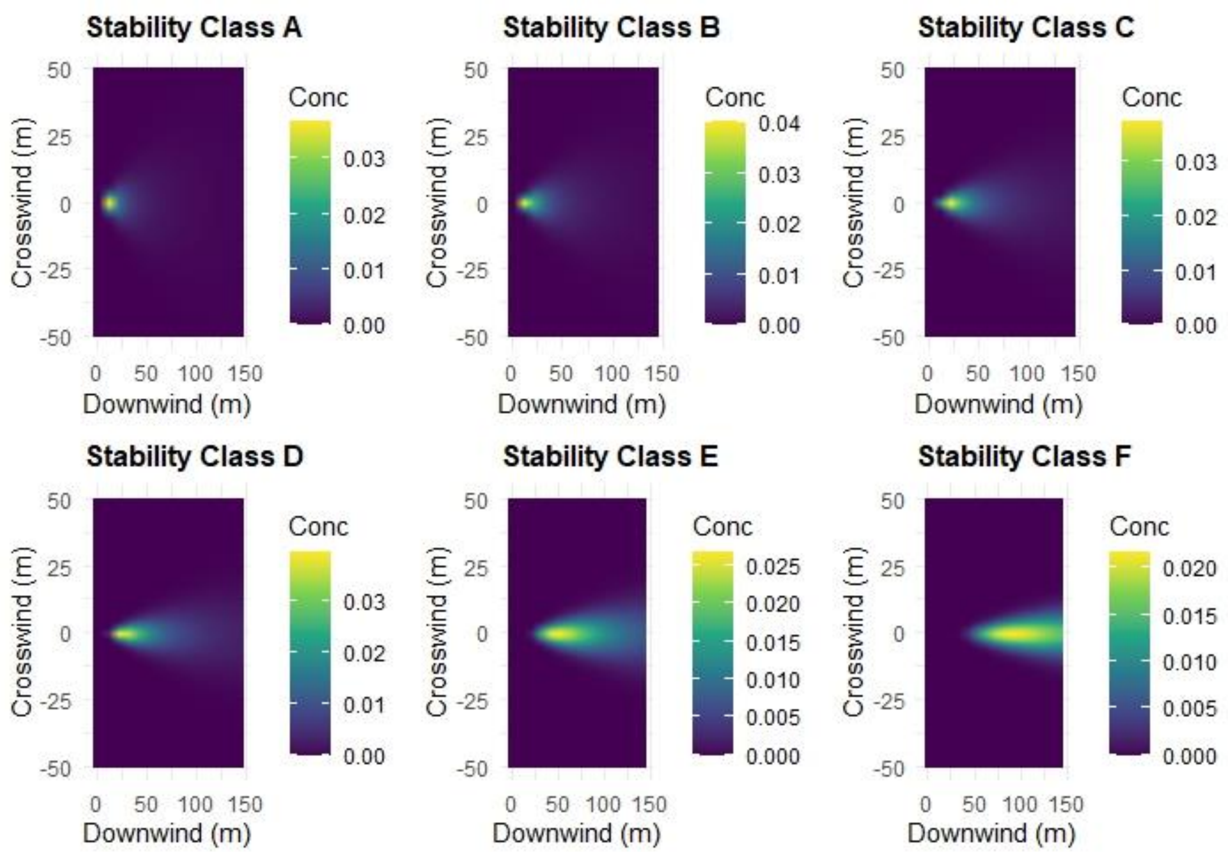

Figure 3: Spatial distribution of H_2S concentration using GPM at Hikman Gas Plant across different stability classes

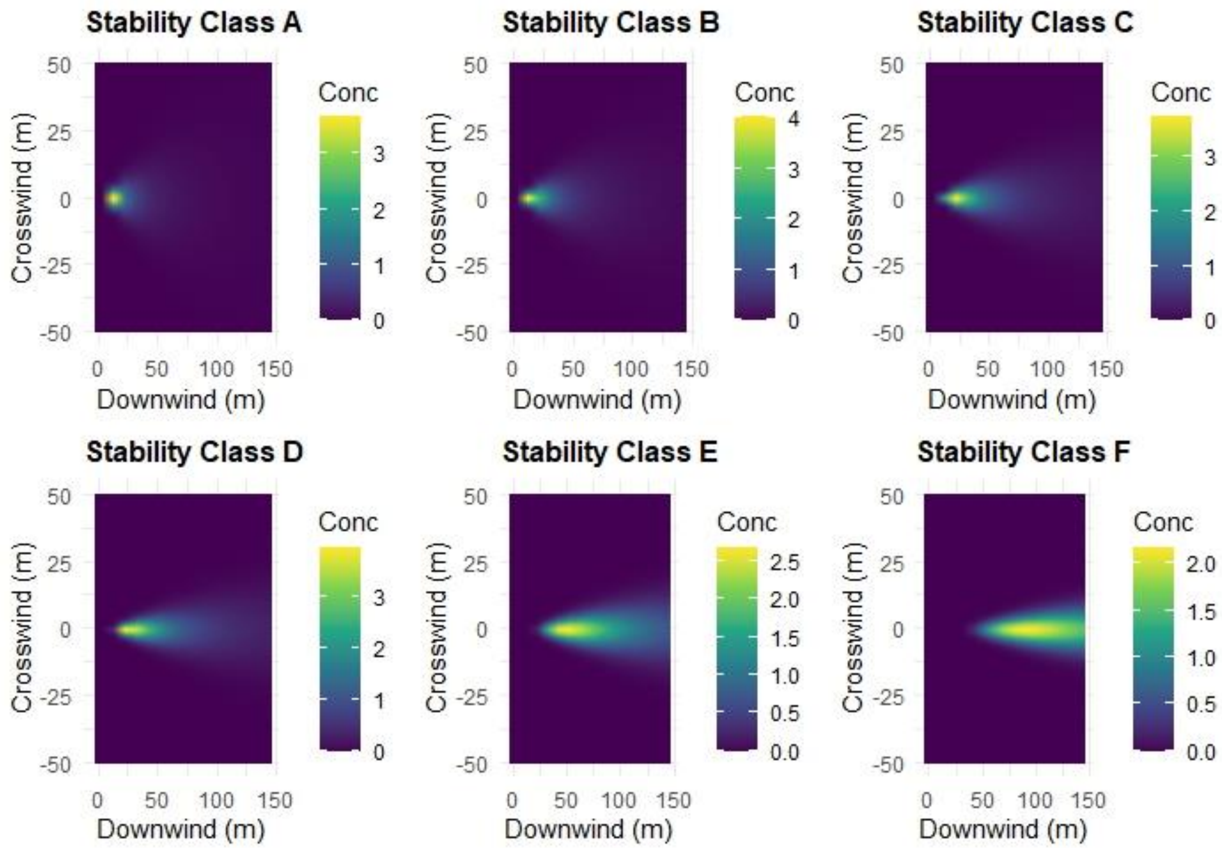

Figure 4: Spatial distribution of PM_1 concentration using GPM at Hikman Gas Plant across different stability classes

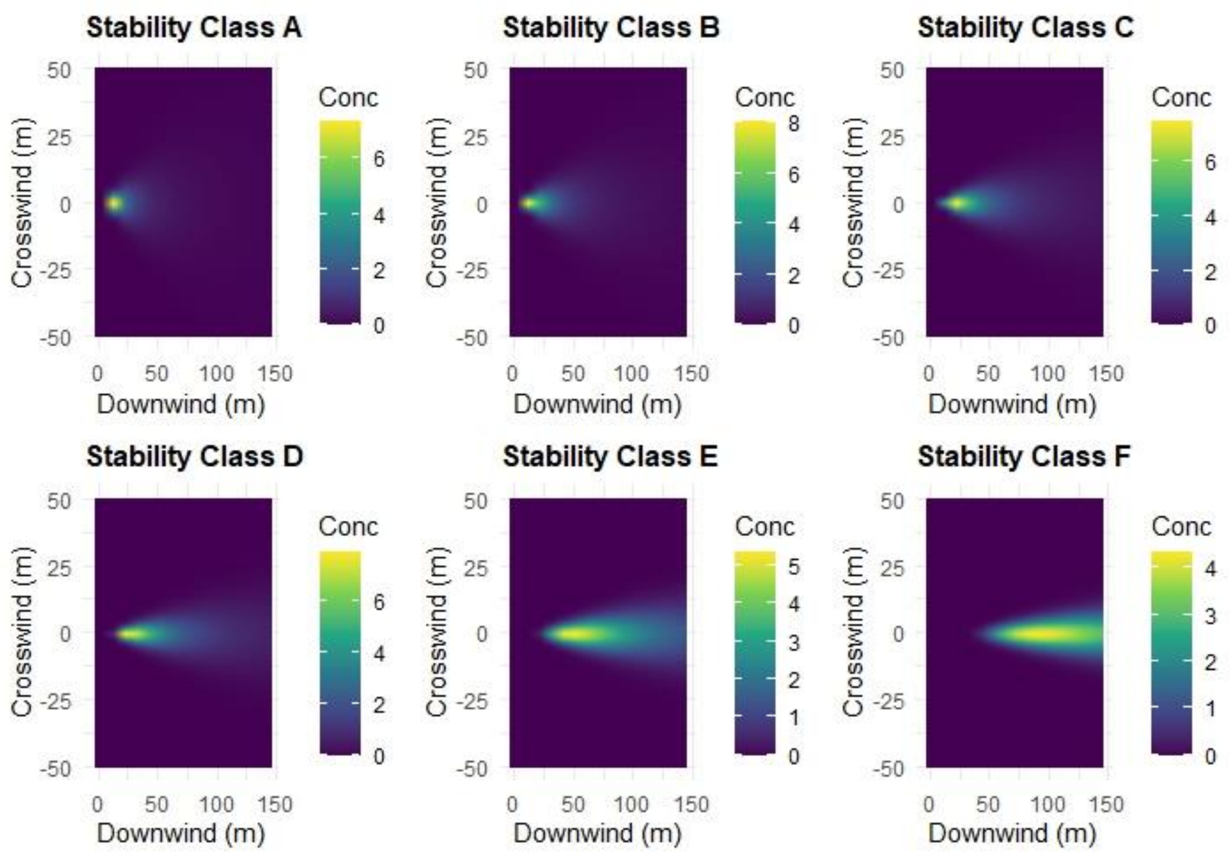

Figure 5: Spatial distribution of $PM_{2.5}$ concentration using GPM at Hikman Gas Plant across different stability classes

This supports [14] and [20], who highlighted atmospheric stability as a determinant of near-ground exposure.

3.3 Comparative Pollutant Behaviour

Particulate pollutants (PM_{10}, $PM_{2.5}$) were more localized than CO and SO_2, reflecting their higher deposition velocities [21]. Figure 6 illustrates that PM_{10} concentrations peaked sharply around the source, while CO dispersed more evenly.

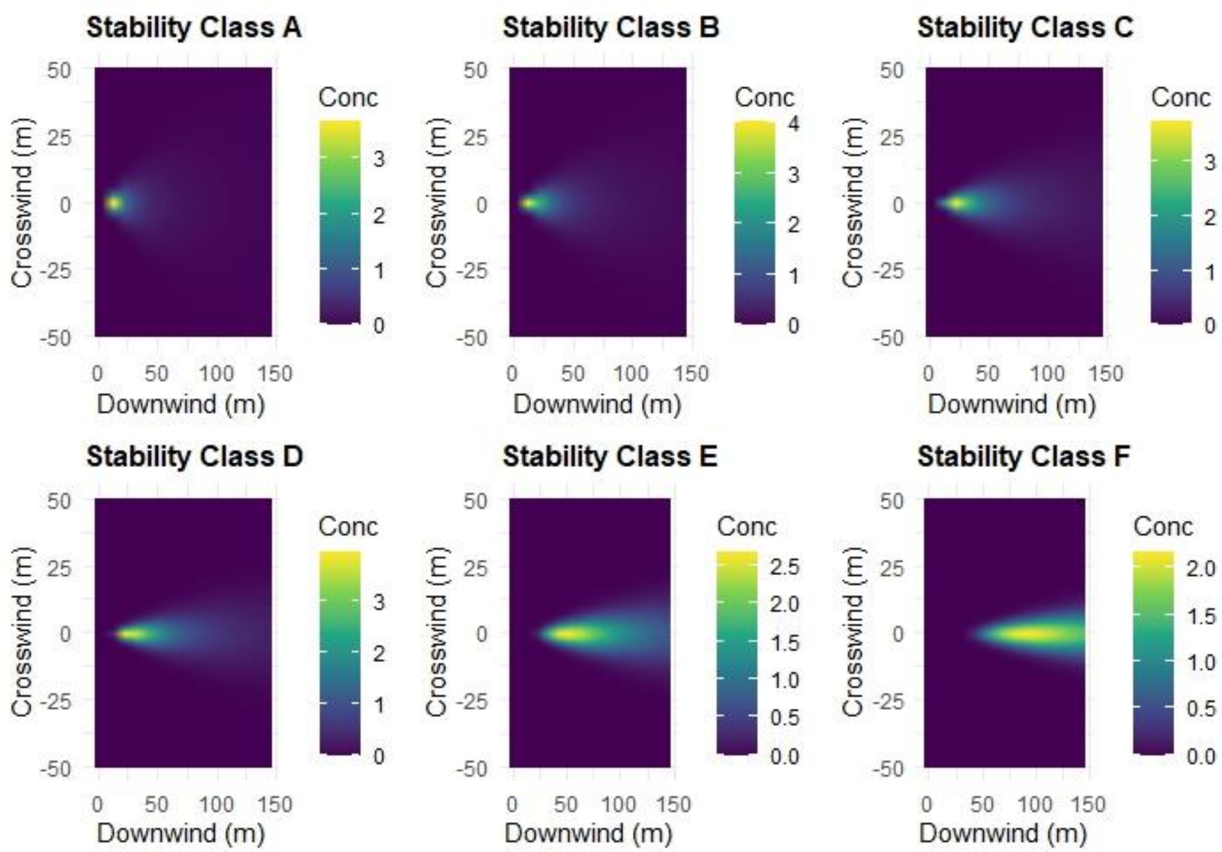

Figure 6: Spatial distribution of PM_1 concentration using GPM at Hikman Gas Plant across different stability classes

3.4 Model Validation

Validation (Table 6) showed RMSE values <10% of observed means, confirming high predictive reliability. For $PM_{2.5}$, RMSE was 4.8 µg/m³, within US EPA acceptance limits (2015). Similar validation success

Table 6: RMSE values for all the pollutants across the stability classes

Pollutant	A	B	C	D	E	F
Kaduna Refinery (stackheight = 7 m)						
CO	5.420	4.780	3.900	3.940	4.680	8.910
H_2S	3.730	3.380	3.000	2.980	3.610	6.870
PM_1	2.380	1.480	1.060	1.020	1.990	3.780
$PM_{2.5}$	4.100	2.630	2.030	1.990	2.700	4.870
PM_{10}	4.100	2.640	2.040	2.000	2.710	4.870
Indomie Factory (stackheight = 5 m)						
CO	7.231	4.655	1.480	0.532	0.000	7.937
H_2S	0.008	0.006	0.002	0.001	0.000	0.000
PM1	0.507	0.229	0.069	0.021	0.000	0.000

$PM_{2.5}$	0.729	0.374	0.122	0.040	0.000	0.000
PM10	0.806	0.412	0.134	0.043	0.000	0.000
Hikmann Gas plant (stackheight = 2 m)						
CO	9.964	7.199	6.289	5.796	20.103	20.677
H2S	4.146	3.756	3.129	2.503	0.973	0.066
PM1	10.240	10.050	9.560	9.170	11.880	12.400
PM2.5	12.950	12.540	11.830	11.310	14.030	14.420
PM10	23.950	23.580	22.720	21.810	25.300	25.650
PZ Cussons Factory (stackheight = 2 m)						
CO	12.151	8.264	6.788	6.362	0.703	0.000
H2S	5.273	5.785	5.656	3.176	0.000	0.000
PM1	13.345	10.974	10.291	8.533	0.004	0.000
PM2.5`	31.623	30.719	29.900	27.663	0.009	0.000
PM10	41.608	40.634	39.937	37.774	0.012	0.000
AA Rano Diesel Plant (stackheight = 2 m)						
CO	25.920	27.910	28.230	25.280	24.170	26.620
H_2S	1.540	1.440	1.570	1.680	1.620	1.720
PM_1	20.560	20.950	21.270	20.670	20.870	21.080
$PM_{2.5}$	20.690	21.040	21.300	20.760	21.040	21.160
PM_{10}	29.130	30.040	30.390	29.170	29.640	30.040

4.0 Discussions

In Indomie Factory, where the stack height is 5 meters, RMSE values are very low under stability classes D and E, suggesting excellent model fit. However, higher RMSEs are observed under classes A and F. In unstable conditions (Class A), excessive turbulence may cause pollutants to disperse rapidly beyond the detection range of ground sensors, while in stable conditions (Class F), limited vertical mixing can lead to concentrated plumes remaining close to the source or dispersing narrowly, again causing a mismatch with sensor readings. The moderate stack height in this case supports a balance between dispersion and ground-level detection, particularly under neutral and slightly stable conditions.

For Hikmann Gas, PZ Cuzzon and AA Rano Diesel Factories with stack heights of 2 meters, RMSE values are generally high across most pollutants and stability classes. In Hikmann Gas Plant, the RMSE values spike significantly, especially under stable conditions (Classes E and F), due to poor vertical dispersion and pollutant accumulation near the ground, which results in high variability in concentrations that may not be well captured by ground sensors. In PZ Cuzzons, very high RMSE values for unstable and neutral conditions (Classes A to D) were observed, while RMSE values are near zero for Classes E and F, possibly indicating that under extremely stable conditions, the pollutants did not disperse far from the source and were either not detected by sensors or were underestimated by the model. However, these near-zero values may be misleading, as they might reflect measurement limitations rather than actual model accuracy. In AA Rano Factory, RMSE values are uniformly high across all stability classes, suggesting a poor model fit regardless of atmospheric condition. This could be due to an overly concentrated plume at such a low release height, leading to discrepancies between predicted and observed concentrations.

Generally, the analysis reveals that the model performs best at higher stack heights (particularly 5–7 m), with stability Class D consistently producing the lowest RMSE values due to its neutral and predictable dispersion characteristics. Unstable conditions (Classes A to C) can lead to over-dispersion, while stable conditions (Classes E and F) often result in poor vertical mixing and narrow plumes, which challenge the model's alignment with ground sensor data. Additionally, low stack heights contribute to higher RMSE values due to limited initial dispersion and strong influence of near-ground turbulence or lack thereof . These findings explain the importance of selecting appropriate stack heights and accounting for atmospheric stability when applying Gaussian plume models to estimate pollutant concentrations and validate them against ground-based observations.

4. Conclusion

The Gaussian Plume Model effectively simulated pollutant dispersion from Kaduna industries, revealing that:

i. particulates dominate industrial emissions.
ii. atmospheric stability strongly controls pollutant concentrations.
iii. model predictions matched measured data with high accuracy.
iv. control strategies must focus on particulates and incorporate meteorological forecasts.

Dispersion modelling should therefore be institutionalized as part of Nigeria’s environmental regulatory framework, complementing routine air quality monitoring and strengthening health protection in industrial cities.

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